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Predicting the value of professional sport clubs. A study of European soccer, 2005–2018

Abstract. This article aims to build a general valuation model that can be applied by investors and current shareholders of professional sport clubs from different countries and leagues. The study is based on panel data on the valuation of soccer clubs published annually by Forbes. Authors analyze all value-drivers that were used previously, expanding the time horizon (number of observations) and incorporating various models including linear and non-linear mixed effect regressions. The best performance is obtained using a mixed-effect model with tree-based fixed part. The following determinants were found significant for the fixed effect: revenue and number of Google search requests. Analysis of actual deals in 2015–2020 confirms the model's predictive ability. It is also shown that since Forbes overestimates the market value of soccer clubs, the proposed model predicts an upper bound on the real value. In this regard, transactions with real value exceeding the estimates are of particular interest. A deeper analysis of such transactions allows to identify additional "non-soccer" factors affecting the deal. Therefore, the proposed model can serve as a tool for the rapid assessment of a soccer club based on open data.

Keywords: sport *club value, valuation of soccer club, sports investments, sports finance, mixed effect model.*

JEL Classification: C13, G12, G17, G32, Z23.

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Introduction

Since 1989 the English Premier League has transformed into business (Conn, 1997); many off field changes have resulted in what can be called the new business of soccer. Among these changes are: growing revenues from television contracts, executive boxes, sponsors and merchandising (according to UEFA, top-division club revenues have increased by 80% over the last ten years, rising from €11,719mln in 2009 to €21,083mln in 2018) clubs as brands; clubs raising capital and listing on the Stock Exchange; investment trusts dedicated to soccer; hostile takeovers; the globalization of the player market; huge financial rewards available for players and directors (Morrow, 1999).

Growing revenues generated an interest of investors, who raised the matter of sport club' value and its determinants. Impressive growth of M&A deals in soccer, new records in transfer, TV- and sponsor contracts, and huge investments in new stadiums prove that soccer clubs are in fact a business. According to (Damodaran, 2014a), "much as we like to glorify the beauty of sports and praise it in its purest forms, it is increasingly a business". European soccer has increasingly become an attractive investment target in recent decades, due to the overall transformation of the industry. The prime motivation of investors, ranging from well-known local businessmen to foreign billionaires,

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from private equity firms to supporter groups, can be explained by the conversion of soccer clubs from community-based non-profit organizations to profit-making brands with global reach. Despite the overall impact of the coronavirus pandemic on the soccer ecosystem has been devastating, the transaction market remained active (KPMG, 2020). Investors treating soccer club as an asset need to adapt traditional valuation models to the specifics of the soccer business and analyse particular value-drivers. This shows the relevance of research, aimed for analysing the determinants of professional soccer club value, and combining them into a single model that could be used by investors.

We use the Forbes value score as the target variable since it is the largest dataset available (299 entries) – the first rating was published back in the year 2004[1]. As exogenous variables that determine the value, we consider various dimensions that are investigated by other authors (Alexander, Kern, 2004; Miller, 2007, 2009; Buschemann, Deutscher, 2011; Scelles et al., 2014, etc). These are financial indicators (for example, revenue and operating income), value of club's assets (transfer contracts), sports achievements (successes in the local championship and international tournaments), as well as infrastructure' base (stadium capacity), attendance and potential of the home region (number of residents and their income).

The Forbes' dataset contains repeated observations at different times, i.e., panel or longitudinal data. Therefore, we consider various options for panel regression, both – linear and non-linear, taking into account fixed and random effects together and separately. The best performance is achieved using a mixed-effect regression with non-linear (namely, tree-based) fixed part. Cross-validation on training data and analysis of actual deals in 2015–2020 confirms the model's predictive ability. We also found that Forbes overestimates the market value of soccer clubs. Therefore, the model trained on Forbes data predicts an upper bound on the real value. In this regard, transactions with real value exceeding the estimates are of particular interest. A deeper analysis of such transactions allows to identify additional non-soccer factors affecting the deal. Therefore, the proposed model can serve as a tool for the rapid assessment of a soccer club based on open data.

Literature review

2.1. Valuation of Soccer Clubs

Forbes published a list of the 20 most valuable European soccer teams back in the year 2004, using the financials for the 2002/2003 season, but never disclose the methodology they used. The only thing available is: "Team values are enterprise values (equity plus net debt) and include the economics of the team's stadium but exclude the value of the real estate" (Forbes, 2019). According to R. Fort (Fort, 2006), Forbes values are calculated as a multiple of revenues.

According to A. Damodaran (Damodaran, 2014b), in relative valuation, the value of an asset is compared to the values assessed by the market for similar or comparable assets. Using the value of these assets on the stock exchange or derived from M&A deals, price multipliers are calculated. Once the multiplier is determined, it is applied to a club under valuation. However, this overly simplistic approach is unsuitable for taking into account differences between soccer clubs in terms of the markets in which they operate, their broadcasting revenue sharing methods, operational efficiency and level of profitability, potential to succeed on-pitch at national and international level, etc.

[1] Last time the rating was published in 2019; it presents valuation for 2018.

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(KPMG, 2019). A. Damodaran (Damodaran, 2014a) states that the Forbes valuations are based on the most recent transaction prices in each sport.

Since 2016, KPMG Football Benchmark is publishing "The European Elite" report on 32 clubs' Enterprise Value, calculated with Revenue Multiple approach. Multipliers are derived from observations of similar clubs which are publicly listed (Comparable Companies Methodology) and acquisitions of similar companies (Comparable Transactions Methodology). Besides the authors mention the following metrics:

1) staff costs-to-revenue ratio;
2) number of Facebook, Twitter, Instagram and YouTube followers;
3) market value of the squad measured by KPMG's Player Valuation tool;
4) broadcasting rights and the distribution method;
5) stadium ownership.

All these items are considered in the "formula" or "algorithm" in KPMG report, but without specifying how to apply them. The study is based on the publicly available financial statements of two seasons (for example the report, published in May 2019 was based on the figures for the 2016/17 and 2017/18 football seasons and did not consider 2018/19 sporting results).

T. Markham in (Markham, 2013) proposed a model to value English Premier League clubs:

$$club\_value = \frac{(Revenue + Net\_Assets)(Net\_Profit + Revenue)}{Revenue} \times \frac{Stadium\_Capacity,\ \%}{Wage\_Ratio,\ \%}.$$

I. Solntsev (Solntsev, 2014) applied income approach to soccer clubs' evaluation and designed a model for estimating their value based on revenue, EBITDA, the value of squad, attendance of matches and engagement of fans in Facebook.

The key issue in modelling is the data. Forbes provides limited financial information for the limited number of years. Hence, we were obliged to use other sources, which could treat some metrics in the other way, taking into account differences in accounting practice, reporting currencies, fluctuation of exchange rates, and year-ends. One more point deals with selection of clubs: Forbes doesn't explain, how it chooses the clubs, confining with "most valuable soccer teams".

