Applied Sports Research Seminar
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The Galácticos Reviewed

A quantitative study on transfer spending and sporting success in elite European football

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Introduction

Professional football is often called a “money game” with Europe’s elite clubs utilizing various strategies to stay competitive. These include investments in state-of-the-art stadiums and forging lucrative sponsorship and media deals. The acquisition of new talent represents the most prominent and publicized channel of investment, with recent media coverage becoming increasingly critical on the ever growing transfer fees for highly valued football players. This phenomenon is not a recent development. In the early 2000s, Real Madrid initiated their renowned galáctico era, characterized by the acquisition of top-tier footballing talents such as Zinedine Zidane and David Beckham. This pattern of acquiring the top of the class continued well throughout the 2010s. Kaká, Cristiano Ronaldo, and Gareth Bale, all joined the club on record transfer fees during this time. The galáctico’ strategy’s sporting success was undeniable and reached its peak in 2015 to 2018, as Real Madrid accomplished the *Champions League* three-peat - the first team to do so in footballing history. This raises the question of whether substantial investments in the transfer market correlate with winning silverware, and if purchasing the most expensive players consistently leads to sporting success. Figure 1.1 examines the relationship between average net spending and average points in two major European football leagues.

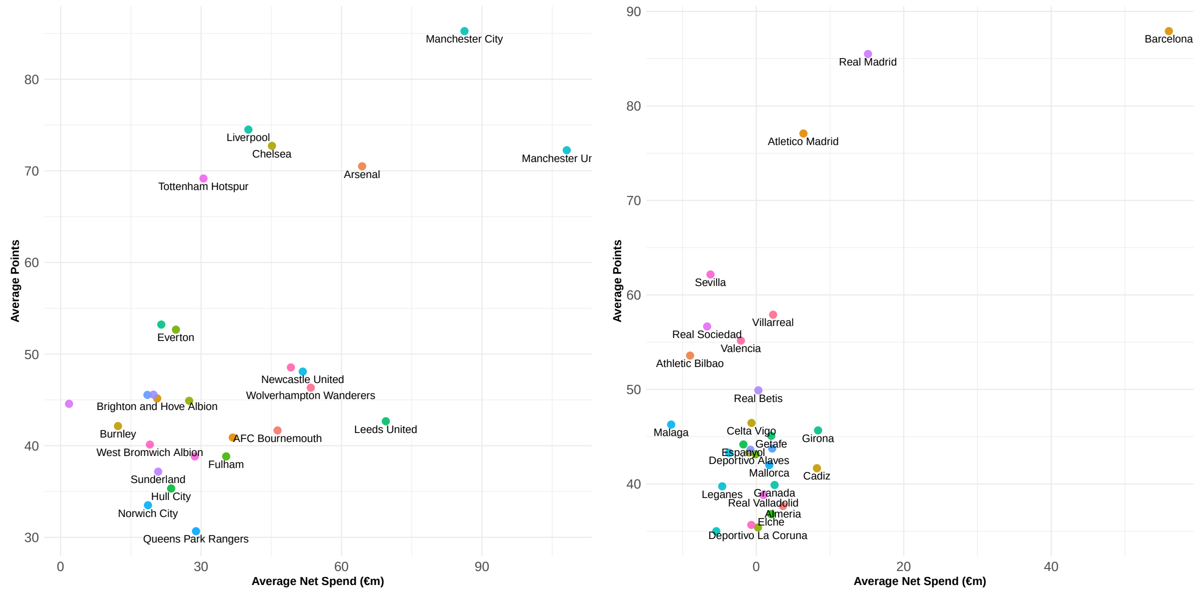

Figure 1.1 – Scatterplots of the average points (y-axis) versus the average net spend (x-axis, in €m) in the PL and LaLiga.

The relationship between team investments and sporting success exhibits a somewhat linear trend in the PL (left figure), while it appears less predictable in LaLiga (right figure). Existing sports economics research, such as that by Rohde and Breuer (2018), has demonstrated a positive correlation between team investments and on-field performance, primarily focusing on Europe's elite football clubs. However, less attention has been given to smaller or less successful clubs, which typically do not purchase superstars. But, even among newly promoted teams, a trend of significant investment is observed (Doyle, 2022). The implications of such financial strategies in football offer a broader perspective on the dynamics between economic power and sporting success. On the one hand, we assess the implications on sporting success of acquiring high-valued, high-profile players. On the other hand we analyze the effect of transfer expenditures for promotees. Additionally, we control for player availability, a factor that often has been ignored in previous research. We find no statistically significant evidence that the magnitude of transfer investments alone has a significant impact on sporting success. Both the impact of the scale of spending of newly promoted teams, and spending money on high-profile players is more ambiguous and further research is needed to conclusively determine their effect on sporting success.

