Received: 29 October 2021 | Revised: 16 October 2022 | Accepted: 5 June 2023

DOI: 10.1111/boer.12407

BULLETIN OF ECONOMIC RESEARCH

RESEARCH ARTICLE

Foreign players, team production, and technical efficiency: Evidence from European soccer

David Boto-García | **Carlos Varela-Quintana** | **Alvaro Muñiz**

Department of Economics, University of Oviedo, Faculty of Business and Economics, Oviedo, Spain

Correspondence
David Boto-García, Department of Economics, University of Oviedo, Faculty of Business and Economics, Campus del Cristo s/n. 33071, Oviedo, Spain.
Email: botodavid@uniovi.es

Abstract

As on-field success is nowadays the main objective of European soccer clubs, good management needs to extract the highest sport success from the squad talent at hand. Because teams differ in their quality, performance needs to be compared with the best practice of comparable units. One remarkable source of heterogeneity across teams is the squad composition, which can produce gains from diversity together with communication costs. The paper studies the efficiency in sporting performance of soccer teams, paying attention to how the number of foreign players relates to productive inefficiency. Using data for 146 teams in the top 5 European leagues during 10 seasons, we estimate a double heteroskedastic True Random Effects Stochastic Frontier team production function. We find that (i) the number of passes, ball recoveries, and shots from the penalty area improve team efficiency, and (ii) a higher number of foreign players increase inefficiency. Our findings suggest that gains from squad diversity might be offset by communication costs.

KEYWORDS
European soccer, foreign players, stochastic frontier analysis, team management, team production

JEL CLASSIFICATION
Z22, D22, M54

1 INTRODUCTION

Elite soccer is one of the most popular sports in the world, especially in Europe. Although many modern soccer clubs operate in the stock market and behave close to profit-maximizing firms, there is consensus in the literature that the ability to outperform rivals on the playground is the major determinant of subsequent club revenues and financial stability, at least on average (Carmichael et al., 2011). That is, professional soccer teams behave more like win-maximizers than like profit-maximizers because the latter strongly depends on the former (Garcia-del-Barrio & Szymanski, 2009).[1] Therefore, the main objective for club owners and managers is to extract the highest sport success from the squad talent at hand.[2]

Although theoretically all soccer teams compete on equal conditions, their aspiration levels and performance capabilities are different. Teams differ on their fan base, squad talent, club history, and team composition. Whereas some compete for winning the title or qualifying to European competitions, others fight for avoiding relegation to the second division. The analysis of efficiency in team management thus needs to consider the differences in talent and technology through playing style that determine the outcome possibilities. The identification of soccer teams' efficiency has important implications, not only for team management but also because performing behind the potential translates into lower fans' satisfaction (González-Gómez & Picazo-Tadeo, 2010).

In this paper, we model soccer teams' technical efficiency taking the number of points per season as the output measure. Therefore, we are concerned about sporting performance (on-field production) rather than economic performance (off-field production). We estimate a stochastic frontier production function by which the total points are modeled as a function of the quantity and quality of the players in the squad through the team market value. Experience and physical conditions are also controlled for by considering team average age.

The role of team composition on productive efficiency has become an issue of interest in the economics literature. There is some evidence that there are spillovers in professional sports team production so that both individual and team performance depend on the composition of the team (Arcidiacono et al., 2017; Gelade, 2018; Torgler & Schmidt, 2007). Whereas traditionally the literature has focused on racial discrimination (Kahane, 2005; Szymanski, 2000), a growing body of research has started to pay attention to the effect of cultural diversity on team performance (Addesa et al., 2022; Beine et al., 2021; Kahane et al., 2013; Tovar, 2020). While several works have detected positive gains from labor factor diversity when working together through skill complementarities (e.g., Roupakias & Dimou, 2020), the international mixing of players into the same squad might on the contrary create communication barriers that produce integration costs, in-line with the seminal works by Lazear (1999a, 1999b). Therefore, it is unclear whether teams benefit or not from internationally diverse squads, which has important economic implications for team management and hiring strategies. Therefore, a second goal of the paper is to study how

[1] Ultimately, club revenues from box offices, TV broadcasting rights, sponsorships, merchandising, or player transfers are heavily dependent on sporting performance.

[2] Hereafter we use the term "manager" to refer to the trainer/coach of the team.

deviations from the frontier are associated with team nationality heterogeneity in terms of the number of foreign players in the squad.

We estimate a double-heteroskedastic True Random Effects (TRE) model (Greene, 2005a, 2005b) that considers time-variant inefficiency together with individual effects capturing unobserved heterogeneity at the team level. We allow the variance of the inefficiency term to be a function of team characteristics, including the number of foreign players in the squad. One novelty of our work is that rather than studying the influence of team composition on performance directly, we study how deviations from the frontier (productive inefficiency) can be attributed to cultural frictions within the team conditional on other factors. That is, we investigate whether the role of players' nationality on team output operates through productive inefficiencies. In addition to this, we take inspiration from the baseball and basketball team performance literatures and consider game-statistics (the total number of passes, the number of ball recoveries, and shots from inside the penalty area) as controls for explaining the differences in team efficiency (Hofler & Payne, 1997; Jewell & Molina, 2004; Lee, 2011; McGoldrick & Voeks, 2005). The impact of participation in a European competition and differences in inefficiency across leagues are also examined. Additionally, our econometric modeling takes into account the degree of *favoritism* of teams by allowing the variance of the random noise to depend on the ex ante winning probabilities based on betting odds.

Our dataset consists of 956 team-level observations on 146 clubs that participate at least during two periods in the 5 most important European leagues over 10 seasons, from 2009–2010 to 2018–2019. Compared to related studies on productive efficiency in soccer, our data is broader (in terms of leagues and teams' coverage) and deeper (concerning the time span). In this vein, whereas most studies focus on a single league, we study productive efficiency exploiting a larger sample size using information for the Big Five. Although some scholars have considered different leagues within the same country (Bridgewater et al., 2011; Feng & Jewell, 2021; Jewell, 2017), there are no studies on productive efficiency that use data for the top five European leagues. Accordingly, we consider our results to be more general than previous research.

We find that, conditional on team quality input, (i) the average age of the squad exhibits a U-shaped relationship with the number of points earned; (ii) offensive and defensive indicators are significant predictors of differences in technical inefficiency across teams, with the number of passes being the variable that most contributes to improve teams' efficiency; and (iii) productive inefficiency increases with the number of foreign players in the squad. We interpret the latter finding as suggestive that integration costs weight more than the potential gains from team diversity. Furthermore, our results show that Spanish teams are, on average, more efficient and that team ranking is strongly associated with technical efficiency in resource management.

The remainder of the paper is structured as follows. After this introductory section, in Section 2 we review the related literature. Section 3 outlines the theoretical framework, the choice of the input and output measures, and the econometric modeling. Section 4 describes the database and reports descriptive statistics. Section 5 presents the model estimates together with a discussion of our findings. Finally, Section 6 concludes.

2 | LITERATURE REVIEW

In this section, we first review the literature on productive efficiency in soccer. Next, we briefly discuss existing evidence on how diversity affects team performance.

2.1 | Productive efficiency in soccer

The analysis of sporting production functions has a long tradition in professional sports. Following the seminal work by Scully (1974), scholars have related measures of team performance (output) to a set of inputs (mainly player's talent) in different sports such as rugby (e.g., Carmichael & Thomas, 1995), baseball (e.g., Jewell &Molina, 2004), soccer (e.g., Feng & Jewell, 2021), American football (e.g., Hadley et al., 2000), basketball (e.g., Lee & Berri, 2008), and hockey (Kahane, 2005). A common interest within this literature is the analysis of technical efficiency (i.e., the management of inputs to produce sporting success).

For the case of soccer, there is a burgeoning body of literature concerned about productive efficiency. Whereas some scholars study cost efficiency (Barros & Leach, 2007; Barros et al., 2009, 2015; Ghio et al., 2019), others focus on sporting productive efficiency (Carmichael et al., 2017; Espitia-Escuer & García-Cebrian, 2010, 2020; Jewell, 2017; Zambom-Ferraresi et al., 2017, 2019).[3] A stylized fact is the existence of high levels of efficiency, which is argued to be due to the highly competitive nature of the leagues.

Earlier studies used Ordinary Least Squares (OLS) regression to model sporting production functions (e.g., Carmichael et al., 2000). However, this approach has the drawback that the estimates represent *average efficiency*. To properly assess productive efficiency, performance needs to be compared to the full efficiency benchmark. That is, a frontier of the maximum attainable output for each level of inputs needs to be estimated. This has been done both using data envelopment analysis (e.g., Espitia-Escuer & García-Cebrián, 2010) and stochastic frontier analysis (SFA) (e.g., Jewell, 2017). To date, none of the two approaches has been shown to be superior. Whereas the former is nonparametric and does not impose any functional form to the production function, the latter has the advantage that it allows for random noise. This seems to be particularly relevant in soccer, as deviations from the frontier might be partially due to events beyond the team performance and the choice of tactics.

Table 1 presents an overview of existing studies concerned about productive efficiency in soccer. The literature concerned about efficiency in costs is not summarized here. Overall, most studies consider team's market value as the main input and the number of points achieved by the end of the season as the output. Data Envelopment Analysis (DEA) is the most used methodology, partly due to the fact, it does not require the researcher to assume any functional form. Importantly, only a few papers have aimed to explain the determinants of inefficiency. These studies have mainly focused on the role of managers' characteristics (Buzzacchi et al., 2021; Dawson & Dobson, 2002; Frick & Simmons, 2008), clubs' value and debt (Halkos & Tzeremes, 2013), or type of club owners (Rohde & Breuer, 2018). We expand this literature by paying attention to the effect of the number of foreign players in the squad and some game statistics.

2.2 | Diversity and team performance

Existing empirical evidence on the influence of diversity on productivity is rather unconclusive to date (see Ozgen, 2021 for a review). Whereas some authors report that that diversity is positively related with labor productivity (Roupakias & Dimou, 2020), others find negative (Dale-Olsen &

[3] A recent stream of literature has started to go beyond and analyze scoring efficiency (e.g., Villa & Lozano, 2016), social efficiency in terms of the capacity to attract people to the stadium (Özaydin & Donduran, 2020) or efficiency in soccer betting markets (e.g., Fischer & Haucap, 2022).

TABLE 1 Summary of studies on soccer productive efficiency.