KPMG values 38 clubs with publicly available statutory financial statements and publish results for top 32 by Enterprise Value. These 38 clubs should be among:

- top 50 European teams by total operating revenues;
- top 50 teams according to the 5-year UEFA coefficient;
- top 30 European teams by the number of social media followers (Facebook, Twitter, Instagram and YouTube combined).

So, both rankings consider only top clubs in different leagues. In terms of the data analyses and interpretation it would be better to have all local rivals, so that we could compare production processes in different leagues.

Finally, all valuations are published in May, based on financial statement as of June, 30 of the previous year (for majority of clubs) with January 1 as valuation date. But the value of soccer clubs could be extremely volatile; this could be seen through the example of public soccer clubs. According to (Gimet, Montchaud 2016), volatility of stock returns seems particularly vulnerable to the overall instability on stock markets and dependent on clubs' profit and net players' transfers and, to a lesser extent, on sporting outcomes.

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Table 1

Different values of the same soccer clubs[2]

Soccer clubs as of June 30, 2018, $Mln	Forbes	KPMG	University of Liverpool	Market cap. + Net debt	The ratio of Forbes' value to the market
Real Madrid	4239	3675			
Barcelona	4021	3050			
Manchester United	3808	3655	2648	3578	1.064
Bayern Munich	3024	3073			
Manchester City	2688	2804	2999		
Chelsea	2576	2538	2049		
Arsenal	2267	2289	1736		
Liverpool	2183	2388	2049		
Tottenham Hotspur	1624	1913	2331		
Juventus	1512	1764		1442	1.049
Paris Saint-Germain	1092	1499			
Atlético Madrid	953	1145			
Borussia Dortmund	896	1236		517	1.733
Schalke 04	683	872			
Inter	672	788			
Roma	622	588		317	1.962
West Ham United	616	658	369		
Milan	583	632			
Everton	476	619	461		
Newcastle United	381		486		

In soccer, success today leads to revenue in the future. P. Sloan (Sloan, 1971) treats maximization of playing success as a subject to a break-even constraint. The authors (Arnold, 1991; Szymanski, Kuypers, 1999) found that sporting success influenced positively revenues and salaries. L. Sánchez (Sánchez et al., 2020) states that profitability and success on the football pitch may be connected in many ways. Sports success may lead to profits because victories on the pitch attract fans to the stadiums and increase attention from the media. This means higher attendance and TV rights and more interest from sponsors. All this implies more revenues. This influence will be positive if the increase in revenues is higher than the costs but will be negative if the increase in revenues is smaller. S. Szymanski (Szymanski, 2017) found than an increase in revenues led to a larger increase in costs for hiring talented players. It is extremely difficult to capture such information in team values.

The creative nature of valuation could be illustrated by comparing the figures from four different sources (table 1): Forbes; KPMG Football Benchmark; Liverpool University; Market capitalization on stock exchange plus net debt.

As Table 1 shows, Forbes' valuation exceeds market valuation. Moreover, this error is small for expensive clubs and dramatically increases for clubs with a smaller capitalization. The comparison of the actual values and Forbes estimates for the six clubs

[2] https://www.forbes.com/soccer-valuations/list/#tab: overall; https://www.footballbenchmark.com/documents/files/public/KPMG%20Football%20Benchmark_Football%20Clubs%20Valuation%20report_2019_WEB.pdf; https://news.liverpool.ac.uk/2019/05/03/man-city-overtake-man-united-as-premier-leagues-most-valuable-club/

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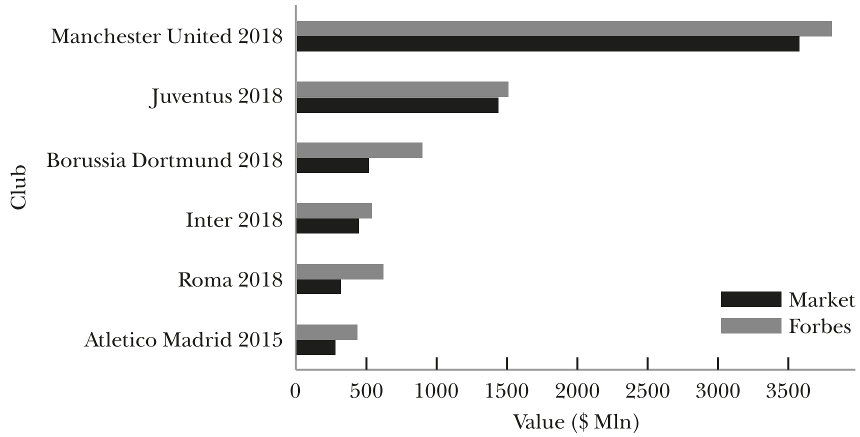

Figure 1
Market value and Forbes evaluations of soccer clubs

for which both figures are available is presented on Fig. 1. Four clubs are presented in Table 1, the deals with shares of two others – Atletico Madrid and Inter Milan – were announced in 2015 and 2016, respectively. According to the amount of deals, market assessment of Atletico Madrid was $280 Mln, corresponding Forbes estimation at the time of deal is $436 Mln. For the Inter Milan, the actual value is $447.8 Mln, and the Forbes estimation was $559 Mln.

Since we are using Forbes data to build the model, we must take this fact into account. Thus, we should consider the estimate derived from such a model as an upper bound for value.

2.2. Determinants of professional sports firm values

The majority of articles, considering value of sport firms, are based on the experience of American sport leagues (MLB, NBA, NFL, NHL). Compared to European practice these leagues use different management and funding models (league formats, salary gaps, an option for franchise to change the region, new taxes as a funding source, etc.), meaning that value determinants for European soccer clubs could differ as well.

Among the determinants of value D. Alexander, W. Kern (Alexander, Kern, 2004) used per capita income explaining the differences in demand for the tickets that affect club's revenues and earnings. The market size is controlled by city's population and regional identity. The authors also used club's final standing from the previous season and indicator called ''new facility'' (1 – if club has a new stadium or 0 – otherwise). All these metrics are considered in terms of ability to generate more revenues and increase the value.

P. Miller (Miller, 2007, 2009) extends sports performance to the current year and use winning percentages instead of standings. He also replaces ''new facility'' by facility age and includes club's age, years in city, and an ownership dummy for the stadium: 1 for clubs, that own the stadium, expecting a positive effect for private ownership.

B. Humphreys, M. Mondello in (Humphreys, Mondello, 2008) consider all professional clubs in a metropolitan area as competitors, meaning that the presence

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of more competitors reduces their value. They also used percentage of wins for the last five years, whereas B. Humphreys and Y. Lee (Humphreys, Lee, 2010) was calculating this percentage over 10 years.