Theory

2.1 Literature Review

The impact of team investments on the sporting and financial success of football clubs is a topic that is regularly discussed in sport's economic science. Already in the late 90s, Szymanski and Smith (1997) documented a positive relation between wages and league position and later on showed that net transfer spending also positively impacts sporting success (Szymański and Kuypers, 1999). Later research was able to confirm these findings and evidence from Greek football clubs showed that higher investments in player contracts result in higher on field success (Dimitropoulos, 2010). However, the study also revealed that the increase in player contracts had a negative impact on the football club's financial performance, confirming the findings of Garcia-del-Barrio and Szymanski (2009) that football clubs primarily aim to maximize sporting success as opposed to financial success. An extensive study by Franck (2010), analyzing the ownership structure of European football clubs, revealed a positive relationship between payroll and sporting performance. A more recent study confirmed the positive relation between player salaries and sporting success, however, it also documented that the magnitude of transfer fees has no positive statistical impact on sporting success (Alaminos et al., 2020). This is in accordance with Ferri et al. (2017), who also established that player salary is the more driving factor for success and not transfer investments. Contrarily, Matesanz et al. (2018) showed that transfer spending is the main driver of sporting success in UEFA and domestic competitions using a machine learning approach.

2.2 Hypotheses

Building upon the foundational research introduced above, we propose to refine the existing understanding of the factors influencing sporting success in professional football leagues. Our study provides a detailed analysis of how investments in the transfer market, controlling for player availability and team promotion dynamics, influence team performance.

H1: Controlling for injuries and league promotions, investments in the transfer market *are positively associated with sporting success.*

This hypothesis seeks to extend previous findings by integrating additional determinants of success that have not been thoroughly explored in past studies. We hypothesize that investing in player transfers generally boosts team performance, assuming the players are available and can be effectively integrated into the team. Newly promoted teams often spend more in the transfer market compared to their low-tiered peers in the top divisions, aiming to close the competitive gap and avoid relegation. We assume that this behaviour in the transfer market is legitimate, anticipating a positive relationship of transfer spending on sporting success for newly promoted teams.

H2: Investments in the transfer market are especially beneficial with respect to sporting success for newly promoted teams.

Drawing from the galácticos narrative discussed in the introduction, this hypothesis explores a specific aspect of player investment: the impact of acquiring high-profile, high-value players on sporting success.

H3: Investing in players with exceptionally high market value (galácticos) positively impacts sporting success.

Existing research confirms a positive link between team market values and success. This hypothesis examines if investing heavily in top-tier players yields better results than spreading funds across lower-valued players.

Methodology

3.1 Data

This study is based on panel data from the teams in the top five European football leagues over the last 12 seasons. In particular, we include data from the *Premier League* (PL), the *Bundesliga* (BL), *La Liga*, *Ligue 1* and *Serie A* from the years 2011 to 2023, creating a sample of $n = 1176$ team-season observations. We have an unbalanced panel due to the fact that the bottom two or three teams (depending on league format) each season get relegated to the second tier division. The raw data can be categorized into four categories:

1. **Results**: The historical league standings are extracted from FotMob (2023) and contain matches played, wins, draws and losses, the resulting points as well as goal difference.

2. **Elo**: We source the elo ratings from ClubElo (2023). ClubElo calculates the ratings for all clubs in the European top divisions based on domestic and non-domestic match results.

3. **Injuries**: WhoScored (2024) is our source for injury data. We collected data on all players who were ruled out for each fixture across all leagues over the past 12 seasons.

4. **Transfers**: Transfer fees and estimated player values for each team are collected from Transfermarkt (2024). These player values are estimated by a crowd sourcing approach based on expert valuations and market expectations. Previous research has showcased that these estimates consistently predict actual transfer fees and are regularly used in scientific studies (Bryson et al., 2013; Herm et al., 2014).

The data has been manually collected or extracted with the `SoccerData` (Robberechts, 2024) Python package. Finally, note that the above is a description of the raw data, which we used to engineer additional measures and variables to ensure a better fit to our estimation models and research idea.