Author	Data	Model	Inputs	Output	Determinants of inefficiency
Dawson et al. (2000a, 2000b)	English Premier League, six seasons (1992–1993 to 1997–1998)	• OLS • FE/RE • Half-normal and truncated SFA	• Market value of the squad (playing talent)	• Winning percentage	
Dawson and Dobson (2002)	Four divisions of English football, six seasons (1992–1993 to 1997–1998)	• SFA	• Team quality index (team league, career appearances, career goals scored, and goals scored in past season)	• Winning percentage • (Wins + 1/3 the number of draws)/number of games	Manager's characteristics (playing career, playing position as player, time in charge of the team, age, experience, prior knowledge of the competition)
Espitia-Escuer and García-Cebrián (2004)	Spanish LaLiga, three seasons (1998–1999 to 2000–2001)	• DEA	• Number of players used • Attack moves • Shots on goal • Ball possession	• Number of points	
Kern and Süssmuth (2005)	German soccer league, two seasons (1999–2000 and 2000–2001)	• SFA	• Wage bill of players • Wage bill of managers	• Revenues • Index of sporting performance in different competitions	
Espitia-Escuer and García-Cebrián (2006)	Spanish LaLiga, six seasons (1998–1999 to 2004–2005)	• DEA	• Number of players used • Attack moves • Shots on goal • Ball possession	• Number of points	

(Continues)

TABLE 1 (Continued)

Author	Data	Model	Inputs	Output	Determinants of inefficiency
Frick and Simmons (2008)	German Bundesliga, 22 seasons (1981–1982 to 2002–2003)	• Panel data SFA	• Relative wage payroll	• Number of points divided by the maximum possible	• Manager's characteristics • Manager's dismiss • Seasons in first division
Espitia-Escuer and García-Cebrián (2010)	UEFA Champions League, five seasons (2003–2004 to 2006–2007)	• DEA	• Number of players used • Attacking moves • Shots and headers • Ball possession	• Number of matches played (before being eliminated)	
Frick and Lee (2011)	German Bundesliga, 22 seasons (1981–1982 to 2002–2003)	• SFA	• Relative wage payroll • Relative manager's salary	• Number of points divided by the maximum possible	
Bridgewater et al. (2011)	Four leagues in English soccer, 12 seasons (1994–1995 to 2006–2007)	• SFA	• Relative wage payroll • Manager's characteristics (experience, played at top level and/or domestically)	• Team's position (in logs) relative to the mean position of the rest (in logs)	

(Continues)

TABLE 1 (Continued)

Author	Data	Model	Inputs	Output	Determinants of inefficiency
Carmichael et al. (2011)	English Premier League, 6 seasons (1998–1999 to 2004–2005)	• OLS and SFA	• Ratio of goals, assists and accurate shots to total shots • Shots on target • Passes, crosses, and dribbles • Ratio of goals to saves	• Percentage share of points relative to the total points achieved in the league	
Halkos and Tzeremes (2013)	Twenty-five richest European football clubs in 2009	• Bootstrap DEA	• Club's revenues	• Sum of domestic championships and cups	• Current Value • Debt
Jewell (2017)	Four divisions of English Football, 29 seasons (1981–1982 to 2009–2010)	• Output distance function using latent class SFA	• Monetary value of players • Value of tangible fixed assets	• Number of points • Total revenue	
Carmichael et al. (2017)	Italian Serie A, 10 seasons (2000–2001 to 2009–2010)	• SFA (True Random Effects)	• Composite indexes of attacking, constructive, and defensive performance • Points in previous season • Managerial change during the season • Ratio of home points to away points	• Number of points as a percentage of the maximum possible	

(Continues)

TABLE 1 (Continued)

Author	Data	Model	Inputs	Output	Determinants of inefficiency
Zambom-Ferraresi et al. (2017)	UEFA Champions League, 10 seasons (2004–2005 to 2013–2014)	• DEA and Bootstrap DEA	• Attempts on target • Ball possession • Total passes • Ball recoveries	• Revenue obtained from UEFA Champions Lague	
Rohde and Breuer (2018)	English Premier League and French Ligue 1, 7 seasons (2005–2006 to 2011–2012)	• SFA	• Market value • Team wage costs	• Operating profits • National league points • Odds of league rank	• Private majority investor dummy • Foreign private majority investor
Zambom-Ferraresi et al. (2019)	English Premier League, three seasons (2012–2013 to 2014–2015)	• DEA and Bootstrap DEA	• Market value of the squad • Match-related statistics (shots on target, passes, ball recoveries) • Wages of the squad	• Number of points • Revenue • Stadium attendance • Social media impact	
Rossi et al. (2019)	Italian Serie A, 10 seasons (2000–2001 to 2009–2010)	• OLS and DEA	• Offensive indicators • Defensive indicators	• Number of points	
Espitia-Escuer and Garcia-Cebrian (2020)	Spanish LaLiga, five seasons (2012–2013 to 2016–2017)	• DEA	• Offensive moves (crosses, shots, assists, and passes) • Defensive moves (defensive actions and saves)	• Number of points • Recovered balls	

(Continues)

TABLE 1 (Continued)

Author	Data	Model	Inputs	Output	Determinants of inefficiency
Feng and Jewell (2021)	Four divisions in English soccer, 30 seasons (1981–1982 to 2010–2011)	• Random coefficient SFA	• Market value of players • Value of tangible fixed assets	• Total revenue • Points per game	
Cifuentes-Faura (2022)	First and second divisions of Spanish La Liga, years 2015 and 2019	• DEA	• Personnel costs • Club debt	• Total income • Inverse of the final classification rank	• Transparency index • Club's total assets • Goals against • Points achieved • Dummy for first division
Buzzacchi et al. (2021)	Serie A Italian league, 22 seasons (1998–1999 to 2019–2020)	• OLS and DEA	• Team value at the beginning of the season	• Average points earned by the manager	Manager's characteristics (age, Italian nationality, international experience, former star, and position as a player)
Pérez-González et al. (2022)	Spanish La Liga (season 2016–2017)	• DEA	• Total assets • Operating expenses	• % Spectator attendance • Followers on social media • Points obtained in all competitions • Business performance (revenues)	

Abbreviation: SFA, stochastic frontier analysis.

Finseraas, 2020; Lyons, 2017) or nonsignificant differences (Homroy & Soo, 2020; Trax et al., 2015). One potential explanation is that different types of diversity (gender, education, race, or nationality) exert distinct effects and vary depending on the case study and type of firm/setting considered. From a theoretical viewpoint, the expected gains are due to skill complementarities, assimilation, and spillover effects (Ozgen, 2021). However, in the case of nationality diversity, these gains might come at a cost of linguistic and cultural frictions, which might narrow down the economic benefits through transaction costs and tensions within workplaces (Lazear, 1999b).

A recent line of research has started to study the role of team diversity in sports teams, documenting mixed findings. Beine et al. (2021) documented that genetic diversity among teammates exerts a positive causal effect on team performance. This likely happens because teams can benefit from a larger variety of skills when the squad is composed of a diverse group. On the contrary, other studies find that the mixing of players from different origins makes integration costs to override the gains from diversity. Addesa et al. (2022) found that team fractionalization in Italian Serie A soccer league exerts a negative effect on performance. Kahane et al. (2013) reported that hockey teams benefit from the presence of foreign players in the squad; however, high levels of multiculturalism result in losses from integration costs. Similarly, Tovar (2020) showed that there is a nonlinear relationship between the predominant nationality of a team's roster and performance; performance improves only when a large share of the squad has the same nationality.

3 | MODEL

3.1 | The production function in sports

A production function specifies the maximum possible output as a function of a set of inputs. Following Scully (1974), the production function in sports can be specified as follows:

$$P = f(L, Z) \tag{1}$$

where P is a measure of team performance (output), L refers to the playing talent, and Z represents a set of contextual factors that affect performance. Therefore, the sporting production function can be understood as a process by which during a match players' talent is combined with managerial guidance to produce the sport result (win, draw or defeat).

3.1.1 Output

The output of a sporting production function is team performance. The total number of points achieved by the end of the league is the most used in soccer (see Table 1).[4] Some studies use the number of points relative to the maximum points attainable (Carmichael et al., 2011, 2017).

[4] Although some scholars have used the number of wins or the winning percentage (Dawson et al., 2000a), this has the drawback that tied matches, which are rewarded 1 point each, are treated in the same fashion as defeats. For some teams, especially weaker ones, draws can be highly valued.

Nevertheless, if the maximum number of points is constant in the sample, this is merely a scale adjustment.[5]

3.1.2 Input

There is an ongoing discussion in the literature about how to define the inputs in professional sports. Whereas scholars agree that players' talent is the main input (Lee & Berri, 2008), the controversy arises regarding how to measure it. To proxy it, some studies have used the team wage bill (Bridgewater et al., 2011; Frick & Simmons, 2008; Kahane, 2005). However, wages tend to be nondecreasing with player's age, reflecting in some cases status due to past contributions to team performance rather than the current value of the marginal product. Differences in salary negotiation ability across players' agents might also be present. Furthermore, information on players' wages is not always available.

As an alternative, we use the market value of the team (*TEAM_VALUE*) prior to the start of each season to measure squad talent, as done by Dawson et al. (2000a), Frick and Simmons (2008), Rohde and Breuer (2018), and Zambom-Ferraresi et al. (2019), among many others. The players' transfer market is assumed to be competitive so that potential buyers and sellers meet under symmetric information (Terviö, 2006). Accordingly, each marginal unit of talent T is equally priced (i.e., there is not price discrimination).[6] The market value of player j (the expected value any other team is willing to pay for hiring him) is a valid proxy of his talent if we take talent price as a numeraire:

$$V_j = pT_j \tag{2}$$

where V_j is the market value of player j, T_j is the units of talent of player j, and p is the equilibrium price per unit of talent in the market. If we aggregate the market value of all the players in the squad, the team market value is

$$TEAM\_VALUE_{it} = \sum_{j=1}^{J} V_{j_{it}} \tag{3}$$

where i indexes teams and t seasons. Squads with greater talent should, *ceteris paribus*, perform better. Note that TEAM_VALUE captures both the size and the overall talent of the team.[7] To allow for a nonlinear effect of this input on the number of points earned, we also considered its square (*TEAM_VALUE2*).

[5] If the dependent variable is expressed in logs, then the log of the maximum points is captured in the constant term of the production function.

[6] During the winter and summer transfer windows, teams can trade players (their property rights). Most transfers are done during the later. Any club can freely bid for any player in other club and start a negotiation process. From this perspective, teams freely compete for hiring players (Frick & Lee, 2011). An overview of labor markets in professional sports is presented in Rosen and Sanderson (2001).

[7] Auxiliary panel regressions (available upon request) with the team effects treated either as fixed or as random show TEAM_VALUE is positively (negatively) and significantly correlated with the goals scored (conceded), suggesting it is a valid indicator of team quality.

3.1.3 Contextual variables

It is common in the soccer literature to consider contextual variables that cannot be considered inputs but exert an effect on the output (Barros et al., 2015). As the soccer product is the result of an interaction between two teams, it seems necessary to control for the quality of the opposite teams (Dawson et al., 2000a). Given a squad talent, teams playing against more talented opponents would find it more difficult to succeed. Therefore, the production function includes the average market value of the opposite teams competing in the same league in season t discounting the corresponding one for team i (*OP_TEAM_VALUE*). This is a common practice in studies concerned about team performance in soccer (Bucciol et al., 2019).