Each person attending the game generates revenue for the club were meaning that the higher the number of attendees, the greater the value. In measuring this revenue stream A. Buschemann, C. Deutscher (Buschemann, Deutscher, 2011) applied Fan Cost Index (FCI), which tracks the cost of attending a sporting event for a family of four. The authors presumed that FCI would be positively related to the value. They also included the clubs' payroll and assume that high payroll expenses would offer a superior team quality and, therefore, would provide a better utility to fans. Hence, they anticipated that higher expenses would positively influence the value.

N. Scelles (Scelles et al., 2013, 2014) tested these variables for European soccer and proposed some new metrics: percentage of championship titles since the beginning of the competition, operating income provided by Forbes, player values provided by transfermarkt.de, and a dummy for new foreign ownership (1 – if new, 0 – if not).

According to (KPMG, 2019), revenue multiple is the most popular metric, since:

– it's quite easy to access and compare, as this item is less distorted by accounting adjustments;

– revenue multiples can be applied to the most troubled clubs with negative earnings;

– low level of volatility (compared to earnings).

However, focusing on revenues could lead to high value for clubs generating large volumes of revenues while making significant losses.

A. Damodaran values the Los Angeles Clippers, using Discounted Cash Flow (DCF) approach, which is based on free cash flow (Damodaran, 2014a). This demonstrates that probably revenues are not enough in determining the value of a soccer club. Expenses in soccer are getting higher each season and definitely should be considered by potential investors.

Potential investors often consider revenue as a key metric in determining the value of an asset. In discussing the English Premier League, S. Szymanski and R. Smith (Szymanski, Smith, 1997) described the following production cycle for a soccer club. Necessary skills are bought on a competitive player's market. The amount of skill acquired by a club determines its sport achievements. Sport results determine the revenue a club earns from prizes, attendance, television rights, sponsorship, etc. Revenue in turn determines investments that club can allocate to improve the skills of the team in the next season.

Later, A. Baroncelli and M. Lago (Baroncelli, Lago, 2006), based on the analysis of the Italian League, extended this definition identifying two alternative models: leading and small clubs. The leading club is aimed at the transformation of sports results in revenue. This is achieved by creating a competitive team with a given amount of money and transforming its potential into revenue, as described by S. Szymanski and R. Smith (Szymanski, Smith, 1997).

A small club generates revenue primarily through the sale of 'home grown' players. The production cycle begins with scouting talented young players for a relatively low price. Next, a club develops these players and transfers the team's potential into sporting results. Finally, such results provide the club with higher revenues (mainly

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through the sale of the players but also from sponsors, television, gate receipts). These financial resources are used to restart the cycle with the acquisition of new players.[3]

Other authors (Scelles et al., 2014; Zelenkov, Solntsev, 2017) also studied soccer clubs the goal of which is not revenue, but rather a positive image of their owners. However, the financial fair play rules established by UEFA restrict the ability to raise funds and strengthen the team from sources not related to operational and sports performance. Therefore, in recent years, such clubs also shifted towards one of the described models.

Thus, the described production processes differ technologically, but they both aim to maximize revenue. Therefore, revenue can be viewed as a universal metric that measures the overall performance of a club regardless of its production model. This is supported by the fact that the correlation between revenue and the Forbes' soccer club evaluation is 0.9.

The determinants of professional sports firm values used by different authors are presented in table 2.

Table 2

Determinants of professional sport club value

Variable	Name	Description	Authors
Operating income, $ Mln	OI	Earnings before interest, taxes, depreciation and amortization, player trading and disposal of player registrations[3]	Scelles et al., 2014
Players value, $ Mln	PV	The transfer value of all players according to *transfermarkt.de*	Scelles et al., 2014
Fan Cost Index	FCI	The FCI tracks the cost of attending a sporting event for a family of four	Buschemann, Deutscher, 2011
Team payroll	TP	Payroll expenses as a measure of team quality	Buschemann, Deutscher, 2011
Facility ownership	FO	1 – if the club owns the stadium, 0 – if not	Miller 2007, 2009; Humphreys, Mondello, 2008; Scelles et al., 2014
New foreign ownership	NFO	1 – if foreign investors bought the club (or share) in previous season, 0 – if not	Scelles et al., 2014
Franchise age	YL	Together with "years in city" metric, another approach – "years in the league"	Miller 2007, 2009; Buschemann, Deutscher, 2011
Facility age	FA	Different approach regarding the redevelopments and renovation	Alexander, Kern, 2004 – "new facility"; Miller 2007, 2009; Scelles et al., 2014; Humphreys, Mondello, 2008; Humphreys, Lee, 2010; Buschemann, Deutscher, 2011
Attendance	AT	Average number of people attending the matches in local competition	Buschemann, Deutscher, 2011; Scelles et al., 2014
National sports performance, t	NPC	Percent of wins in domestic league: – t is a valuation year (season); – $(t-1)$ is the previous season	Miller 2007, 2009; Scelles et al., 2014
National sports performance, $t-1$	NPP		Alexander, Kern, 2004 – standings; Miller 2007, 2009; Buschemann, Deutscher, 2011; Scelles et al., 2014
National historical sports performance	NH	Percent of champion titles since the start of national competitions	Humphreys, Mondello, 2008–5 years; Humphreys, Lee, 2010–10 years; Scelles et al., 2014

[3] https://www.forbes.com/pictures/5b0d3f1aa7ea436b547e91f8/soccer-team-values-2018/#2516a46e2d28

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End of Table 2

Variable	Name	Description	Authors
Continental sports performance, t	CPC	Corresponds to a measure in a current (t) and previous ($t-1$) season with a predetermined code: 6 — for a champion title; 5 — for final; 4 — for semifinal; 3 — for quarterfinal; 2 — for the last 16; 1 — for elimination during the group stages; 0 — for no participation	Scelles et al., 2014
Continental sports performance, $t-1$	CPP		Scelles et al., 2014
Continental historical sports performance	CH	Percent of wins in Champions league	Scelles et al., 2014
Local competition strength	LCS	The number of other clubs ranked in Forbes in the league	Humphreys, Mondello, 2008; Scelles et al., 2014
Population in functional urban area (FUA)	POP	To control for market size	Alexander, Kern, 2004; Miller, 2007, 2009; Humphreys, Mondello, 2008; Humphreys, Lee, 2010; Scelles et al., 2014
Regional annual real per capita income in FUA	RAI	To control for differences in demand	Alexander, Kern, 2004; Scelles et al., 2014

Proposed Method

3.1. Prediction Model

The Forbes' dataset based on which we develop our model contains repeated observations of objects at different times, i.e., panel or longitudinal data. Let y_{it} be the target variable measured for the i^{th} object in time t, x_{it} is the set of k explanatory variables, and ϵ_{it} is the corresponding error; $i=1,\ldots,n$; $t=1,\ldots,T$.

The simplest form is the pooled model

$$y_{it} = \beta x_{it} + \epsilon_{it}. \quad (1)$$

The pooled model does not take into account the panel data structure. It also assumes that all errors are not correlated with each other and with x_{it}.