3.2 Measures and Variables

3.2.1 Sporting Success Measures

To calculate measures that are used to indicate domestic sporting success, we primarily use the data that is included in the historical league tables. Although using *season league rank* and *season points scored* as measures of sporting success might initially seem logical, it is important to consider that the five leagues vary in format, affecting both the achievable ranks (due to different size) and the maximum points that can be earned (due to different amounts of games played). To make sporting success comparable we need to use relative measures. The primary metric we use to measure success is *points per game* (*PPG*) for team i in season t. This is calculated by dividing the total points scored by team i during the season by the total number of matches it played, providing a standardized measure of performance irrespective of the number of games:

$$\mathrm{PPG}_{it} = \frac{\mathrm{P}_{it}}{\mathrm{MP}_{t}}.$$

Additionally, we utilize the *logarithm of the odds rank* (*LOR*), a measure of sporting success introduced by Szymanski and Smith (1997) and widely applied in subsequent research (Garcia-del-Barrio and Szymanski, 2009). This metric is calculated using the formula:

$$\mathrm{LOR}_{it} = \log\left[\frac{X - R_{it}}{R_{it}}\right],$$

where X is the number of teams in the league plus one and R_{it} is the league position achieved by team i in season t. This quantifies the relative performance of the teams and provides a robust measure, as it approximately normalizes the distribution of the rankings, as illustrated in figure 3.1. Note that a higher *LOR* indicates a more successful season domestically.

Since UEFA club coefficients are only available for clubs that consistently qualify for the European cup competitions, we use *elo ratings* as an alternative to measure international success. Elo is a measure of success that can be applied to the teams regardless of the format they play in. The system quantifies each team's relative strength by evaluating every match played and estimates the likelihood of winning based on the ratings difference between teams. Following each match, clubs exchange points based on the outcome, adjusting their scores to better reflect

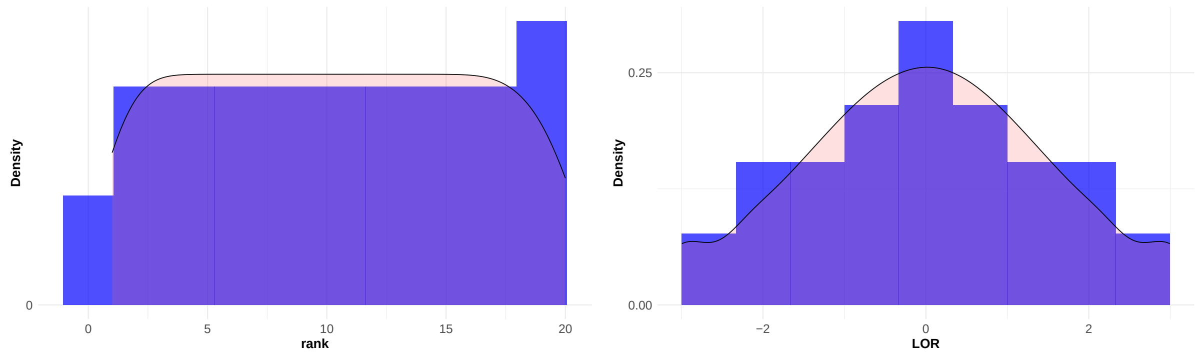

Figure 3.1 – Histogram and distribution of league rankings and the logarithm of *odds rank*.

their current performance levels (ClubElo, 2023). Moreover, winning (losing) against a relatively higher (lower) rated opponent results in gaining (losing) more points. Note that international fixtures are weighted more in the calculation of the rating, meaning that clubs that reach the later stages of the European cups usually have higher ratings.

3.2.2 Transfer Investment Measures

Our primary measure to asses transfer market investments is *net spend*, which balances player acquisition costs against player sales income. To enable comparisons across leagues and over time, we adjust for increasing transfer costs and inflation effects, as shown in figure 3.2. This is essential for ensuring that our financial data remains comparable and relevant under changing market conditions. Similarly to Gerhards and Mutz (2017), we achieve this by z-transforming each team's net spend on the league and season level. The *league normalized net spend* (*NNS*) for team i in season t is thus given by

$$\mathrm{NNS}_{it} = \frac{\mathrm{NS}_{it} - \overline{x}(\mathrm{NS}_t^L)}{s(\mathrm{NS}_t^L)},$$

where NS_{it} denotes the nominal net spend (in €m) of team i in season t. Further, $\overline{x}(\mathrm{NS}_t^L)$ denotes the sample mean and $s(\mathrm{NS}_t^L)$ the sample standard deviation of the net spend in league L during season t. The result is a robust measure for transfer investment that is both comparable across leagues and across seasons. This measure also accounts for variations in transfer fee baselines due to differences in purchasing power or transfer fee premiums across leagues, as discussed by Depken and Globan (2021). Finally note that the net spend includes incoming and outgoing transfer fees for the summer and winter window.