The second control variable considered is the average age of the squad (*TEAM_AGE*). On the one hand, Carmichael et al. (2001) argued that, together with squad talent, the physical conditions of the players in terms of form and fitness are important determinants of team success. Weimar and Wicker (2017) showed that the distance run and the number of intensive runs (as effort proxies) are significant predictors of the winning probability. On the one hand, older players are expected to have greater experience, which conveys an advantage through a better knowledge of the game and tactical learning. Therefore, the average age of the squad captures both players' experience and physical conditions. Carmichael and Thomas (1995) and Dawson and Dobson (2002) included it in the sporting production function and found an inverted U-shaped relationship between team average age and performance: Up to a point, the positive effect of experience is overshadowed by worsening physical performance. By contrast, Torgler and Schmidt (2007) documented that younger teams perform better, documenting a U-shaped relationship. In this respect, Sal de Rellán-Guerra et al. (2019) evaluated that the effects of age on competitive match performance play and report that players older than 30 show lower performance in the distance covered and number of fast runs (worsening of physical conditions), but that the ability to make successful passes increases with age (experience effect). Similar findings are reported in Zhou et al. (2020). Overall, the effect of squad average age on the output is undetermined a priori. To allow for nonlinearities, we include this variable in levels and in a squared form (*TEAM_AGE2*).

Additionally, we include a set of team individual effects. This aims to capture time-invariant team characteristics such as the population size of the club's hometown, the number of supporters, the size of the stadium, or the history of the club. Empirical evidence documents that the local fan base and club size positively impact team performance (Barros & Leach, 2007). These individual effects therefore control for omitted variable bias due to team unobserved heterogeneity.

3.2 | Econometric modeling

Traditionally, studies that apply SFA to soccer specify the inefficiency term to be time invariant. This has the drawback that any time-invariant cross unit heterogeneity is collapsed into the inefficiency term (Greene, 2005a). In the soccer context, this assumption is inappropriate because there might be some team-specific characteristics that affect performance and are not inefficiency. Models that assume the inefficiency increases or decreases smoothly over time are neither well suited, as the zero-sum game of the round-robin competition makes it unlikely that the inefficiency of all the teams follows the same trajectory (Lee & Berri, 2008). We need a model that separates inefficiency from unobserved heterogeneity at the same time that it allows inefficiency to vary over time without any rigid structure. Therefore, we use the TRE model developed by Greene (2005a, 2005b). The model is specified as follows:

$$\log y_{it} = \alpha + \beta_1 \log TEAM\_VALUE_{it} + \beta_2 \left(\log TEAM\_VALUE_{it}\right)^2 + \delta Z_{it} + \gamma_i + v_{it} - u_{it} \quad (4)$$

where $\log y_{it}$ is the log of the output for team i ($i = 1, \ldots, N$) in season t ($t = 2009-$ $-2010, \ldots, 2018 - -2019$), α is the intercept, $\log TEAM\_VALUE_{it}$ is the team quality input, Z_{it} is a set of contextual variables (log *TEAM_AGE*, log *TEAM_AGE2*, and log *OP_TEAM_VALUE*), γ_i is a team-specific effect that captures time-invariant heterogeneity, v_{it} is a normally distributed error term with zero mean and variance σ_v that captures statistical noise, u_{it} is a nonnegative time-variant inefficiency term with variance σ_u, and β_1, β_2, and δ are parameters to be estimated.

Deviations from the frontier that are due to chance or back luck are captured in v_{it}, whereas those due to inefficiency are gathered in the one-sided inefficiency term u_{it}. Different distributions have been proposed for the inefficiency term. Here we specify u_{it} as a half-normal truncated at zero, which is the most common. The total variance of the composite error term is given by $\sigma^2 = \sigma_u{}^2 + \sigma_v{}^2$. If the signal-to-noise ratio ($\lambda = \sigma_u / \sigma_v$) is statistically different from zero, which means that part of the error term is due to the one-sided inefficiency term, and therefore the SFA model is preferred over a deterministic frontier. The inefficiency scores (i.e., the amount by which a team fails to reach the frontier) are subsequently calculated using the procedure developed by Jondrow et al. (1982), which derives the conditional expectation of u_{it} based on the realized value of the composite error term ($\varepsilon_{it} = v_{it} - u_{it}$) as follows:

$$\widehat{u_{it}} = E\left(u_{it}|\varepsilon_{it}\right) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi\left(a_{it}\right)}{1-\theta\left(a_{it}\right)} - a_{it}\right] \quad (5)$$

where $a_{it} = \varepsilon_{it}\,\lambda/\sigma$, $\phi(.)$ denotes the standard normal density function, and $\theta(.)$ indicates the cumulative density function. Individual-specific output-oriented technical efficiency scores are subsequently computed as $TE_{it} = \exp(-u_{it})$. These technical efficiency scores therefore measure the ratio of the observed output to the maximum feasible output so that

$$TE_{it} = \exp\left(-u_{it}\right) = \frac{y_{it}}{f\left(x_{it}, \beta\right)\exp\left(v_{it}\right)} \quad (6)$$

In our model specification, the individual effects are treated as "random" rather than as "fixed". This is because in short/unbalanced panels Greene's True Fixed Effects model might produce a problem of incidental parameters bias (Belotti & Ilardi, 2018). This would lead to inconsistent estimates of the team-specific intercept, which in turn affects the inefficiency estimates. Even though our dataset covers 10 seasons, the relegation and promotion system make some teams to be only observed for a reduced number of periods. Accordingly, the TRE is a three-part disturbance model that is a special case of the random parameter SFA with a random intercept.[8] The model is estimated by maximum simulated likelihood using Halton draws. Further details on the model estimation can be found in Greene (2005a, 2005b).

Contrary to other panel data applications, our model does not include time effects. This is due to the joint product characteristic of the sports industry (zero-sum game). As in soccer the average

[8] This modeling framework assumes that productive heterogeneity is captured in the intercept but that clubs share the same technology. Although some related studies have relaxed this using latent class (Barros et al., 2009; Jewell, 2017) or random parameter (Feng & Jewell, 2021) SFA models, these models require large datasets for reliable parameter identification.

winning (losing) percentage is 0.33, there are no reasons to believe that the average efficiency of the industry would change over time (Dawson et al., 2000a; Frick & Lee, 2011; Lee, 2009; Lee & Berri, 2008). However, note that our inefficiency term is time-varying because teams might have different temporal variations in inefficiency relative to each other.

3.2.1 Determinants of the variance of inefficiency

An interesting aspect of the SFA analysis is the possibility of explaining the determinants of inefficiency. Studies by Hofler and Payne (2006) and del Corral et al. (2017) in basketball, Dawson and Dobson (2002), Frick and Simmons (2008) and Rohde and Breuer (2018) in soccer, and Kahane (2005) in hockey have explored the determinants of the mean (or variance) of inefficiency using SFA. In the same spirit, we allow the variance of the half-normal inefficiency term to be an exponential function of team characteristics as follows:

$$\sigma_{u_{it}} = \exp\left(\theta_0 + \theta_1 Team_{it}\right) \tag{7}$$

where $Team_{it}$ is a set of time-varying team characteristics, θ_0 is a constant term, and θ_1 are parameters to be estimated.[9] Specifically, we consider the following team characteristics:

- Number of foreign players in the squad: As discussed in Section 2, team composition might play an important role for successful cooperation among teammates. Team's interactive capabilities on the playground depend on the interactive capacities of its individual players (see Prat (2002) for a theoretical characterization). To explore whether the number of foreign players exerts any influence on productive inefficiency, we consider the number of foreign players in the squad (in logs), denoted by log FOREIGN. As a robustness check, we also consider the share of foreign players over total players in the squad (also in logs), denoted by log *SHARE_FOREIGN*.
- Game statistics: Managers play a key role in team performance through team management (Frick & Simmons, 2008), as they are responsible for the choice of the squad composition for the season, the starting 11 and the changes, the playing style, the training sessions, and the motivation and effort of the players (Dawson et al., 2000a). Given a squad talent, managerial styles might produce important differences in team outcomes (Boto-García et al., 2020; Bucciol et al., 2019). In this regard, some studies have used managers' characteristics like experience or having been a good player as determinants of inefficiency (Bridgewater et al., 2011; Buzzacchi et al., 2021; Dawson & Dobson, 2002; Frick & Simmons, 2008; Hofler & Payne, 2006).

When team performance is not as desired, it is highly usual to dismiss the manager. This makes manager turnover to depend on short-term bad or under-expected performance (d'Addona & Kind, 2014). In some cases, teams have even more than two managers during the same season. When using seasonal-level data, this imposes problems at the time of considering managers' characteristics in the model.[10] Even if we do, managers' characteristics are likely to be endogenous

[9] If the inefficiency term u_{it} is allowed to be heteroskedastic, it implies that the expected mean of the inefficiency is also a function of the inefficiency determinants (Kumbhakar et al., 2020). This is because the expected value of u_{it} includes the conditional variance (Equation 5).

[10] As our analysis considers the five most important European leagues, the same manager can train two teams from different leagues in our sample during the same season (Dawson & Dobson, 2002).

because they vary with performance (Carmichael et al., 2011, 2017).[11] As discussed in Bridgewater et al. (2011), finding suitable instruments to consider such sorting is difficult. Most importantly, managers do not directly produce output. The relevant issues are their decisions (e.g., choice of tactics) for transforming a given talent into team success. Because of this, rather than managers' characteristics, we consider three indicators of the playing style chosen by the manager as inefficiency determinants. In this way, we examine how, conditional on the playing talent, team coaching and management style through game statistics (team functioning) affect team efficiency.

As discussed in Carmichael et al. (2000, 2001), a match is characterized by a variety of moves in open play. From an attacking perspective, passing the ball to teammates and shooting on goal could be considered the two most important indicators of offensive performance (Lago-Peñas et al., 2010; Torgler, 2004). Defensively, the number of ball recoveries (interceptions) has been one of the most used defensive plays.[12] Therefore, to measure team playing style, we consider two offensive (total passes and total shots from inside the penalty area, denoted by *TOTAL_PASSES* and *SHOTS_PA*, respectively) and one defensive indicator (ball recoveries, denoted by *BALL_RECOVER*).

- Participation in European competitions: Productive inefficiency can be associated with participation in European competitions. Teams that play both during the weekends in the domestic league and at midweek for European competitions might be more physically fatigued and affected by injuries. This could make them to perform worse than other teams with the same inputs but playing only for the domestic league.[13] Furthermore, managers might prioritize European competitions at the knock-out stage and use reserve players in some domestic games. We define a dummy variable labeled EUROPE that takes value one if team i plays either the UEFA Champions League or the Europa League in season t and zero otherwise.
- League dummies: In our analysis, we pool teams from the most important five European leagues. To capture heterogeneity in efficiency levels depending on the league arising from differences in competitive balance or organizational structures (Terrien & Andreff, 2020), we include a set of league dummies as inefficiency shifters (LIGUE 1, SERIE A, BUNDESLIGA, and PREMIER, with LA LIGA acting as the reference category).

3.2.2 Favoritism as a source of heteroskedasticity

The SFA literature has devoted great attention to the potential risk of identifying inefficiency as heteroskedasticity (e.g., Caudill et al., 1995). In our case, the variability in the match-winning probability, conditional on the inputs and the individual effects, is affected by the ex ante *favoritism* of each team. Due to sanctions, injuries, potential referee biases (Garicano et al., 2005), and even the match being played in the middle of the week (Krumer & Lechner, 2018), there is some within season variability in how likely is for each team to win each match. If we ignore this potential source of heteroskedasticity, the efficiency estimates could be biased (Kumbhakar & Lovell, 2000).