This type of model was used by N. Scelles et al. (Scelles et al., 2014), but the authors' goal was to investigate the determinants of the value of soccer clubs rather than build a predictive model. Nevertheless, they obtained a fairly high coefficient of determination ($R^2 = 0.915$), which allowed them to make some conclusions regarding the structure of value.

The fixed effect model allows taking into account effects associated on the one hand with the observed entities, and on the other hand, over time:

$$y_{it} = \alpha_i + \beta x_{it} + \mu_t + \epsilon_{it}, \quad (2)$$

where α_i is an individual effect of the object i, which is independent of time and μ_t is the time effect, which is the same for all entities at the time t.

This model is widely used for econometric analysis; however, it has limitations that oppose its application as a predictive model. The point is that effects are determined only for objects (entity or time) presented in the training set; the model does not have the means to predict them for unseen examples. So, we reduce this model considering an entity effect only (i.e., $\mu_t = 0$). To predict the value of y_{it} for out of sample object, the model Eq. (2) must be supplemented with the predictor of α_i, i.e., this requires yet another regression model $\alpha_i = f(x_{it})$. The alternative random effect model assumes that individual differences between objects are random.

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The mixed-effects model allows us to take into account the fixed effects as well as random effects at the same time. In matrix notation linear mixed-effect (LME) model can be represented as

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{Zu} + \varepsilon, \quad (3)$$

where $\mathbf{y}$ is a known vector of observations with expected value $E(\mathbf{y}) = \mathbf{X}\beta$; $\mathbf{X}$ is the matrix of fixed-effect covariates; $\mathbf{Z}$ is the matrix of random effect covariates; β and $\mathbf{u}$ are unknown vectors of fixed and random effects correspondingly; $E(\mathbf{u}) = 0$ and $\mathrm{var}(\mathbf{u}) = G$. The limitation of this model (and all those described above) is the hypothesis that the dependence of target on covariates is linear.

To overcome this limitation, models were proposed, which exchange fixed part of Eq. (3) by a non-linear function $f(\mathbf{X})$

$$\mathbf{y} = f(\mathbf{X}) + \mathbf{Zu} + \varepsilon, \ \mathbf{u} \sim N(0, G), \quad \varepsilon \sim N(0, \sigma). \quad (4)$$

The random part, $\mathbf{Zu}$, is assumed linear. It is also assumed in this formula that $\mathbf{u}$ and ε are independent and normally distributed and that the between-object observations are independent.

The authors (Hajjem et al., 2011; Sela, Simonoff, 2012) independently proposed to use the decision tree algorithm within the expectation maximization framework for $f(\mathbf{X})$ modelling in Eq. (4). Later, A. Hajjem (Hajjem et al., 2014) extended this solution using the random forest algorithm (Breiman, 2001).

Thus, we will consider the following alternative approaches to predict the value of a soccer club:

– the Pooled model (Eq. 1) since it was used in (Scelles et al., 2014) to analyze determinants of soccer club value;

– the Panel model (Eq. 2), augmented by a regression $e_{it} = f(x_{it})$ for predicting the effects. In this case, the linear model (Eq. 2) is first trained, and the effects e_{it} are calculated. Next, the second regression model is trained to predict the effects based on the matrix of covariates $\mathbf{X}$. To obtain a prediction for a new object, the results of the Panel model and second regression model are summed up. Since the effects e_{it}, in general, are non-linear, we will use the Gradient Boosting algorithm to model them. Further, we will refer to this approach as the Panel-GB model;

– the Linear Mixed Effect model (LME) presented by Eq. (3);

– the Random Effects Expectation Maximization (RE-EM) tree proposed in (Sela, Simonoff, 2012);

– the Mixed Effed Random Forest (MERF) proposed in (Hajjem et al., 2014);

– the RE-EM and MERF are based on Eq. (4).

3.2. The Data

All factors, described in previous research (Table 2), would be used in this paper together with some additional features, which potentially could determine the value of soccer club. Table 3 lists the parameters collected for clubs from nine countries that have been included in the Forbes rankings in 2005–2018 (299 entries). Column R^2 contains the correlation coefficient with the target variable (*Value*).

According to N. Scelles et al. (Scelles et al., 2014), the capacity to control costs and generate operating income is a determinant of value, but not a necessary condition. A club can counterbalance a negative operating income, but in any case, it is preferable to maximize operating income. For some years Forbes didn't publish operating

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Table 3

Summary statistics

Variable	Source	Mean	SD	Min	Max	R^2
Value, $Mil	Forbes	941	915	106	4239	1
Operating income, $Mil	Forbes, The Swiss Ramble	48	60	−123	288	0.695
Revenue, $Mil	The Swiss Ramble	316.9	179.3	81.0	896.0	0.900
Players value ($Mil)	transfermarkt.de	343	209	69	1210	0.803
Attendance	european-football-statistics.co.uk	51576	14813	18085	81178	0.522
Facility age	wiki	12	7	0	35	0.064
Facility ownership	wiki	0.582	0.494	0	1	0.295
Stadium seats	wiki	60935	17978	22500	99354	0.390
Percent capacity, %	european-football-statistics.co.uk	87	15	38	100	0.156
National sports performance, t, %	whoscored.com	55	15	8	87	0.458
National sports performance, $(t-1)$, %	whoscored.com	55	15	8	87	0.459
National historical sports performance, %	whoscored.com	13	11	0	44	0.370
Continental sports performance, t	whoscored.com	1.719	1.812	0	6	0.422
Continental sports performance, $(t-1)$	whoscored.com	1.635	1.824	0	6	0.458
Continental historical sports performance, %	whoscored.com	3	5	0	21	0.492
Local competition strength	Forbes	5.261	2.584	1	10	0.026
Population in functional urban area, Mln	stats.oecd.org	5.718	3.388	0.662	14.161	0.181
The annual number of search requests made to Google about the club, Mln	trends.google.com	20.06	19.33	0.974	100.0	0.852

income. Missing date was taken from The Swiss Ramble and annual reports available in public access. Figures in Euro and GB Pounds were recalculated to US Dollars, using an average exchange rate for particular year.

As discussed above, the Forbes valuation is calculated as a multiplier of revenue (Fort, 2006; Scelles et al., 2014), so this factor should be added to the model. As shown in Table 2, its correlation with the target variable of 0.9 should support good predictive ability.

Based on the same considerations, the players' value is also a potentially important metric, as it allows us to assess the club's prospects. Player values are taken from German website (www.transfermarkt.de), which estimates it according to fans' discussions and experts' evaluations (Scelles et al., 2014).

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To account for efficiency in terms of facility' management and communication with fans, together with attendance a percent capacity (i.e., the mean number of stadium seats occupied by the visitors) was used.