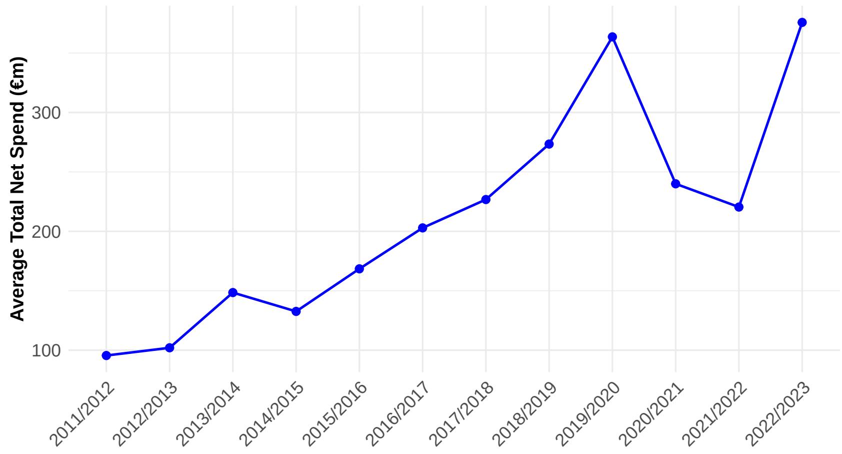

Figure 3.2 – Average of the aggregated club net spend for all leagues from 2011 to 2023.

To refine our analysis of the impact of high-value player acquisitions on team performance, we introduce the *galácticos* variable. This variable is calculated by first determining the 95th percentile of all transfer fees paid within a specific league during a particular season. This gives us a threshold to identify transactions that involve exceptionally high-valued players. Once the threshold is established, we proceed to determine the involvement of each team in these transactions. We count the number of players each team acquires whose transfer fees exceed the threshold. If a team acquired one or more players above the threshold, the categorical *galácticos* variable takes value one.

3.2.3 Control Variables

To accurately model the impact of clubs' transfer investments on sporting success, it's crucial to control for variables that may account for variations in success metrics. Similar to previous research, we use team market values (in €m) as a proxy for team quality. We aggregated individual player values within each team in each season to get the team market values and applied the above introduced z-transformation. The *league normalized team value* (NTV) accounts for inflation and the general increase in player values. Additionally, we gathered data on player availability for each match across all leagues. The average number of players unavailable per team per season defines our *out* variable. Additionally, newly promoted clubs in each league are marked with the categorical variable *promoted* ($= 1$ for promoted teams).

Variable	Type	Description	Engineered
PPG	Success	Points scored divided by matches played	Yes
elo	Success	Elo rating calculated by fixture results	No
LOR	Success	Logarithm of odds rank	Yes
NNS	Investment	League normalized net spend (in €m)	Yes
LNTV	Control	League normalized team market value (in €m)	Yes
galácticos	Investment	Indicates above 95th percentile fee acquisition	Yes
out	Control	Average players out due to injury per season	Yes
promoted	Control	Indicates newly promoted team	No

Table 3.1 – Overview of relevant variables for estimation methods.

3.3 Estimation

3.3.1 Exploratory Data Analysis

Table 3.2 provides summary statistics for the key measures and variables utilized in the estimation. Note that we assess the original values of *net spend* and *team value* below, and do not present their league normalized counterparts. *PPG* varies from 0.42 to 2.68, reflecting a broad spectrum of team performance across seasons and leagues. The elo ratings range from 1407.1 to 2089.3, highlighting substantial differences in team skills and strengths, with an average of 1684.8 and a standard deviation of 122.7. The financial metrics show stark contrasts in clubs' investment strategies and economic standing. The *net spend* ranges from -€221.4m (sales outweigh acquisitions) to €231.8m pointing to significant disparities that likely influence strategic decisions in the transfer market.

Variable	Mean	Median	SD	Variance	Min	Max
PPG	1.37	1.29	0.45	0.20	0.42	2.68
elo	1684.83	1670.88	122.69	15053.89	1407.10	2089.27
LOR	0.00	0.10	1.49	2.23	-3.00	3.00
NS (€m)	10.32	2.40	40.76	1661.07	-221.40	231.79
TV (€m)	218.59	131.60	215.82	46579.73	18.40	1203.45
galácticos	0.22	0.00	0.41	0.17	0.00	1.00
out	2.90	2.74	1.13	1.28	0.52	7.63
promoted	0.14	0.00	0.35	0.12	0.00	1.00

Table 3.2 – Summary statistics for the measure and control variables.