[11] Scully (1994) showed that managerial efficiency is a good predictor of expected manager's survival time.

[12] Nevertheless, ball recoveries due to high press could also be partially understood as offensive actions.

[13] For instance, Villarreal CF was relegated to the Spanish second division in 2012 after having played in the Champions League that season.

Pre-match betting odds can be considered a valid proxy for the degree of favoritism (based on bettors) of each team at each match.[14] As shown by Del Corral et al. (2017), it is important to consider outcome expectations in the analysis of productive efficiency. Therefore, we model the variance of the idiosyncratic error term to be an exponential function of the expected winning probability as follows:

$$\sigma_{v_{it}} = \exp\left(\varphi_0 + \varphi_1 winprob_{it}\right) \tag{8}$$

The winning probability is computed as the inverse of the average betting odds for team *i*'s victory over the season. In doing so, we adopt the standard normalization of dividing the inverse odds by the booksum. This data comes from www.oddsportal.com, which provides the average odds from different bookmakers. By modeling both, the variance of the inefficiency and the variance of the random noise as a function of variables, our model becomes a double heteroskedastic SFA model in the sense of Hadri et al. (2003).

4 | DATA

Our database is drawn from two public-access websites about soccer statistics: (i) *WhoScored* (www.whoscored.com) and (ii) *Transfermarkt* (www.transfermarkt.com). The former provides a vast number of statistics about game-related aspects of professional soccer leagues. These statistics include the total number of points, goals scored and conceded, saves, ball possession, shots on target, fouls or the number of yellow cards, among many others. All of them are expressed as season totals. The data comes from OPTA Sports, the company with the largest databases of European professional sports. Data from OPTA has been previously used in Carmichael et al. (2000, 2001), Zambom-Ferraresi et al. (2019), and Carmichael et al. (2011, 2017), among others. *Transfermarkt* website also contains detailed statistics about soccer performance but is more concerned about the economic side of the industry. This platform provides information about the market value of players, squad composition, and so on. Prockl and Frick (2018) showed that the players' market values offered by *Transfermarkt* are an excellent proxy of their quality.[15]

We collected information for the five most important European soccer leagues (*La Liga*, *Premier League*, *Bundesliga*, *Serie A* and, *Ligue 1*) for 10 seasons, from 2009–2010 to 2018–2019. Except German *Bundesliga* that contains 18 teams, each league involves 20 teams competing each season for the title. Each team plays a complete set of round-robin matches against all other teams, once at their own ground and once at the opposite ground. Therefore, each season each team plays 38 matches (34 matches for the case of *Bundesliga*). Each victory is awarded with three points, whereas draws reward each team with a point. The team with the highest number of points at the end of the season wins the title, whereas the three teams with the lowest points are relegated to the second division and replaced by the three best performing ones in that league. Because of this, our database is an unbalanced panel. Those teams that only remained in the first division for one season (24) are removed from the sample. Therefore, our dataset contains 956 team-season

[14] Although there is no consensus in the literature, the betting market can be assumed to be weakly efficient (Forrest & Simmons, 2008).

[15] Similarly, Peeters (2018) provided fair evidence that the information provided by this website based on crowd member preferences accurately predicts soccer results, even better than FIFA ranking and ELO ratings. Herm et al. (2014) showed that *Transfermarkt* values are excellent predictors of actual transfer fees.

TABLE 2 Variable definition and descriptive statistics ($N = 956$).

Variable	Description	Mean	SD	Min	Max
Output					
P	Total number of points	52.67	16.55	15	102
Input					
TEAM_VALUE	Team value (million euros)	236.91	224.35	22.84	1172.70
Contextual variables					
TEAM_AGE	Average age of the team (years)	24.42	1.054	21.10	28.10
TEAM_VALUE_OP	Average team value of opposite teams in the same league (million euros)	236.91	75.22	93.54	431.04
Inefficiency determinants					
FOREIGN	Number of foreign players	18.30	6.85	1	57
TOTAL_PASSES	Total passes	16,511	2924	9538	28,576
SHOTS_PA	Shots for in the penalty area	31.18	10.35	8.74	78.16
BALL_RECOVER	Number of ball recoveries	621.12	161.39	311.6	1398.4
EUROPE	Dummy if the team plays either the Champions League or the EUROPA LEAGUE	0.34	0.47	0	1
PWIN	Average winning probability based on betting odds	0.349	0.148	0.132	0.830

observations corresponding to 146 different teams (23 from German *Bundesliga*, 30 from Spanish *LaLiga*, 31 from French *Ligue 1*, 32 from English *Premier League*, and 30 from Italian *Serie A*).

During the study period, 17 teams won at least once the title considering the five leagues, with 43 teams remaining in the first division during the 10 seasons. Table 2 presents summary statistics of the variables used in the analysis. We present the output, the input, the contextual variables, and the determinants of inefficiency introduced before. To make the figures comparable because *Bundesliga* involves fewer games, all the performance indicators for *Bundesliga* have been adjusted to reflect the equivalent values in a league with 38 matches. Therefore, the time dimension of the database is the season. To control for inflation in players' market value, TEAM_VALUE has been deflated taking the mean levels in the last season as the base period. This follows standard practice (Frick & Simmons, 2008; Jewell, 2017; Zambom-Ferraresi et al., 2019).

The average number of points is 52.6, ranging from 15 (Pescara, season 2016–2017) to 102 (Juventus, season 2013–2014) out of the maximum attainable of 114 (3×38). Average team value is 224 million euros, with an average squad age of 24.4. Descriptive binned scatterplots of log *P* on log *TEAM_VALUE* (Figure A1) and log *P* on log *TEAM_AGE* (Figure A2) with quadratic fit (Stepner, 2013) suggest that performance increases at an increasing rate with team value but exhibits an inverse relationship with team age. Around 34% of the sample competes in their league while also playing in a European competition (either in the Champions League or the Europa League). On average, teams shoot on goal from inside the penalty area 31.18 times per season, with 16,511 passes and 621.12 ball recoveries. Nonetheless, there is large variability in these game-related statistics according to the standard deviations. Differences in the capacity of managers to translate team input (players' quality) into points (i.e., inefficiency) can be attributed to differences in the playing style. Finally, the winning probability over the season is 35% on

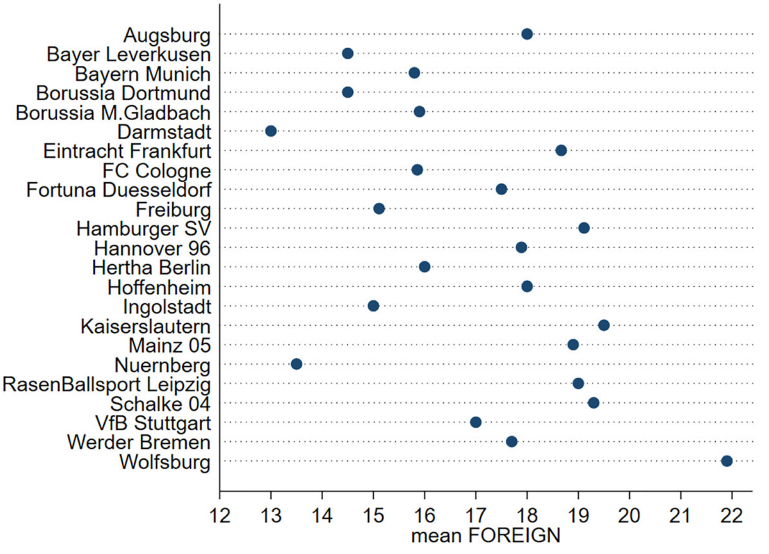

FIGURE 1 Mean number of foreign players per club in Bundesliga. [Colour figure can be viewed at wileyonlinelibrary.com]

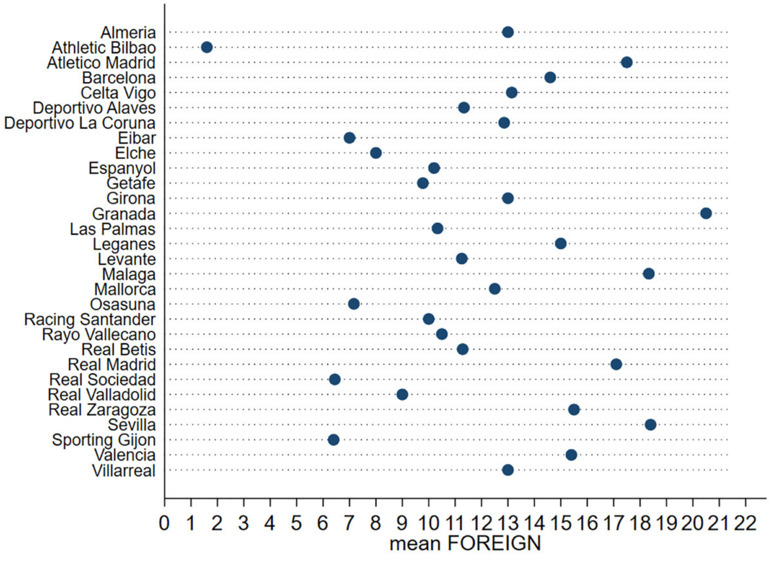

FIGURE 2 Mean number of foreign players per club in La Liga. [Colour figure can be viewed at wileyonlinelibrary.com]

average but with large variability, ranging from 13.2% (Hellas Verona, season 2017–2018) to 83% (Paris Saint German, season 2017–2018).

The average number of foreign players in sample is 18. Figures 1–5 plot the mean values over the study period per club and league. We see high dispersion across teams, with some squads being mainly composed of national players (e.g., Athletic Club), whereas others hiring foreign players only (e.g., Monaco). In cases like Athletic Club, the low number of foreign players reflects a club

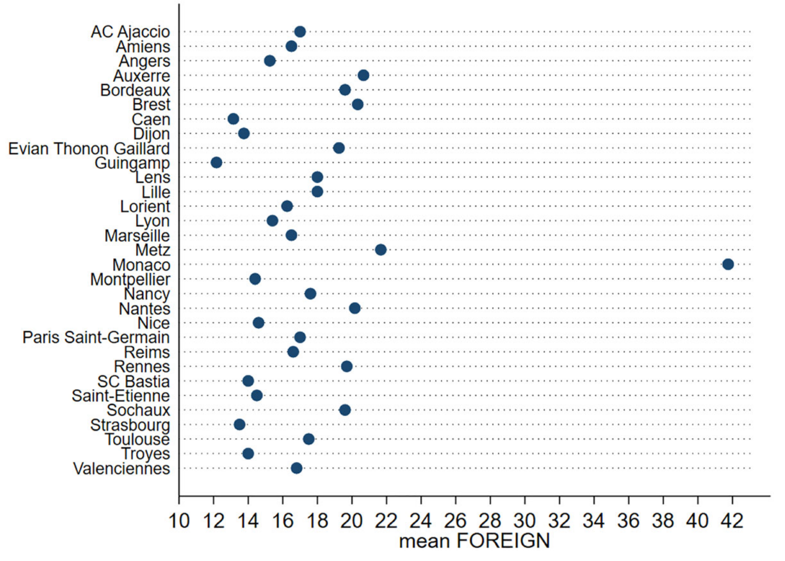

FIGURE 3 Mean number of foreign players per club in Ligue 1. [Colour figure can be viewed at wileyonlinelibrary.com]