Fans are the most important asset for every sport club (but not recognized as an asset in financial statement), impacting all revenue streams. According to N. Scelles et al. (Scelles et al., 2013), social media data could be used in valuation models. The number of fans on Facebook or the number of followers on Twitter can be a measure of an international dimension. Number of fans in social media could have a positive impact on values. The problem, however, is that this data is not available for all the years in the sample. In this research we use Google Trends metric, describing the search interest relative to the highest point on the chart for particular year (average) worldwide. A value of 100 is the peak popularity for the term. A value 50 means that the term is half as popular.

To get the distribution of this metric over the years, we summarized the monthly values obtained from the Google Trends app and then normed those to the highest value (FC Barcelona in 2017). Thus, the measurement of search requests on FC Barcelona in 2017 is 100, the indicators of other clubs show the level of interest compared with this peak. This metric has a correlation with the value of 0.852.

Some metrics are tricky in terms of treating the data. For example, N. Scelles et al. (Scelles et al., 2014) used the date of construction in calculating the facility age and had the maximum number of 136 years for it. Indeed, some stadiums were built in the 19th century, for example, Stamford Bridge — in 1877 and Enfield — in 1884. But since then they were rebuilt, and in our model, we used the date of such renovation.

In terms of sport results, we used the same approach as (Scelles et al., 2014). Juventus Football Club, which was relegated in 2006 and ranked last for the season 2005/2006 in the Italian Serie A, was allocated with seven wins — the same number of points, earned by Treviso, the team that finished last. For season 2006/2007 in Italian Serie B, Juventus FC's percentage of wins was divided by 2. We proceeded in the same way for Leeds United in 2004–2005 and Newcastle United in 2009–2010. In the Champions League, sports performance in t and $t-1$ corresponds to a measure with a predetermined code: 6 — for a champion title; 5 — for final; 4 — for semi-final; 3 — for quarterfinal; 2 — for the last 16; 1 — for elimination during the group stages; 0 for no participation.

Finally, we chose a logarithm of Value as a target variable because it is not equally distributed (Buschemann, Deutscher, 2011; Scelles et al., 2014). We also performed logarithmic transformations for some other exogenous variables (Revenue, Attendance, Player value, Population, and Stadium seats) for a similar reason.

We also ran tests for structural breaks to prove data continuity. As we are dealing with panel data with gaps (not all objects are observed in all periods), the structural break test is a problem, despite the number of published methods, there is no generally accepted approach. Therefore, we used the rolling Chow test for the mean log(*Value)* time series, testing for a possible break between 2007 and 2015. All corresponding *p*-values are above 0.9, so we must accept the hypothesis that the regression coefficients before and after the possible break are equal, i.e., there is no structural break in the data.

3.3. Experiment design

Each model under consideration should be tuned based on the data to ensure maximum performance. The tuning process includes the selection of significant features, as well as tuning hyperparameters. To do this, we used a combination of several

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methods. For statistical models (Pooled, Panel, LME), this is a selection of features by the *T* statistics. For machine learning models (GB, RE-EM, MERF), we used a grid search for optimal hyperparameter values.

To estimate the performance of these models, we used a classic *N*-fold cross-validation procedure with $N = 10$. The dataset is split into *N* parts; at each iteration, $(N–1)$ of them are used for training, last one for testing.

4. Results

Table 4 lists the results of hyperparameter optimization. The main metric that we used is the mean squared error (MSE), for reference, the R^2 value is also used. Table 4 shows the mean values and standard deviations (in brackets) of MSE and R^2 obtained from 10 folds cross-validation.

As a source for statistical models (Pooled, Panel), we used the LINEARMODELS[4] Python library. On the base of it, we implemented code that combines the panel regression model with effect predictor. To implement effect predictor, we used Gradient boosting regressor presented in SCIKIT-LEARN[5] library.

Since the implementation of the panel regression in LINEARMODELS allows us to consider separately fixed (entities and time) and random effects, we defined these attributes as hyperparameters. Also, we tuned the learning rate (LR) of Gradient boosting regressor (our experiments showed that other parameters have little effect on performance, so they were left with the default value). The optimal hyperparameter values for each panel regression configuration are presented in Table 4.

To evaluate the LME model, we used an implementation from the STATMODELS[6] library (Seabold, Perktold, 2010). Just like pooled regression, it does not involve tuning hyperparameters, so we just evaluated its performance using cross-validation.

The RE-EM method is based on a classification and regression tree (CART), so the only model hyperparameter is the maximum tree depth (*max_depth*). This parameter needs to be adjusted because trees that are not limited in depth are prone to overfitting. For experiments, we used *R* package REEMtree[7] (Sela, Simonoff, 2011).

Table 4

Performance of compared models

Model	Hyperparameters	MSE ($Mln)	R^2
Pooled	NA	89.4 (59.0)	0.822 (0.127)
Panel-GB	Effect = fixed (Entity & Time), LR = 0.030	129.5 (86.4)	0.745 (0.149)
	Effect = fixed (Entity), LR = 0.310	90.7 (59.7)	0.833 (0.088)
	Effect = fixed (Time), LR = 0.660	105.0 (79.3)	0.804 (0.158)
	Effect = random, LR = 0.19	82.3 (58.5)	0.853 (0.086)
LME	NA	135.9 (102.2)	0.762 (0.114)
RE-EM	*max_depth* = 3	**63.9 (27.8)**	0.841 (0.068)
MERF	$n_e = 20$	70.8 (52.5)	**0.860 (0.145)**

[4] https://bashtage.github.io/linearmodels/index.html

[5] https://scikit-learn.org/stable/index.html

[6] https://www.statsmodels.org/stable/index.html

[7] https://cran.r-project.org/web/packages/REEMtree/index.html

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Since the base model for MERF is a random forest, this model requires tuning the number of estimators (n_e). For experiments, we used the implementation of this algorithm presented in the Python library MERF[8].

5. Discussion

5.1. Performance of models

Based on the tests (see Table 4), we can draw the following conclusions. First, nonlinear models overcome linear ones in prediction accuracy. To check how outliers affect linear models, we conducted some additional tests. To identify outliers, we built a Pooled model on all data and excluded those observations whose residuals exceed a certain threshold. We chose the optimal value of this threshold so that the model built on the data without outliers has the minimum MSE. As a result, we obtained for the model on outlier-free data (278 observations from 299 available) MSE = 89.8 (60.7) and R^2 = 0.815 (0.135), which is worse than the Pooled model built on all data (Table 4). Similar results are obtained for all other models. Thus, it can be concluded that removing outliers did not improve the predictive ability of the models, moreover, it increases both bias and variance.

Of the linear models, the random effect regression shows the best performance. This suggests that from the point of view of linear models, there are no specifics in club management, and there is no time impact, which is similar for all clubs.

Both models (RE-EM and MERF), which include a nonlinear fixed effect, provide much more accurate predictions. RE-EM has the best performance in terms of MSE; MERF outperforms all other models according to R^2. Perhaps these results are explained by the fact that MERF is a more complex model, so it overfits to training data. Therefore, it predicts the overall trend quite well (and therefore has a better R^2), but at the same time, produces a relatively high bias.