Interesting to note is that the mean of the net spend is only around €10m, while the maximum value €231.8m is *Manchester United's* transfer expenditure in the 2022/2023 season. Additionally, there is a large amount of variability in team values as illustrated by the large standard deviation of €215.8m. Another interesting fact is that the highest team value of €1203.5m belongs to *Manchester City's* 2018/2019 team, while their treble winning team of the 2022/2023 season is valued around €60m less. In fact, the distribution of the team values has a significant right skew (figure 3.3), indicating a heavy right tail of extremely high market value teams. The average for *galácticos* is 0.22, indicating that a large amount of teams do not partake in exceptionally high valued player acquisition.

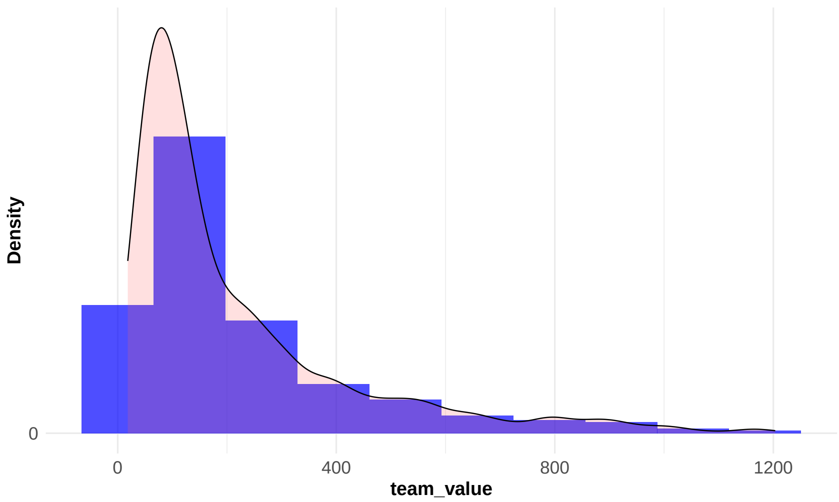

Figure 3.3 – Distribution of team values (in €m) with a significant right skew.

Examining the correlation plot presented in figure 3.4, we observe several expected positive correlations between the SMs. Notably, there is a strong positive correlation between the *galácticos* variable and *team value*. This correlation is logical, as teams with higher overall market values have more likely invested in high-profile players. For this reason, we use the team value lagged by one season in the estimation methods. We argue that teams with high quality in the last season, as reflected by last season's market value, are very likely to be high quality teams in the current season. This should address any collinearity concerns between the proxy for team strength and *galácticos*, as there should be little correlation between the amount of high profile players purchased in this season and the market value of the team last season. Interestingly, the correlation between*net spend* and *galácticos* is notably low. This finding can be attributed to the fact that the majority of teams in our dataset do not engage in purchasing these highly valued players. Therefore, while *net spend* may reflect broader financial activity within the transfer market, it does not necessarily correlate with investments in the upper echelons of player acquisitions.

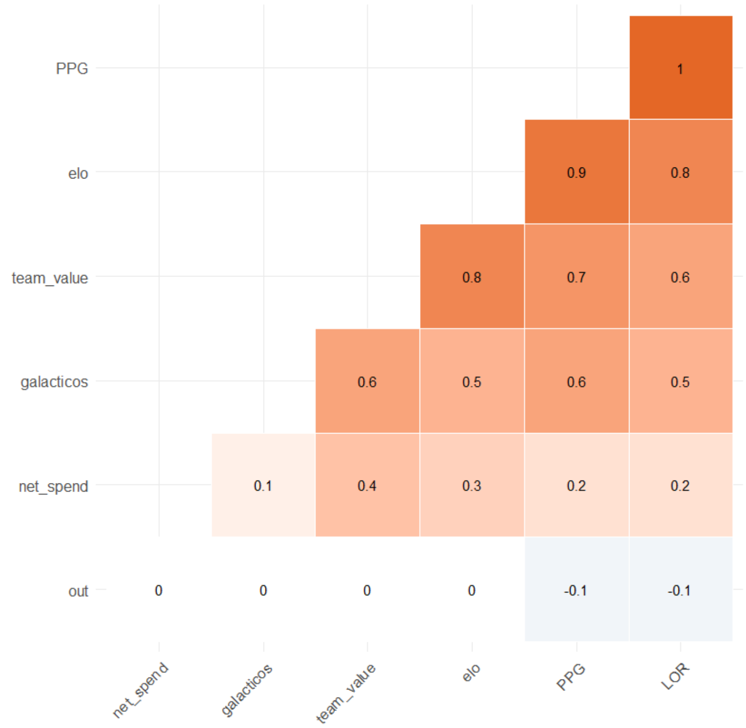

Figure 3.4 – Correlation plot of the measures and control variables.