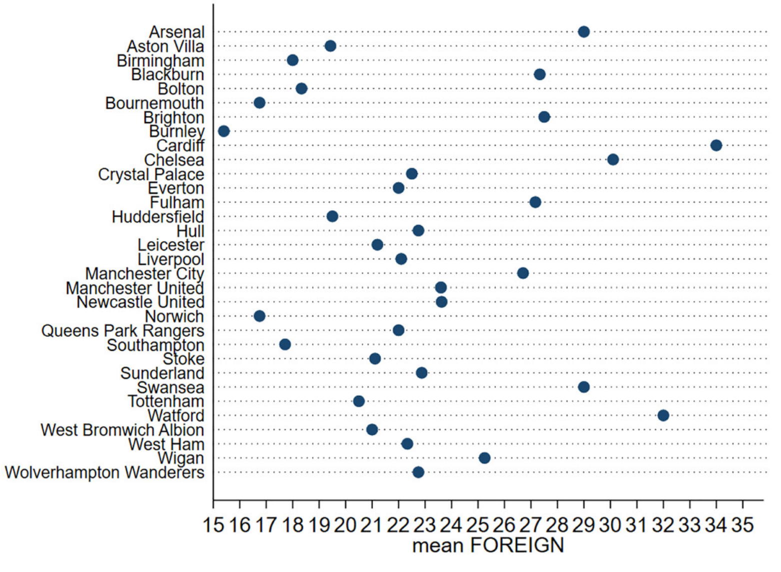

FIGURE 4 Mean number of foreign players per club in Premier League. [Colour figure can be viewed at wileyonlinelibrary.com]

idiosyncrasy of prioritizing Basque-born players as a symbol of regional identity (Gómez-Bantel, 2016). Nonetheless, in general terms, hiring strategies with regard to nationality are not driven by fans' discriminatory preferences but rather by club management strategies (Wilson & Ying, 2003). For instance, some teams have a wide network of scouters around the world aimed at discovering and hiring young talented players at low cost to later sell them to top teams in the transfer market if they eventually become superstars (Garcia-del-Barrio & Pujol, 2007). By league, the English

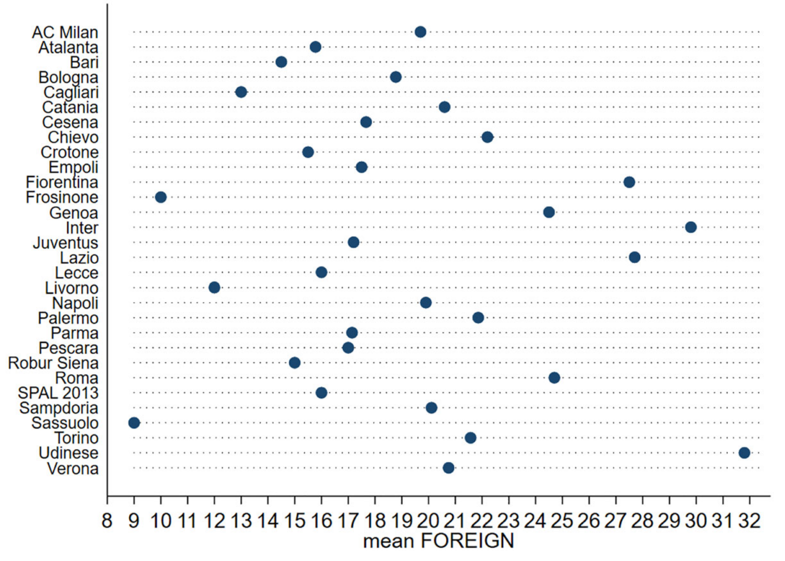

FIGURE 5 Mean number of foreign players per club in Serie A. [Colour figure can be viewed at wileyonlinelibrary.com]

Premier League and the Spanish La Liga are the ones with the greatest (23.3) and lowest (12.3) number of foreign players.[16]

To inspect the sources of heterogeneity in the number of foreign players across teams and over time, Table 3 presents an OLS regression of log *FOREIGN* on *TEAM_VALUE* and *TEAM_AGE* (in logs), league and season dummies, the binary indicator for playing a European competition, and the average points earned by the team in the previous five seasons (*AV_P_5SEASONS*). We see that the number of foreign players is positively associated with team value but inversely related to teams' average age. In-line with descriptive statistics, there are significant differences across leagues, but the number of foreign players is unrelated to performance in the previous five seasons.

5 | RESULTS

5.1 | Production frontier and technical efficiency estimates

Table 4 presents the parameter estimates of the TRE specified in Equation (4).[17] Standard errors have been clustered at the league level to consider potential cross-sectional dependence arising from teams competing against each other in the same league. Prior to estimation, the input variable and the output were normalized by their respective geometric mean in the sample. Therefore, the first-order coefficient of TEAM_VALUE is directly interpreted as the output elasticity at the sample means.

[16] A descriptive binned scatterplot of log P on log FOREIGN (residualized by team-fixed effects) indicates there is a negative association between the number of foreign players in the squad and team performance (Figure A3).

[17] The model has been estimated using the *sfpanel* module (Belotti et al., 2013) in Stata 16.

TABLE 3 OLS coefficient estimates of the drivers of log FOREIGN.

Dependent variable: log FOREIGN	
Explanatory variables	**Coefficient (SE)**
Log *TEAM_VALUE*	0.173**
	(0.047)
Log *TEAM_AGE*	−1.257**
	(0.407)
BUNDESLIGA	0.416***
	(0.014)
LIGUE 1	0.486***
	(0.026)
SERIE A	0.541***
	(0.010)
PREMIER LEAGUE	0.649***
	(0.026)
EUROPE	−0.127*
	(0.046)
AV_P_5SEASONS	0.010
	(0.075)
SEASON: 2010–2011	0.036
	(0.031)
SEASON: 2011–2012	0.044
	(0.043)
SEASON: 2012–2013	0.079
	(0.081)
SEASON: 2013–2014	0.163
	(0.087)
SEASON: 2014–2015	0.081
	(0.070)
SEASON: 2015–2016	0.118
	(0.058)
SEASON: 2016–2017	0.146*
	(0.061)
SEASON: 2017–2018	0.118
	(0.070)
SEASON: 2018–2019	0.185
	(0.096)
Constant	5.462**
	(1.271)
Team-season observations	956
Teams	146

Note: Clustered standard errors at the league level in parentheses.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

TABLE 4 SFA (stochastic frontier analysis) production function parameter estimates.

Dependent variable: log *P*	
Explanatory variables	**Coefficient (SE)**
Log *TEAM_VALUE*	0.212***
	(0.016)
Log *TEAM_VALUE2*	0.070**
	(0.030)
Log *TEAM_AGE*	−19.435***
	(1.189)
Log *TEAM_AGE2*	3.006***
	(0.206)
Log *TEAM_VALUE_OP*	−0.190***
	(0.041)
Constant	32.592***
	(1.811)
Inefficiency variance	
Log *FOREIGN*	1.171***
	(0.270)
Log *TOTAL_PASSES*	−4.208***
	(0.304)
Log *BALL_RECOVER*	−0.744***
	(0.160)
Log *SHOTS_PA*	−2.068***
	(0.303)
EUROPE	−0.077
	(0.171)
BUNDESLIGA	0.284**
	(0.136)
SERIE A	−0.026
	(0.097)
LIGUE 1	−0.649**
	(0.286)
PREMIER	0.018
	(0.160)
Constant	46.101***
	(3.718)
Error term variance	
PWIN	−1.336**
	(0.663)
Constant	−3.586***
	(0.232)
Team-season observations	956
Teams	146

Note: Clustered standard errors at the league level in parentheses.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

The estimates show that the number of points vary by 0.21 percentage points (hereafter pp) if the market value of the team (TEAM_VALUE) is increased by 1%.[18] This is consistent with previous studies on soccer efficiency that document that the team market value is the key input (Feng & Jewell, 2021; Zambom-Ferraresi et al., 2019). As expected, the number of points decreases with the mean market value of the competitors in the league (*TEAM_VALUE_OP*). This means that performance is strongly related with the relative position in the distribution of team ability within the league. Interestingly, the average age of the team (TEAM_AGE) exhibits a U-shaped relationship with the number of points earned by the end of the season, in-line with Torgler and Schmidt (2007). The minimum locates at 25.5 years old, suggesting that either young (through better physical conditions) and elderly (through an experience effect) squads perform relatively better. This falls in-line with Sal de Rellán-Guerra et al. (2019) and Zhou et al. (2020) who also showed a trade-off between physical conditions and experience throughout the players' career.

As we introduce heteroskedasticity in both the inefficiency and the idiosyncratic-error scale parameters, the signal-to-noise ratio (λ) varies per observation (Belotti et al., 2013). Considering the ratio of the expectations of both terms, the mean signal-to-noise ratio is 1.72. This means that a relevant share of the composite error term comes from the half-normal inefficiency, which justifies the estimation of the stochastic frontier model.

Moving to the determinants of the variance of the inefficiency term, the parameter estimates are not very informative about the effect of the variables on inefficiency apart from their sign. This is because the expectation of inefficiency is nonlinear in the conditional variance. Following Kumbhakar et al. (2020), the average partial effect (APE) of a given inefficiency determinant $z_{it} \subset Z_{it}$ is given as follows:

$$APE\left(z_{it}\right) = \frac{\partial E(u_{it}|Z_{it})}{\partial z_{it}} = \theta\overline{\sigma_{u_{it}}}\sqrt{2/\pi} \tag{9}$$

where $\overline{\sigma_{u_{it}}}$ is the mean value of the conditional variance, and θ the corresponding parameter estimate.

Table 5 presents the APE on inefficiency for each inefficiency determinant. A 1% increase in the number of foreign players (FOREIGN) increases productive inefficiency by 0.21 pp, on average. This finding is in-line with Lyons (2017) and Addesa et al. (2022). Assuming each unit of talent is equally valued by the market across nationalities, we interpret the negative effect as stemming from communication costs. This does not only refer to language differences but also may reflect differences in social and work norms. Although there might be gains from an internationally diverse squad as documented in the literature (Beine et al., 2021), it seems that integration costs weight more here.[19] As shown by Lazear (1999a, 1999b), in a competitive environment in which a cohesive and harmonized team is essential, the greater the number of foreign players, the greater the communication costs and the lower the gains from diversity. Potential stereotypes and animosity against players from other countries might also play a role.

The total number of passes (TOTAL_PASSES) significantly reduces inefficiency. Remarkably, this variable is the one that exhibits the largest effect on inefficiency: A 1% increase in the number

[18] If we compute the output elasticity with regard to TEAM_VALUE for each data point, we verify that the average sample elasticity is 0.21.

[19] Some skills might be disjoint across nationalities and therefore culture-specific (e.g., Brazil has historically had great forwards whereas Italy has produced high-quality defenders) so that there are potential gains for an internationally diverse squad.

TABLE 5 Average partial effects on inefficiency.