Since our aim is to build a predictive model with high accuracy, we consider MSE to be the more informative metric. In addition, it is important for investors to understand the reasons for the proposed decision. From this point of view, RE-EM, which is based on a single regression tree, is much easier to interpret than MERF, which is based on random forest. Therefore, we will use RE-EM model below (Section 5.3) to analyze M&A deals in soccer.

5.2. Determinants of value

Understanding the factors that affect the value of the club is vital for investors, as it allows them to make reasonable decisions. In this section, we analyze the significance of the variables used to build the predictive models (see Table 4).

Table 5 lists the variables that are significant for the Panel-GB model with a random effect. The presented data is the covariate, its corresponding coefficient β (cf. Eq. (2)) with standard error, *T* statistics and p-value.

Since MERF uses Random Forest to model the fixed effect, we can determine the importance of each covariate using the impurity-based approach. The importance of a covariate is computed as the normalized total reduction of the MSE brought by that feature (this approach is also known as a Gini importance). The higher is this value, the more important the covariate. Corresponding values are presented in column MERF in Table 5.

[8] https://pypi.org/project/merf/

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Table 5

Determinants of Football Club Value

Parameter	Random Effect model				MERF
	Coeff	Std. Err	T-stat	p-value	
log Revenue	0.6964	0.0723	9.6261	0.0000	0.9048
The annual number of searches in Google	0.0065	0.0013	4.8646	0.0000	0.0226
log Player value	0.3708	0.0556	6.6715	0.0000	0.0179
Operating income	0.0014	0.0003	4.7467	0.0000	0.0049
Continental historical sports performance	3.0506	0.7594	4.0172	0.0001	0.0025

Presented data shows that, according to MERF, the main determinant of the fixed effect is the logarithm of Revenue (we used logarithmic transformations of the target variable and few covariates as described above).

Similarly, we can analyze the fixed-effect of PE-EM model represented by the tree in Fig. 2. As we can see, this tree divides the target range into intervals based on the logarithm of Revenue. The last interval corresponding to the maximum value of the logarithm of Revenue is divided into two in accordance with the popularity of the club (i.e., the number of searches in Google). Each interval corresponds to a fixed value of $f(\mathbf{X})$, which is complemented next by the random effect $\mathbf{Zu}$ to predict the target (cf. Eq. (4)).

Note that since we use the logarithmic transformation of the target variable, the predictive formula based on equation (4) is $Value = e^{f(\mathbf{X})} e^{\mathbf{Zu}}$.

Analyzing the data presented, we can conclude that the non-linear fixed effect associated with the characteristics of each club is almost entirely determined by its revenue. The next most important determinant is the annual number of Google searches, but it has much less impact and significant only for high-value clubs. Note that according to Table 2, these variables have the highest correlation coefficient with the target variable, 0.9 and 0.852, respectively, however, this relation is nonlinear.

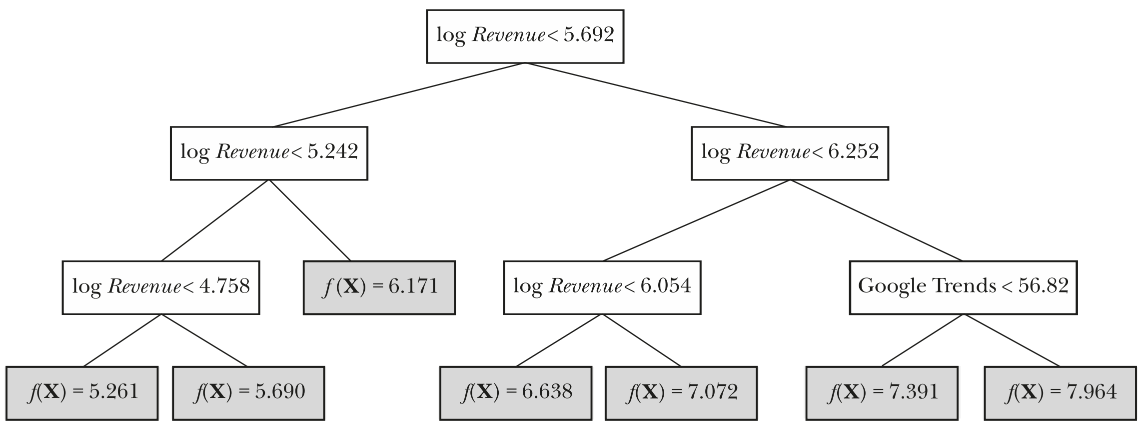

Figure 2

PE-EM nonlinear fixed effect model

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5.3. Analysis of actual deals

To check the prediction power of our model, we've calculated the value of soccer clubs, which were bought by private investors previously and the price of the deal was disclosed. These deals are presented in Table 6. The Table 6 shows the amount of the transaction, as well as the stake acquired by the investors. Based on this data, we can calculate the total market value of the club. The column 'Predicted value' lists assessments computed on the base of the RE-EM model. Both values are also shown in Fig. 3. The last column of Table 6 shows the bias, calculated as the model error divided by the actual value. The total MSE is 16.096 and R^2 is 0.965.

As we discussed above, our model, trained on Forbes data, defines the upper bound on the possible value of the club. As seen from Fig. 3 in most of the cases consi-

Table 6

M&A deals in soccer and prediction power of designed model

Club	Value*, $Mln	Stake*, %	Date of the deal	Total value (100%), $Mln	Predicted value, $Mln	Bias
Nice	111.74	100	Aug, 2019	111.7	145.5	0.303
Wolverhampton Wanderers	58.00	100	Jul, 2016	58.0	103.9	0.791
Espanyol	168.54	100	2015–2016	168.5	179.8	0.067
Atletico Madrid	56.00	20	Jan, 2015	280.0	363.0	0.297
Olympique Lyonnais	112.00	20	Aug, 2016	560.0	518.6	−0.074
Fiorentina	165.00	100	Jun, 2019	165.0	177.9	0.078
Inter Milan	307.00	68.55	Jun, 2016	447.8	462.3	0.032
PFC CSKA Moscow**	242.00	77.64	Apr, 2020	311.7	246.7	−0.208

Примечание. * https://www.footballbenchmark.com/library/foreign_investors_in_european_football_can_italy_become_the_next_preferred_target