3.3.2 Model Estimation

To evaluate the relationship between sporting success and financial variables, we employ two modeling techniques: multiple ordinary least squares (OLS) regression and fixed effects (FE) regression. The OLS framework serves as the foundational model for estimating the linear relationships between our success metrics (SM) and investment metrics (IM), while accounting for additional factors that could influence on-field performance. We advance from a baseline model to a extended one as follows:

$$\text{SM}_{it} = \beta_0 + \beta_1 \text{NNS}_{it} + \beta_2 \text{gal}_{it} + \epsilon \tag{3.1}$$

$$\text{SM}_{it} = \beta_0 + \beta_1 \text{NNS}_{it} + \beta_2 \text{gal}_{it} + \beta_3 \text{LNTV}_{it} + \beta_4 \text{out}_{it} + \beta_5 \text{prom}_{it} + \epsilon \tag{3.2}$$

Additionally, we want to estimate the effect of *net spend* for newly promoted teams and thus introduce a model with an interaction term:

$$\text{SM}_{it} = \beta_0 + \beta_1 \text{NNS}_{it} + \beta_2 \text{gal}_{it} + \beta_3 \text{LNTV}_{it} + \beta_4 \text{out}_{it} + \beta_5 \text{prom}_{it} + \beta_6 (\text{prom}_{it} \times \text{NNS}_{it}) + \epsilon \tag{3.3}$$

The baseline model gives us a basic idea of the linear change in the SMs that can be explained by the observations of our independent variables of interest. The extended model then allows us to correct the effect induced by the baseline model by accounting for other relevant factors of sporting performance. Finally, the model with the interaction term allows us to assess the effect of net spending in the market on the SMs for newly promoted teams. It's crucial to recognize that the OLS assumption of independent observations is likely violated in panel data analysis due to the non-stationary nature of time-series observations for the same agents. While we address some non-stationary issues by normalizing the data, we still have to be mindful of this when interpreting the results. Moreover, endogeneity concerns are significant, such as potential correlations between *net spend* and past success, which might influence the models' outcomes. Finally, omitted variable bias and heterogeneous club characteristics, such as club culture or youth development strategy, also pose challenges and could affect the OLS results.

To address some of the pitfalls of the OLS approach we use a FE estimation approach. Accounting for FEs should mitigate the influence of within-entity white noise caused by club heterogeneity that is not addressed by standard OLS. The FE model assumes that our unobserved variables induced by club-specific characteristics are correlated with the observed variables. Formally, the FE model differences out any influence that does not vary over time. In the context of football clubs, this includes previously mentioned factors like club culture as well as factors like location and brand reputation. In theory, accounting for FE should significantly diminish omitted variable bias. Note that the FE model focuses solely on the within-entity changes of investment strategy and high-profile player acquisition and how these impact the sporting SM. The model is given by

$$\mathrm{SM}_{it} = \alpha_i + \beta_1 \mathrm{NNS}_{it} + \beta_2 \mathrm{gala}_{it} + + \beta_3 \mathrm{LNTV}_i + \beta_4 \mathrm{out}_i + \mathrm{prom}_{it} + \beta_6 + (\mathrm{prom}_{it} \times \mathrm{NNS}_{it}) + \epsilon \quad (3.4)$$

where α_i are the club specific intercepts of the model that try to capture the heterogeneous time independent characteristics of the football clubs. The pitfall of FE models is that they lose a lot of statistical power, because only within entity variation is used to estimate changes in the dependent variable. Thus, if the within club variation of our independent variables is small, the data is not suited to use in this setting and we have concerns of model inconsistency. This effect is amplified when we use unbalanced panels, as missing data tends to increase bias.

Results

Table A.1 summarizes the results from our OLS estimation on *PPG* with respect to the different model sizes and can be found in the appendix. The baseline model on *PPG* accounts for approximately 62% of the variance in the data and is statistically significant with an F-statistic of 589.4. Because the largest model shows the best fit to our data for all SMs, we will not discuss the smaller model specifications.

We first discuss the results of the OLS regression as outlined in table 4.1. Consistent with prior research, *LNTV* emerges as the primary driver for sporting success, with high statistical significance. The *NNS* coefficient shows no statistical significance but has the expected sign in all OLS models. The *galácticos* coefficient exhibits statistical significance, indicating a *PPG* increase of about 0.082 for teams that acquired a galáctico as opposed to teams that did not. This pattern is consistent across the other SMs: acquiring high-valued players leads to a 84.19 *elo* and a 0.98 *LOR* increase, respectively. The model highlights that for newly promoted teams, a one unit increase in *NNS* corresponds to a *PPG* increase of 0.165, suggesting that heavy spending is beneficial for teams that got promoted to the top division. Results for the *LOR* model parallel those of the *PPG* model with *galácticos* as well as the interaction of *NNS* and *promoted* showing positive and significant effects. Note that the R^2 for the *elo* and the *LOR* model is slightly lower than in the *PPG* model, suggesting a slightly lower ability to explain the variation in the dependent variable. It is worthwhile to note that both the *out* and the *promoted* control show high statistical significance in all OLS models and have the expected sign. In particular, a larger average amount of injured players per season has a negative linear effect on all SMs. Also, the indicator coefficient for freshly promoted teams suggests that they perform worse than their established counterparts.