Variable	APE
Log *FOREIGN*	0.213***
Log *TOTAL*_PASSES	−0.767***
Log BALL_RECOVER	−0.135***
Log *SHOTS*_PA	−0.376***
EUROPE	−0.014
BUNDESLIGA	0.051**
SERIE A	−0.005
LIGUE 1	−0.118**
PREMIER	0.003

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

of passes decreases inefficiency by 0.76 pp. Therefore, for the same squad quality, teams with a greater ability to keep ball possession through passes (constructive play) appear to be more efficient. Similarly, the shots from the penalty area (SHOTS_PA) are negatively related with inefficiency (−0.37 pp). As scoring a goal depends, among others, on distance to goal and angle (everything else being equal), the higher the shots from inside the penalty area, the lesser the distance to the production frontier. The total number of ball recoveries as an indicator of defensive play also decreases productive inefficiency (−0.13 pp). Conditional on the quality of contenders, teams with greater capacity to recover the ball perform significantly better. Interestingly, participation in a European competition is not significantly associated with technical inefficiency. As for league differences, it appears that inefficiency is greater (lower) among teams playing in Bundesliga (Ligue 1), with no significant differences among La Liga, the Premier League, and the Serie A. These differences could be partially due to heterogeneity in organizational structures and practices across leagues as documented in Terrien and Andreff (2020).

Finally, we document that the variance of the error term is negatively related with the ex ante average winning probability (PWIN). As such, performance becomes more deterministic and less stochastic as the team is more favorite (prior to the match) to win (on average). As we control for team quality in the frontier, this variable captures sources of heteroskedasticity in the random noise not attributable to inefficiency that make teams to underperform such as injuries, disciplinary sanctions, or differences in the time elapsed among contenders since the previous match. Note that this variable does not only contain information about the team's pre-match circumstances but also implicitly about the opposite teams.

Figure A4 depicts a kernel density plot with the efficiency scores $TE_{it} = \exp(-\hat{u}_{it})$ derived from the model estimates in Table 4 following Jondrow et al. (1982). The average technical efficiency is 0.84, ranging from 0.344 (Aston Villa, season 2015–2016) to 0.982 (Paris Saint-Germain, season 2015–2016). Table A1 presents summary statistics of the technical efficiency (TE) estimates by league. Figure 6 plots the distribution of these TE scores by league. From Table A1 and Figure 6, we document that the distribution of the efficiency estimates is similar across leagues, although teams in Spanish *LaLiga* are, on average, more efficient. A full list of the teams ordered by their mean TE scores is provided in Table A2.

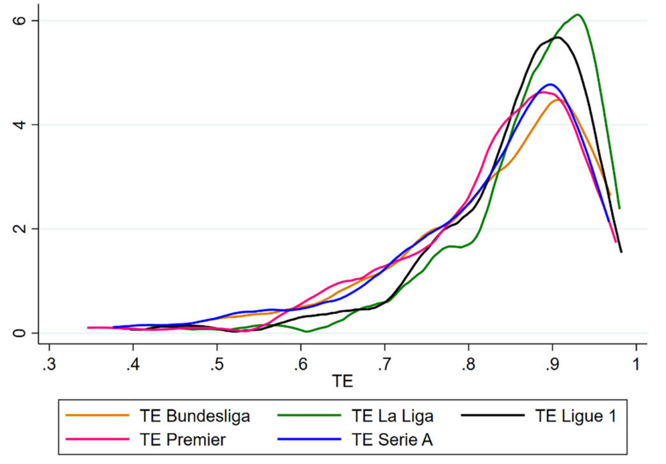

FIGURE 6 Kernel density plot for technical efficiency estimates by competition. [Colour figure can be viewed at wileyonlinelibrary.com]

5.2 | Robustness checks

We performed some checks to our analysis. Possibly the most important concern is that the number of foreign players in the squad can be endogenous, either because of reverse causality or due to omitted variables. Dealing with this potential endogeneity issue is challenging, as it is not easy to find suitable instruments in this context. To inspect the sensitivity of our findings to this, we did the following checks. First, we performed a panel fixed effects regression of the number of foreign players in season t on the number of points of the team in the previous season (Table A3 and Figure A5). There is no evidence of a significant relationship between past performance and the current number of foreign players, suggesting that hiring strategies on this respect do not seem to react to good or bad performance in the previous year. Second, we constructed the following instrumental variable for FOREIGN as follows:

$$Z_{it} = \frac{FOREIGN_{it-1}}{NUM.PLAYERS_{it-1}} \times NUM.PLAYERS_{it} \tag{10}$$

That is, we created a "fake" number of foreign players as the share of foreigners in the team in the previous season times the current number of players. This variable is expected to be highly correlated with FOREIGN (see Figure A6) but to be independent from the inefficiency term at period t. Next, we estimated a panel SFA model allowing for endogeneity in the variance of the inefficiency term following the methods developed by Karakaplan and Kutlu (2017) and Karakaplan (2022). The eta endogeneity test proposed by these authors does not reject the null hypothesis that the correction for endogeneity is not necessary ($\text{chi}^2(1) = 0.26$, p-value $= 0.61$). Although these auxiliary diagnostic checks do not detect evidence of endogeneity, the observational nature of our research and the possibility that this auxiliary variable does not satisfy the exclusion restriction precludes us to give our findings a causal interpretation.

Some additional checks are the following. First, the inefficiency estimates (and therefore the input-oriented technical efficiency scores) were derived using the formula proposed by Battese and Coelli (1988) rather than the one by Jondrow et al. (1982) and outlined in Equation (5). The pairwise correlation between the two inefficiency estimates is 0.99. Second, we estimated the model assuming (i) both the variances of the inefficiency and the random noise are homoskedastic, (ii) only the variance of the random noise is allowed to be heteroskedastic, and (iii) only

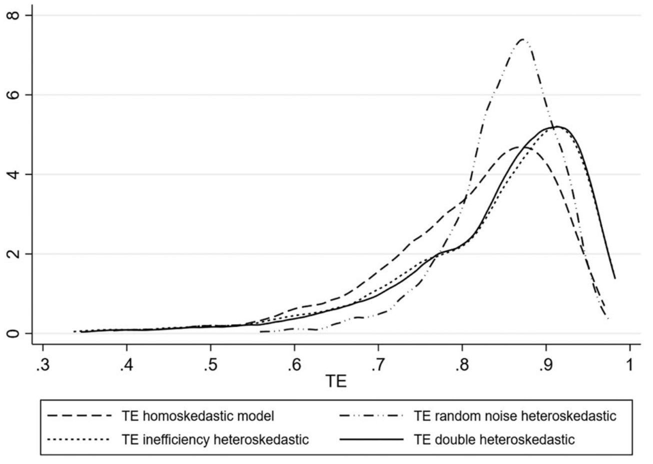

FIGURE 7 Kernel density plot for technical efficiency estimates under different heteroskedastic models.

variance of the inefficiency term is allowed to be heteroskedastic. The coefficient estimates can be found in Table A4. The corresponding input-oriented technical efficiency estimates are presented in Figure 7. As can be seen, TE scores derived from a homoskedastic model appear to be downward biased. This is because neglected heteroskedasticity biases the parameters in the production function (Kumbhakar & Lovell, 2000). In-line with Hadri et al. (2003), Figure 7 therefore illustrates that ignoring heteroskedasticity, either in the inefficiency term or in the random noise, could produce misleading results.

Third, we tested alternative assumptions for the distribution of the inefficiency term. Instead of assuming it is half-normal distributed, we estimated the model under the assumption it follows (i) a truncated normal distribution, and (ii) an exponential distribution. The estimates are presented in Table A5. Results remain consistent with the main analysis. Fourth, we examined the validity of treating the individual time-invariant effects as "random" (i.e., uncorrelated with the explanatory variables). As the True Fixed Effects model leads to incidental parameter bias because the panel is quite unbalanced, we run an auxiliary panel random effects regression of the output on the input and the control variables, including the time means à la Mundlak. A chi-squared test does not reject the null hypothesis that the time means are globally equal to zero ($\text{chi}^2(3) = 3.68$, p-value $= 0.297$), suggesting that the random effects can be taken as uncorrelated with the explanatory variables. Fifth, we reestimated the model using (i) the average market value per player instead of the total team value, (ii) the (log of) the share of foreign players instead of the (log of) the number of foreign players, and (iii) excluding TEAM_AGE as a control from the frontier (Tables A6–A8, respectively). The results from these alternative specifications are very similar, with the difference that PWIN becomes nonsignificant. Sixth, we used the points earned over the maximum points attainable ($\log P/\max P$) as the dependent variable due to the fact that Bundesliga involves fewer teams (matches) and therefore our results could be sensitive to that. However, the estimates are almost unchanged (Table A9). Finally, we considered expanding the model specification for the production frontier by including (i) the average age of the opposite teams, (ii) the number of foreign players, and (iii) an interaction term between TEAM_VALUE and TEAM_AGE, separately. None of these variables were found to be statistically significant in the frontier (available upon request), so we opted for a parsimonious specification (also to avoid collinearity issues).

TABLE 6 Coefficient estimates and Average Marginal Effects (AME) for panel ordered probit.

Dependent variable: RANK	Coefficient (SE)	AME prob (RANK = 1)	AME prob (RANK = 2)	AME prob (RANK = 3)	AME prob (RANK = 4)
TE	−22.449***	2.022***	0.877***	−0.889***	−2.010***
	(1.572)	(0.174)	(0.097)	(0.220)	(0.104)
Log *L*	−600.86				
Obs	956				
Teams	146				

Note: Bootstrapped standard errors in parentheses.
***$p < 0.01$.

5.3 | Technical efficiency and ranking in the table

Next, we explore in more detail the linkages between technical efficiency and the ranking in the table. The related literature typically finds most efficient teams to be the better classified ones (Carmichael et al., 2017; Jewell, 2017; Zambom-Ferraresi et al., 2017), although this is not always the case (Espitia-Escuer & García-Cebrián, 2004). To this end, we first define the variable RANK as an ordered indicator that takes value 1 if the team ends in any of the positions that qualify for playing the Champions League in the following season ($n = 190$), value 2 for the Europa League ($n = 90$), value 3 in case the team does neither qualify for a European competition but remains in the first division ($n = 469$), and value 4 if the team is relegated to the second division ($n = 207$).[20]

Similar to Feng and Jewell (2021), we estimate a panel ordered probit regression with team-specific random effects in which RANK is regressed on TE. Note that although the ranking position is related to the number of points (our output), the same number of points can lead to very different positions depending on the competitive balance of each league in each season.[21]

Table 6 presents the coefficient estimates and the average marginal effects for each value of RANK. As TE are estimates themselves, standard errors have been bootstrapped after 1000 repetitions. We find that TE scores are positively related with ranking position in the league. Specifically, a marginal increase in technical efficiency increases the probability of qualifying for the Champions League and the Europa League by 2.0% and 0.87%, respectively. However, increases in technical efficiency reduce the likelihood of relegation by 2.0%. This result is in-line with Feng and Jewell (2021), who showed that technical efficiency is negatively associated with the likelihood of relegation. Accordingly, conditional on team quality and squad characteristics, teams that are more efficient in the management of their resources rank better and are more likely to achieve their season objectives.