** **https:**//sportrbc.ru/news/5ed1391d9a794786241d14d1

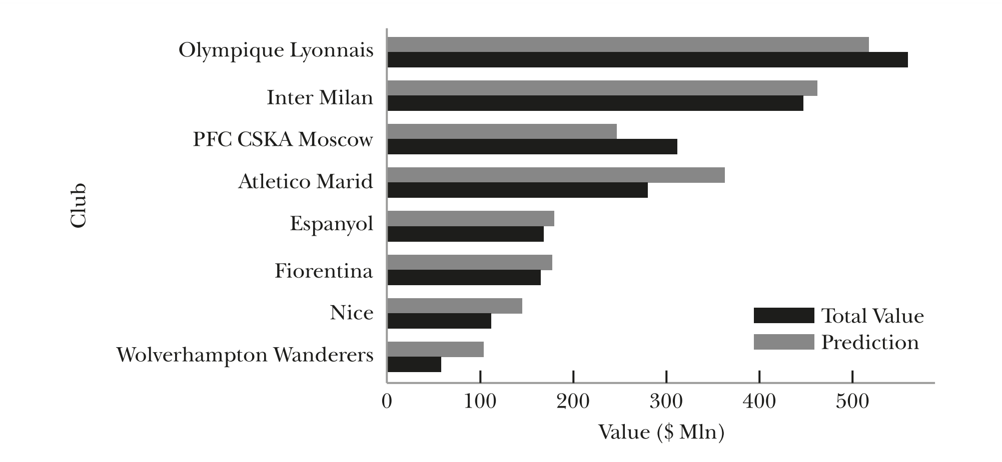

Figure 3

Total market values and corresponding predicted values

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dered, the actual price is less than the value we predicted, which is consistent with this hypothesis. Therefore, the greatest interest is attracted by transactions in which the actual price exceeds our estimates. These are PFC CSKA Moscow and Olympique Lyonnais. These cases need to be analyzed in detail, since here, most likely, there are non-soccer factors that influence the value but were not taken into account in our model.

The case of PFC CSKA could be explained by the non-market nature of the deal — the valuation was based on the construction costs associated with the stadium. One more issue — the stadium incorporates commercial premises, which provide majority of value, but don't belong to operating activity of soccer club. This proves that from investment perspective the value of the club should be significantly less than the official figure and the results provided by the model fairly describes it.

In case of Olimpique investor — Chinese investment fund IDG Capital Partners bought 20% of capital at 3.34 euros per share, 18.5% above their last closing price on the stock exchange[9]. The difference with predicted value could also be explained by the structure of the deal: apart from the shares, the Chinese group acquired subordinated convertible bonds.

Another interesting case is Atlético, where the discrepancy between our estimate ($363, Mln) and the actual value ($280 Mln) is maximum (note also that Forbes'estimate was $436 Mln). Wanda bought a 20% stake in Atletico in January 2015 for $56 Mln (and sold it to Israeli billionaire Idan Ofer for an undisclosed sum next year)[10]. The difference could be explained by the following reasons:

– the valuation could be based on interim financial statements or management accounts, that may differ from official figures;

– the final price is negotiated and depends on the circumstances of the deal (enforced sale for current shareholder or desire to acquire an asset on the part of the buyer, aimed at improving brand awareness or public image);

– the deal was closed at price significantly lower compared with market value of players — $392 Mln according to transfermarkt.de. This also confirms our predictions being slightly higher.

Our model shows the largest relative error (0.791) at Wolverhampton Wanderers. This club was sold to Fosun group of companies back in 2016 for £45 Mln (€52.2 Mln / $58 Mln). In October 2019 the group announced the plans to sell a 20-percent stake in the Club for between £50 Mln and £100 Mln. This would value the club at around £350 Mln[11]. Due to the lack of data, value ranges for small clubs estimated by Forbes could be quite large, so our model trained on this data contains this error.

6. Conclusion

In this article, we modelled a value of major European soccer teams over the period 2005–2018 based on Forbes data. The obtained results show that the models with the non-linear fixed effect have the best predictive ability. We got a fairly compact model that allows predicting the upper bound of the club's value including only club-based data.

Following directions of future research could improve the model:

– collecting the data, describing financial results of European soccer clubs: Net income and Free Cash Flow;

[9] https://www.reuters.com/article/ol-groupe-stake-idUSL8N1AT4US

[10] https://www.reuters.com/article/us-atletico-dalian-wanda/chinas-dalian-wanda-sells-17-percent-stake-in-spains-atletico-madrid-idUSKCN1FY0XJ

[11] https://www.sportbusiness.com/news/wolves-confirm-investment-plan-fosun-eyes-wider-vision/

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– analyzing the assets of clubs and its value: stadiums, brands and home-grown young players;

– considering social networks of clubs, that shouldn't be limited to the number of fans and followers, and cover more advanced characteristics – the structure of communities, dynamics of message distribution, their emotional coloring, etc. Such an analysis will also be useful for clubs in developing their policy of negotiations with fans. In our work, we added the number of Google search requests to the list of value determinants. This variable has a high correlation with the target variable, which positively affects the prediction quality;

– adding new sources of value, namely – M&A deals and shares prices. Unfortunately, at the moment the number of such deals is not yet big. As for the public soccer clubs, shares of only 21 entities are traded on the stock exchange[12]. However, we expect that with the growing interest in soccer as a business, number of deals and IPOs will grow.

In conclusion, it should be noted that the COVID-19 pandemic may limit the use of our model in current form. It caused a sharp decline in the value of players and was likely to adversely affect the value of clubs. KPMG observed a minus 29% drop in value for a selection of soccer clubs listed on various stock exchanges since the first three months of 2020. However, there was an EV recovery in late May following the intentions to complete the season, albeit behind closed doors. The company forecasts the devaluation of the soccer sector at the top end of the market as 20–25%, when compared with the figures as of 1 January 2020, depending on the strength of a particular club's balance sheet, level of debt, structure of revenue mix and dependence on player trading activities. Obviously, each club's value will need to be assessed individually upon availability of their 2019/2020 financial statements[13]. This fact is bringing out one more topic for future research.

REFERENCES

Alexander D.A., Kern W. (2004). The economic determinants of professional sports franchise values. *Journal of Sports Economics*, 5 (1), 51–66. DOI: 10.1177/1527002503251715

Arnold A.J. (1991). An industry in decline? The trend in football league gate receipts. *Service Industries Journal*, 11 (2), 179–188.

Baroncelli A., Lago U. (2006). Italian football. *Journal of Sports Economics*, 7 (1), 13–28. DOI: 10.1177/1527002505282863

Breiman L. (2001). Random forests. *Machine Learning*, 45 (1), 5–32.

Buschemann A., Deutscher C. (2011). Did the 2005 collective bargaining agreement really improve team efficiency in the NHL? *International Journal of Sport Finance*, 6 (4), 298–306.

Conn D. (1997). *The football business: Fair game in the '90s?* Mainstream Publishing.

Damodaran A. (2014a). *Ballmer's bid for the clippers: Investment, trade or expensive toy?* Available at: http://aswathdamodaran.blogspot.com/2014/06/ballmers-bid-for-clippers-investment.html

Damodaran A. (2014b). *The sporting business: Value and price.* Available at: http://people.stern.nyu.edu/adamodar/pdfiles/country/MITSportsPresentation.pdf

Forbes (2019). *The World's most valuable soccer teams 2019: Real Madrid is back on top, at $4.24 billion.* May 29. Available at: https://www.forbes.com/sites/mikeozanian/2019/05/29/the-worlds-most-valuable-soccer-teams-2019/#7c9fb9ee40d6

Fort R. (2006). The value of major league baseball ownership. *International Journal of Sport Finance*, 1 (1), 9–20.