The FE models explain a great amount of variable in our success measures ranging from $R^2 = 0.69$ in the *PPG* model to $R^2 = 0.853$ in the *elo* model. The FE models reveal that both *NSS* and *galácticos* shrink in magnitude and statistical significance when accounting for club fixed effects. Interestingly, the same happens to the interaction terms. Solely in the *PPG* model the coefficient remains statistically significant, attributing an increase of 0.082 *PPG* for a unit increase in *NNS* for newly promoted teams. We notice that all coefficients for *NNS* are relatively low. Based on the FE models we can therefore not make the claim that the impact of the investment measures is statistically different from zero. In accordance with the OLS models, both *LNTV* and *out* are the primary drivers in changes in the SMs. The promotion status, on the other hand, also loses significance when accounting for fixed effects. We have to keep in mind, however, the unbalanced nature of our panel data. By construction, there are less time-season observations for the newly promoted teams, meaning that their estimates might introduce bias in the model.

4.1 Future Research

Building on the findings of how high-value transfers or large amounts of net player investments impact a single season's performance, future research could examine their long-term effects across multiple seasons. Figure A.1 in the appendix illustrates a sudden change of dynamics in spending pattern from season to season, meaning accounting for investments that happened more than one season ago might lead to interesting insights. Furthermore, one could extend the considerations with respect to the transfer market actions of newly promoted teams that this thesis introduced by dissecting the made transactions in more detail. Additionally, the differences across leagues with respect to culture and style of play are well documented (Sarmento et al., 2013). Focusing on how these differences affect the spending behaviours of clubs in the transfer market could be interesting. A huge determining factor for sporting success in the world of football is the influence of coaching. While previous studies, such as Szymanski (2013), have explored the relationship between managerial wages and team performance, a further extension could examine how a manager's past success influences current spending patterns. Finally, acknowledging the complex setting of competitive football, one could apply more sophisticated approaches, such as random forests or neural network estimation, to assess team investment and its influence on team sporting performance, arguing that these methods explore dependencies that conventional models might miss.

Table 4.1 – Summary of OLS and FE regression models with SMs as dependent variables.

	OLS PPG	**OLS Elo**	**OLS LOR**	**FE PPG**	**FE Elo**	**FE LOR**
(Intercept)						
	(0.024)	(6.820)	(0.088)			
NNS	0.009	0.262	0.005	0.000	0.958	−0.006
	(0.009)	(2.651)	(0.034)	(0.010)	(1.976)	(0.031)
LNTV	0.331***	84.189***	0.983***	0.119***	49.424***	0.285**
	(0.012)	(3.553)	(0.046)	(0.038)	(10.472)	(0.134)
galácticos1	0.082***	31.660***	0.275**	0.017	2.634	0.082
	(0.029)	(8.429)	(0.109)	(0.032)	(6.881)	(0.103)
out	−0.046***	−8.930***	−0.141***	−0.060***	−11.493***	−0.181***
	(0.007)	(2.094)	(0.027)	(0.009)	(2.027)	(0.035)
promoted1	−0.133***	−36.931***	−0.564***	−0.014	−18.213**	−0.005
	(0.032)	(9.077)	(0.117)	(0.034)	(7.309)	(0.136)
NNS × promoted1	0.165***	5.853	0.653***	0.082*	8.651	0.322
	(0.057)	(16.356)	(0.211)	(0.049)	(9.056)	(0.196)
R2	0.639	0.598	0.543	0.750	0.853	0.689
R2 Adj.	0.637	0.595	0.541	0.702	0.825	0.629
F	321.430	269.464	216.084			
Std.Errors				by: team	by: team	by: team
FE: team				X	X	X
FE: season				X	X	X

* p < 0.1, ** p < 0.05, *** p < 0.01

Conclusion

This study assessed the impact of transfer market investments on sporting success across the top five European football associations from the 2011/2012 to 2022/2023 seasons. Testing *H1*, it found that general net spending (*NNS*) does not significantly enhance sporting success, even when accounting for player injuries and league promotions. This conclusion held true both in OLS models and when considering club-specific heterogeneous fixed effects, indicating that simply increasing spending does not correlate with improved sporting SMs.