[20] As the number of teams allowed to participate in European competitions varies per league, the variable RANK does not exactly correspond to the same table positions across leagues.

[21] For example, Deportivo de la Coruña was relegated in the season 2010–2011 with 43 points, whereas Granada remained in *LaLiga* with 35 points in the season 2014–2015. Manchester United won the *Premier League* in 2016 with 80 points, whereas Manchester City required 98 points to win the title in 2017 (Liverpool ended in the second position with 97 points).

6 | CONCLUSIONS

6.1 | Summary of findings

In this paper, we have studied the technical efficiency of European soccer clubs considering on-field success as the output to be maximized. Using a large dataset covering 146 teams playing in the top 5 European leagues during 10 seasons, we have estimated a stochastic production frontier using TREs model. Team market value has been used as a proxy of the playing talent input. Our econometric model considers time-invariant individual random effects in the frontier together with the average market value of opposite teams and the average age of the squad as contextual variables. The inefficiency term is allowed to vary over time but without imposing all the units to follow the same temporal pattern. We have specified the variance of the inefficiency term to be an exponential function of a set of team characteristics to examine potential sources of inefficiency. In particular, we have studied whether the team composition in terms of the number of foreign players in the squad affects productive inefficiency. Furthermore, similar to previous sports literature, we have considered some game-related statistics as additional inefficiency determinants. In doing so, we assume that manager's choice of tactics and team's playing style determine the performance possibilities. We have specifically considered the total number of passes, ball recoveries, and shots from inside the penalty areas as inefficiency shifters.

Our results show that, conditional on their playing talent, teams with a greater number of passes, ball recoveries, and shots from inside the penalty area are more efficient. The total number of passes is the playing indicator with the largest effect on the inefficiency variance. The estimates also show that teams with a greater number of foreign players are more inefficient, ceteris paribus. This result could reflect the fact that the potential gains from having an internationally diverse squad are offset by integration and communication costs. Additionally, we have found that teams in the Spanish league are, on average, more efficient. This suggests that this league is the most competitive and requires teams to be highly efficient for reaching their objectives. Moreover, we have shown that the efficiency scores derived from our model are good predictors of the ranking position in the table.

The study adds to a large body of literature concerned about managerial efficiency in professional sports. From a methodological perspective, the paper has two features that distinguish it from related applications. Unlike previous literature, we have modeled the variance (and therefore the mean) of the inefficiency term as a function of team characteristics to explore potential sources of heterogeneity. Unlike previous analysis, we have considered the degree of pre-match *favoritism* by allowing the random noise to depend on winning probabilities based on betting odds. In this way, at the same time, we control for potential heteroskedasticity, our model acknowledges that part of the variability in sporting results is due to factors beyond team performance that cannot be attributed to inefficiency. Indeed, we find that *favoritism* makes performance more deterministic. Accordingly, our double heteroskedastic frontier model identifies inefficiency conditional on how tied matches are expected to be.

Our study is also related to the literature on organizational management and how firm heterogeneity relates to performance. Specifically, we document that the higher the number of foreign players in the squad, the greater the inefficiency. Consistent with the literature on teammates, although hiring foreign players might allow the team to broaden its collective sets of skills and abilities, at the same time, this could lead to communication and integration costs stemming from language and cultural differences.

6.2 | Implications and recommendations for the industry

Some managerial implications for the soccer industry can be derived from our work. On the one hand, the results highlight the importance of offensive and defensive indicators in the analysis of sporting performance. Given playing talent, a greater volume of passes, recoveries, and shots decrease inefficiency, pushing teams toward their output potential. Accordingly, accumulating a high number of passes and patient build-up, pressing tactics aimed at recovering the ball at opposite's third, and a high volume of shots could be promising strategies for managers to maximize their team's performance. On the other hand, the fact that a high number of foreign players in the squad are associated with worse sporting performance deserves further attention by soccer team managers. Teams opting for hiring players from different countries and cultures should devote greater effort to cohesiveness and the team integration of recently arrived foreign players, particularly during their first year. Asking them to learn the local language or implementing group coaching methods that foster team spirit might be interesting options.

6.3 | Limitations and future research

The paper has some limitations that can be considered avenues for future research. First, the identification of the real mechanism underlying the negative association between the number of foreigners and team efficiency is complex in this context. Although we interpret it in terms of communication costs and cultural frictions, other factors could also explain this result. Future work should deepen more into this. Second, our work focuses on sporting performance measured in terms of total the number of points earned in the domestic league by the end of the season. However, teams also participate in other competitions like UEFA Champions League/UEFA Europa League and national Cup tournaments. It could be the case that teams do not achieve their potential in the domestic league (therefore being inefficient) because they prioritize other competitions. Future studies could expand our work by considering a more general indicator of sporting performance that encompasses performance in different competitions. This is not an easy task, though, since not all the teams compete in the same competitions. Third, we have considered three of the most important game statistics as potential explanations of differences in sporting efficiency. As differences in efficiency are found to be strongly related to the playing style, future research should deepen into how the tactical modules and playing philosophy adopted by coaches affects sporting performance. Finally, the negative effects in terms of efficiency of an internationally diverse squad could be moderated by the manager's language knowledge and communication ability. This seems to be another fruitful are for future research.

ACKNOWLEDGMENTS

The authors wish to thank Julio del Corral for helpful comments and suggestions.

FUNDING

None.

CONFLICT OF INTEREST STATEMENT

None.

ORCID

David Boto-García https://orcid.org/0000-0001-8065-0983

REFERENCES

Addesa, F., Pazzona, M., & Rossi, G. (2022). Migrant diversity and team performance in a high-skilled labour market. *Kyklos*, *75*, 365–384.

Arcidiacono, P., Kinsler, J., & Price, J. (2017). Productivity spillovers in team production: Evidence from professional basketball. *Journal of Labor Economics*, *35*(1), 191–225.

Barros, C., del Corral, J., & Garcia-del-Barrio, P. (2009). Identification of segments of soccer clubs in the Spanish League First Division with a Latent Class Model. *Journal of Sports Economics*, *9*(5), 451–469.

Barros, C. P., & Leach, S. (2007). Technical efficiency in the English Football Association Premier League with a stochastic cost frontier. *Applied Economics Letters*, *14*, 731–741.

Barros, C., Wanke, P., & Figueiredo, O. (2015). The Brazilian Soccer Championship: An efficiency analysis. *Applied Economics*, *47*(9), 906–915.

Battese, G. E., & Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics*, *38*, 387–399.

Beine, M. A., Peracchi, S., & Zanaj, S. (2021). *Genetic diversity and performance: Evidence from football data* (CESifo Working Papers No. 9188). CESifo.

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontier analysis using Stata. *Stata Journal*, *13*(4), 719–758.

Belotti, F., & Ilardi, G. (2018). Consistent inference in fixed-effects stochastic frontier models. *Journal of Econometrics*, *202*, 161–177.

Boto-García, D., Bucciol, A., & Zarri, L. (2020). *Managerial beliefs and firm performance: Field evidence from professional elite soccer* (University of Verona Working Paper Series No. 19). University of Verona.

Bridgewater, S., Kahn, L. M., & Goodall, A. H. (2011). Substitution and complementarity between managers and subordinates: Evidence from British football. *Labour Economics*, *18*, 275–286.

Bucciol, A., Hu, A., & Zarri, L. (2019). The effects of prior outcomes on managerial risk taking: Evidence from Italian professional soccer. *Journal of Economic Psychology*, *75*, 102090.

Buzzacchi, L., Caviggioli, F., Milone, F. L., & Scotti, D. (2021). Impact and efficiency ranking of football managers in the Italian Serie A: Sport and financial performance. *Journal of Sports Economics*, *22*(7), 744–776.

Carmichael, F., McHale, I., & Thomas, D. (2011). Maintaining market position: Team performance, revenue and wage expenditure in the English Premier League. *Bulletin of Economic Research*, *63*(4), 464–497.

Carmichael, F., Rossi, G., & Thomas, D. (2017). Production, efficiency, and corruption in Italian Serie A football. *Journal of Sports Economics*, *18*(1), 34–57.

Carmichael, F., & Thomas, D. (1995). Production and efficiency in team sports: An investigation of rugby league football. *Applied Economics*, *27*, 859–869.

Carmichael, F., Thomas, D., & Ward, R. (2000). Team performance: The case of English Premiership football. *Managerial and Decision Economics*, *21*, 31–45.

Carmichael, F., Thomas, D., & Ward, R. (2001). Production and efficiency in Association Football. *Journal of Sports Economics*, *2*(3), 228–243.

Caudill, S. B., Ford, J. M., & Gropper, D. M. (1995). Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity. *Journal of Business and Economic Statistics*, *13*, 105–111.

Cifuentes-Faura, J. (2022). Efficiency and transparency of Spanish football clubs: A non-parametric approach. *Managerial and Decision Economics*, *43*, 1850–1860. https://doi.org/10.1002/mde.3492

D'Addona, S., & Kind, A. (2014). Forced manager turnovers in English soccer league: A long-term perspective. *Journal of Sports Economics*, *15*, 150–179.

Dale-Olsen, H., & Finseraas, H. (2020). Linguistic diversity and workplace productivity. *Labour Economics*, *64*, 101813.

Dawson, P., & Dobson, S. (2002). Managerial efficiency and human capital: An application to English Association Football. *Managerial and Decision Economics*, *23*(8), 471–486.

Dawson, P., Dobson, S., & Gerrard, B. (2000a). Stochastic frontiers and the temporal structure of managerial efficiency in English soccer. *Journal of Sports Economics*, *1*(4), 341–362.

Dawson, P., Dobson, S., & Gerrard, B. (2000b). Estimating coaching efficiency in professional team sports: Evidence from English association football. *Scottish Journal of Political Economy*, *47*(4), 399–421.

Del Corral, J., Maroto, A., & Gallardo, A. (2017). Are former professional athletes and native better coaches? Evidence from Spanish basketball. *Journal of Sports Economics*, *18*(7), 698–719.

Espitia-Escuer, M., & García-Cebrián, L. I. (2004). Measuring the efficiency of Spanish first-division soccer teams. *Journal of Sports Economics*, *5*(4), 329–346.

Espitia-Escuer, M., & García-Cebrián, L. I. (2006). Performance in sports teams: Results and potential in the professional soccer league in Spain. *Management Decision*, *44*(8), 1020–1030.

Espitia-Escuer, M., & García-Cebrián, L. I. (2010). Measurement of the efficiency of football teams in the Champions League. *Managerial and Decision Economics*, *31*, 373–386.

Espitia-Escuer, M., & García-Cebrián, L. I. (2020). Efficiency of football teams from an organisation management perspective. *Managerial and Decision Economics*, *40*, 321–338.

Feng, G., & Jewell, T. (2021). Productivity and efficiency at English football clubs: A random coefficient approach. *Scottish Journal of Political Economy*, *68*(5), 571–604.