[12] https://www.footballbenchmark.com/library/stock_exchange_football_clubs

[13] https://www.footballbenchmark.com/library/how_much_has_covid_19_degraded_the_value_of_europe_s_elite

Журнал НЭА, № 4 (56), 2022, с. 28–46

Gimet S., Montchaud S. (2016). What drives European football clubs' stock returns and volatility? *International Journal of the Economics of Business*, 23 (3), 351–390. DOI: 10.1080/13571516.2016.1204686

Hajjem A., Bellavance F., Larocque D. (2011). Mixed effects regression trees for clustered data. *Statistics & Probability Letters*, 81(4), 451–459. DOI: 10.1016/j.spl.2010.12.003

Hajjem A., Bellavance F., Larocque D. (2014). Mixed-effects random forest for clustered data. *Journal of Statistical Computation and Simulation*, 84 (6), 1313–1328. DOI: 10.1080/00949655.2012.741599

Humphreys B.R., Lee Y.S. (2010). Franchise values in North American professional sports leagues: Evidence from the repeat sales method. *International Journal of Sport Finance*, 5 (4), 280–295.

Humphreys B.R., Mondello M. (2008). Determinants of franchise values in North American professional sports leagues: Evidence from a hedonic price model. *International Journal of Sport Finance*, 2 (3), 98–105.

KPMG (2019). *Football benchmark. Football clubs' valuation: The European elite 2019.* May. Available at: https://www.footballbenchmark.com/documents/files/public/KPMG%20Football%20Benchmark_Football%20Clubs%20Valuation%20report_2019_WEB.pdf

KPMG (2020). *Football benchmark. Pandemic not discouraging football club investors.* November 11. Available at: https://footballbenchmark.com/library/pandemic_not_discouraging_football_club_investors

Markham T. (2013). *What is the optimal method to value a football club?* SSRN: 2238265. DOI: 10.2139/ssrn.2238265

Miller P. (2007). Private financing and sports franchises values: The case of Major League Baseball. *Journal of Sports Economics*, 8 (5), 449–467. DOI: 10.1177/1527002506292583

Miller P. (2009). Facility age and ownership in major American team sports leagues: The effect on team franchise values. *International Journal of Sport Finance*, 4 (3), 176–191.

Morrow S. (1999). *The new business of football. Accountability and Finance in football.* London: Springer.

Sánchez L.C., Barajas A., Sanchez-Fernandez P. (2020). Profits may lead teams to lose matches, but scoring goals does not lead to profit. *European Research on Management and Business Economics,* 26, 1, January–April, 26–32. DOI: 10.1016/j.iedeen.2019.12.007

Scelles N., Helleu B., Durand C., Bonnal L. (2013). Determinants of professional sports firm values in the United States and Europe: A comparison between sports over the period 2004–2011. *International Journal of Sport Finance*, 8 (4), 280–293.

Scelles N., Helleu B., Durand C., Bonnal L. (2014). Professional sports firm values: Bringing new determinants to the foreground? A study of European soccer, 2005–2013. *Journal of Sports Economics*, 17 (7), 688–715. DOI: 10.1177/1527002514538976

Seabold S., Perktold J. (2010). Stats models: Econometric and statistical modeling with python. *Proceedings of the 9th Python in Science Conference (SCIPY2010).* Available at: https://pdfs.semanticscholar.org/3a27/6417e5350e29cb6bf04ea5a4785601d5a215.pdf

Sela R.J., Simonoff J.S. (2011). *REEMtree: Regression trees with random effects. R package version 0.90.3.* [Computer software]. Available at: https://cran.r-project.org/web/packages/REEMtree/index.html

Sela R.J., Simonoff J.S. (2012). RE-EM trees: A data mining approach for longitudinal and clustered data. *Machine Learning*, 86, 169–207.

Sloane P.J. (1971). The economics of professional football: The football club as a utility maximiser. *Scottish Journal of Political Economy*, 18, 121–146.

Журнал НЭА, № 4 (56), 2022, с. 28–46

Solntsev I. (2014). Application of income approach for valuation of football club. In: *Social Networks and the Economics of Sports*, 9–40. (Switzerland): Springer.

Szymanski S. (2017). Entry into exit: Insolvency in English professional football. *Scottish Journal of Political Economy*, 64 (4), 419–444.

Szymanski S., Kuypers T. (1999). *Winners and losers: The business strategy of football*. London: Viking.

Szymanski S., Smith R. (1997). The English football industry: Profit, performance and industrial structure. *International Review of Applied Economics*, 11 (1), 135–153. DOI: 10.1080/02692179700000008

Zelenkov Y., Solntsev I. (2017). Measuring the efficiency of Russian football premier league clubs. *Electronic Journal of Applied Statistical Analysis*, 10 (3), 773–789. DOI: 10.1285/i20705948v10n3p773

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Оценка стоимости профессиональных спортивных клубов. Анализ европейского футбола, 2005–2018 гг.

Аннотация. Данная статья посвящена построению общей модели оценки стоимости, которую смогут применять инвесторы и акционеры профессиональных спортивных клубов, представляющих разные страны и спортивные лиги. Исследование основано на панельных данных об оценке стоимости футбольных клубов, ежегодно публикуемых Forbes. Авторы анализируют все факторы стоимости, которые использовались ранее, расширяя временной горизонт (число наблюдений) и применяя различные модели, включая линейные и нелинейные регрессии со смешанными эффектами. Наилучшая точность результатов достигается при использовании нелинейной модели со смешанными эффектами с оценкой фиксированного эффекта на основе дерева решений. Наиболее значимыми детерминантами являются доход клуба и число поисковых запросов о данном клубе в Google. Анализ реальных сделок слияния-поглощения на футбольном рынке за период 2015–2020 гг. подтверждает прогностическую способность модели и доказывает, что Forbes часто завышает рыночную стоимость футбольных клубов. Следовательно, разработанная модель предсказывает верхнюю границу реальной стоимости. В связи с этим особый интерес для дальнейшего анализа представляют сделки, реальная стоимость которых превышает расчетную. Более глубокий анализ таких сделок позволит выявить дополнительные «нефутбольные» факторы, влияющие на стоимость. На текущем этапе предлагаемая модель может служить инструментом экспресс-оценки стоимости футбольного клуба на основе открытых данных.

Ключевые слова: *стоимость спортивного клуба, оценка футбольного клуба, инвестиции в спорт, финансирование спорта, модель со смешанными эффектами.*

Классификация JEL: C13, G12, G17, G32, Z23.

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