Analyzing the interaction of net spend and new promotions, the OLS models revealed a positive, statistically significant relationship between transfer expenditures and sporting SMs relating to league standings (*PPG* and *LOR*) for newly promoted teams. Given that elo reflects relative strength, and assuming that newly promoted teams typically improve their elo ratings against similarly ranked, lower-half table teams, the statistical insignificance of the interaction term in the elo model seems logical. The positive effect was confirmed only for *PPG* when accounting for fixed effects, rendering the broader implications of hypothesis *H2* inconclusive within this study's framework.

The third hypothesis focused specifically on the impact of investing in high-profile, high-value players. Similar to *H2*, the OLS analysis robustly supported the hypothesis, demonstrating strong statistical significance for the *galácticos* coefficient. This result indicates a significant positive impact of high-value player acquisitions on the sporting SMs within the dataset. However, we cannot confirm these findings when accounting for club fixed effects. Again, the results regarding the hypothesis were ambiguous, indicating that the relationship under investigation may be influenced by variables not considered in the current study.

This study's findings highlight the importance of nuanced player investment strategies rather than indiscriminate spending to enhance team performance. Further, this study contributes to a striving academic field, highlighting the importance of more nuanced considerations when assessing the impact of team investments on sporting performance. Finally, applying this framework to a more balanced, less heterogeneous panel might yield more conclusive results.

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Appendix

A.1 Graphs

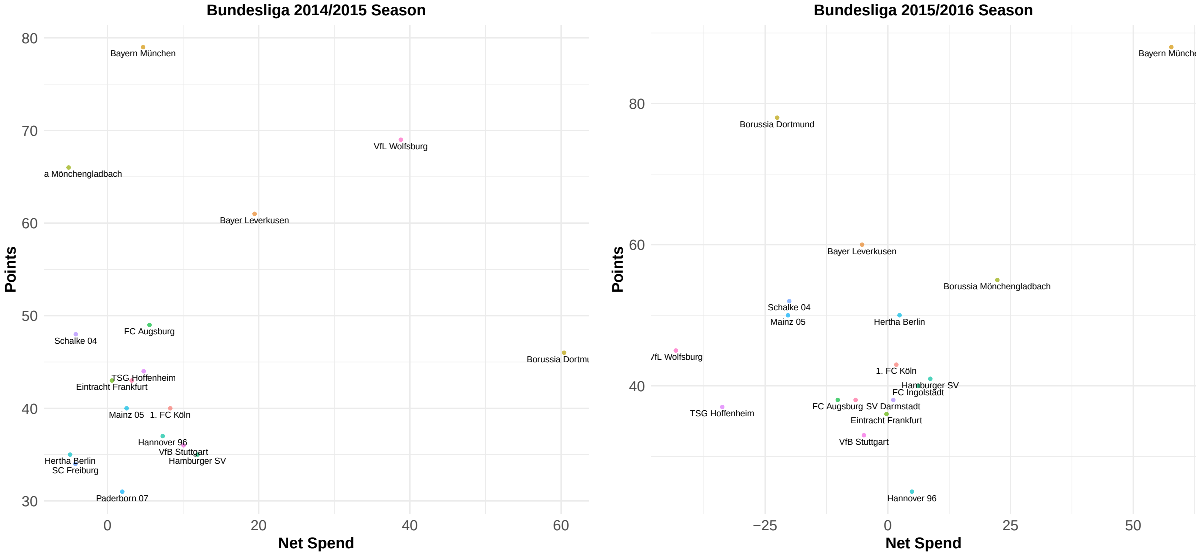

Figure A.1 – Change in net spending (in €m) dynamics across the 2014/2015 and 2015/2016 BL seasons.

A.2 Results

Table A.1 – OLS regression summary with PPG as dependent variable and different model sizes.

	Base PPG	Comp PPG	Inter PPG
(Intercept)	1.381***	1.527***	1.523***
	(0.011)	(0.024)	(0.024)
NNS	0.011	0.012	0.009
	(0.009)	(0.009)	(0.009)
LNTV	0.337***	0.330***	0.331***
	(0.013)	(0.012)	(0.012)
galácticos1	0.076**	0.083***	0.082***
	(0.030)	(0.030)	(0.029)
out		−0.047***	−0.046***
		(0.007)	(0.007)
promoted1		−0.122***	−0.133***
		(0.032)	(0.032)
NNS × promoted1			0.165***
			(0.057)
R2	0.618	0.636	0.639
R2 Adj.	0.617	0.635	0.637
F	589.420	381.489	321.430

* p < 0.1, ** p < 0.05, *** p < 0.01