Fischer, K., & Haucap, J. (2022). Home advantage in professional soccer and betting market efficiency: The role of spectator crowds. *Kyklos*, *75*, 294–316. https://doi.org/10.1111/kykl.12291

Forrest, D., & Simmons, R. (2008). Sentiment in the betting market on Spanish football. *Applied Economics*, *40*, 119–126.

Frick, B., & Lee, Y. H. (2011). Temporal variations in technical efficiency: Evidence from German soccer. *Journal of Productivity Analysis*, *35*, 15–24.

Frick, B., & Simmons, R. (2008). The impact of managerial quality on organizational performance: Evidence from German soccer. *Managerial and Decision Economics*, *29*, 593–600.

Garcia-del-Barrio, P., & Pujol, F. (2007). Hidden monopsony rents in winner-take-all markets—Sport and economic contribution of Spanish soccer players. *Managerial and Decision Economics*, *28*(57), 57–70.

Garcia-del-Barrio, P., & Szymanski, S. (2009). Goal! Profit maximization versus win maximization in soccer. *Review of Industrial Organization*, *34*, 45–68.

Garicano, L., Palacios-Huerta, I., & Presdergast, C. (2005). Favoritism under social pressure. *The Review of Economics and Statistics*, *87*(2), 208–216.

Gelade, G. A. (2018). The influence of team composition on attacking and defending in football. *Journal of Sports Economics*, *19*(8), 1174–1190.

Ghio, A., Ruberti, M., & Verona, R. (2019). Financial constraints on sport organizations' cost efficiency: The impact of financial fair play on Italian soccer clubs. *Applied Economics*, *51*(24), 2623–2638.

Gómez-Bantel, A. (2016). Football clubs as symbols of regional identities. *Soccer & Society*, *17*(5), 692–702.

González-Gómez, F., & Picazo-Tadeo, A. J. (2010). Can we be satisfied with our football team? Evidence from Spanish professional football. *Journal of Sports Economics*, *11*(4), 418–442.

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis*, *23*, 7–32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimator of the stochastic frontier model. *Journal of Econometrics*, *126*, 269–303.

Hadley, L., Poitras, M., & Ruggiero, J. (2000). Performance evaluation of National Football League teams. *Managerial and Decision Economics*, *21*(2), 63–70.

Halkos, G. E., & Tzeremes, N. G. (2013). A two-stage double bootstrap DEA: The case of the top 25 European football clubs' efficiency levels. *Managerial and Decision Economics*, *34*, 108–115.

Herm, S., Callsen-Bracker, H. M., & Kreis, H. (2014). When the crowd evaluates soccer players' market values: Accuracy and evaluation attributes of an online community. *Sport Management Review*, *17*(4), 484–492.

Hadri, K., Guermat, C., & Whittaker, J. (2003). Estimation of technical inefficiency effects using panel data and doubly heteroscedastic stochastic production frontiers. *Empirical Economics*, *28*, 203–222.

Hofler, R. A., & Payne, J. E. (1997). Measuring efficiency in the National Basketball Association. *Economics Letters*, *55*, 293–299.

Hofler, R. A., & Payne, J. E. (2006). Efficiency in the National Basketball Association: A stochastic frontier approach with panel data. *Managerial and Decision Economics*, *27*(4), 279–285.

Homroy, S., & Soo, K. T. (2020). Team diversity and individual performance. *The Manchester School*, *88*, 507–530.

Jewell, R. T. (2017). Technical efficiency with multi-output, heterogeneous production: A latent class, distance function model of English football. *Journal of Productivity Analysis*, *48*, 37–50.

Jewell, R. T., & Molina, D. J. (2004). Productive efficiency and salary distribution: The case of US Major League baseball. *Scottish Journal of Political Economy*, *51*(1), 127–142.

Jondrow, J., Lovell, C. A. K., Materov, I., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, *19*, 233–238.

Kahane, L. (2005). Production efficiency and discriminatory hiring practices in the National Hockey League: A stochastic frontier approach. *Review of Industrial Organization*, *27*(1), 47–71.

Kahane, L., Longley, N., & Simmons, R. (2013). The effects of coworker heterogeneity on firm-level output: Assessing the impacts of cultural and language diversity in the National Hockey League. *The Review of Economics and Statistics*, *95*(1), 302–314.

Karakaplan, M. U. (2022). Panel stochastic frontier models with endogeneity. *The Stata Journal*, *22*(3), 643–663.

Karakaplan, M. U., & Kutlu, L. (2017). Handling endogeneity in stochastic frontier analysis. *Economics Bulletin*, *37*(2), 889–901.

Kern, M., & Süssmuth, B. (2005). Managerial efficiency in German top league soccer: An econometric analysis of club performance on and off the pitch. *German Economic Review*, *6*(4), 485–506.

Krumer, A., & Lechner, M. (2018). Midweek effect on soccer performance: Evidence from the German Bundesliga. *Economic Inquiry*, *56*(1), 193–207.

Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge University Press.

Kumbhakar, S. C., Parmeter, C. F., & Zelenyuk, V. (2020). Stochastic frontier analysis: Foundations and advances I. In *Handbook of production economics*. Springer.

Lago-Peñas, C., Lago-Ballesteros, J., Dellal, A., & Gómez, M. (2010). Game-related statistics that discriminated winning, drawing and losing teams from the Spanish soccer league. *Journal of Sports Science and Medicine*, *9*, 288–293.

Lazear, E. P. (1999a). Culture and language. *Journal of Political Economy*, *107*, S95–S126.

Lazear, E. P. (1999b). Globalisation and the market for team-mates. *The Economic Journal*, *109*(454), C15–C40.

Lee, Y. H. (2009). Comment to: Identification of segments of soccer clubs in the Spanish League First Division with a Latent Class Model. *Journal of Sports Economics*, *10*(6), 651–659.

Lee, Y. H. (2011). Is the small-ball strategy effective in winning games? A stochastic frontier production approach. *Journal of Productivity Analysis*, *35*, 51–59.

Lee, Y. H., & Berri, D. (2008). A re-examination of production functions and efficiency estimates for the National Basketball Association. *Scottish Journal of Political Economy*, *55*(1), 51–66.

Lyons, E. (2017). Team production in international labor markets: Experimental evidence from the field. *American Economic Journal: Applied Economics*, *9*(3), 70–104.

McGoldrick, K., & Voeks, L. (2005). "We got game"! An analysis of win/loss probability and efficiency differences between the NBA and WNBA. *Journal of Sports Economics*, *6*(1), 5–23.

Özaydin, S., & Donduran, M. (2020). Efficiency analysis of social performance—The case of Turkish super league. *International Journal of the Economics of Business*, *27*(3), 391–409.

Ozgen, C. (2021). The economics of diversity: Innovation, productivity and the labour market. *Journal of Economic Surveys*, *35*(4), 1168–1216.

Peeters, T. (2018). Testing the Wisdom of Crowds in the field: *Transfermarkt* valuations and international soccer results. *International Journal of Forecasting*, *34*, 17–29.

Pérez-González, A., de Carlos, P., & Alén, E. (2022). An analysis of the efficiency of football clubs in the Spanish First Division through a two-stage relational network DEA model: A simulation study. *Operational Research*, *22*, 3089–3112. https://doi.org/10.1007/s12351-021-00650-5

Prat, A. (2002). Should a team be homogeneous? *European Economic Review*, *46*, 1187–1207.

Prockl, F., & Frick, B. (2018). Information precision in online communities: Player valuations on www.transfermarkt.de. *International Journal of Sport Finance*, *13*(4), 319–335.

Rohde, M., & Breuer, C. (2018). Competing by investments or efficiency? Exploring financial and sporting efficiency of club ownership structures in European football. *Sport Management Review*, *21*(5), 563–581.

Rosen, S., & Sanderson, A. (2001). Labour markets in professional sports. *The Economic Journal*, *111*, F47–F68.

Rossi, G., Goossens, D., Di Tanna, G. L., & Addesa, F. (2019). Football team performance efficiency and effectiveness in a corruptive context: The Calciopoli case. *European Sport Management Quarterly*, *19*(5), 583–604.

Roupakias, S., & Dimou, S. (2020). Impact of cultural diversity on local labor markets. Evidence from Greece's "age of mass migration". *The Manchester School*, *88*, 282–304.

Sal de Rellán-Guerra, A., Rey, E., Kalén, A., & Lago-Peñas, C. (2019). Age-related physical and technical match performance changes in elite soccer players. *Scandinavian Journal of Medicine & Science in Sports*, *29*(9), 1421–1427.

Scully, G. W. (1974). Pay and performance in major league baseball. *American Economic Review*, *64*, 915–930.

Scully, G. W. (1994). Managerial efficiency and survivability in professional team sports. *Managerial and Decision Economics*, *15*, 403–411.

Stepner, M. (2013). BINSCATTER: Stata module to generate binned scatterplots [Statistical Software Components S457709]. Boston College Department of Economics.

Szymanski, S. (2000). A market test for discrimination in the English Professional Soccer leagues. *Journal of Political Economy*, *108*(3), 590–603.

Terrien, M., & Andreff, W. (2020). Organisational efficiency of national football leagues in Europe. *European Sport Management Quarterly*, *20*(2), 205–224.

Terviö, M. (2006). Transfer fee regulations and player development. *Journal of the European Economic Association*, *4*(5), 957–987.

Torgler, B. (2004). The economics of the FIFA football World Cup. *Kyklos*, *57*, 287–300.

Torgler, B., & Schmidt, S. L. (2007). What shapes player performance in soccer? Empirical findings from a panel analysis. *Applied Economics*, *39*(18), 2355–2369.

Tovar, J. (2020). Performance, diversity and national identity: Evidence from Association Football. *Economic Inquiry*, *58*(2), 897–916.

Trax, M., Brunow, S., & Suedekum, J. (2015). Cultural diversity and plant-level productivity. *Regional Science and Urban Economics*, *53*, 85–96.

Villa, G., & Lozano, S. (2016). Assessing the scoring efficiency of a football match. *European Journal of Operational Research*, *255*, 559–569.

Weimar, D., & Wicker, P. (2017). Moneyball revisited: Effort and team performance in professional soccer. *Journal of Sports Economics*, *18*(2), 140–161.

Wilson, D. P., & Ying, Y. H. (2003). Nationality preferences for labour in the international football industry. *Applied Economics*, *35*(14), 1551–1559.

Zambom-Ferraresi, F., Iráizoz, B., & Lera-López, F. (2019). Are football managers as efficient as coaches? Performance analysis with ex ante and ex post inputs in the Premier League. *Applied Economics*, *51*(3), 303–314.

Zambom-Ferraresi, F., García-Cebrián, L. I., Lera-López, F., & Iráizoz, B. (2017). Performance evaluation in the UEFA Champions League. *Journal of Sports Economics*, *18*(5), 448–470.

Zhou, C., Lorenzo, A., Gómez, M. A., & Palao, J. M. (2020). Players' match demands according to age and playing position in professional male soccer players. *International Journal of Performance Analysis in Sport*, *20*(3), 389–405.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Boto-García, D., Varela-Quintana, C., & Muñiz, A. (2023). Foreign players, team production, and technical efficiency: Evidence from European soccer. *Bulletin of Economic Research*, *75,* 1209–1241. https://doi.org/10.1111/boer.12407