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Football Fan Satisfaction Based on Ticket Price. A Dynamic Hedonic Pricing Model Approach

Daniel Megía-Cayuela

University of Málaga, Málaga, Spain

Correspondence: Daniel Megía-Cayuela (danimegia@uma.es)

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ABSTRACT

Objectives: This study analyzes the different components and attributes that make up a football ticket based on the tastes and preferences of fans. The aim is to categorize preferences by type of attribute and assign the corresponding weight to each variable. The theoretical framework will focus on the Spanish First Division, La Liga Santander, during the 2016–2019 seasons.

Methods: The methodology used is based on calculating the level of fan satisfaction, with ticket price being the variable most sensitive to the consumer, applying a hedonic pricing model derived from the maximization of a Cobb–Douglas function, such as consumer theory.

Results: The results obtained will indicate the level of satisfaction and the behavior of these fan bases. This article lies in the use of an empirical tool for the professionalization of football clubs, allowing them to gain insights into their fans' preferences with the goal of making optimal decisions regarding ticket pricing.

1 | Research Question

This research study will focus on the analysis of ticket prices for football matches in Spain's First Division, known as La Liga Santander. The analysis period covers the 2016–2019 seasons. The system employed will be a hedonic pricing analysis, combined with calculating results based on a Cobb–Douglas preference maximization function. According to Rosen (1974), "Hedonic prices are defined as the implicit price of a good, which is composed of a series of attributes where economic agents associate an economic value to each variable or attribute." Similarly, Triplett (1973) considered the final price of a good as the individual sum of the value of each attribute that comprises said good. Hedonic pricing has been the subject of many previous research articles in various economic fields. For example, Griliches (1971) examined market pricing in the automobile sector; Stewart and Jones (1998) analyzed professional sports, valuing potential transfers based on the statistics of baseball players in the MLB. Wilhelmsson (2002) applied it to the real estate market, and Gustafson et al. (2016) set wine prices based on harvest attributes.

The hedonic pricing method presents several advantages and disadvantages when applied to the valuation of differentiated goods. Among its main strengths is its ability to capture the implicit economic value of individual attributes within a heterogeneous good, such as size, location, or age in the housing market. This approach is flexible and can be implemented in diverse markets where products are differentiated, including real estate, automobiles, airline tickets, or tickets for cultural and sporting events. Additionally, the method is grounded in robust microeconomic theory, specifically consumer choice theory and utility maximization, which confers conceptual validity and analytical rigor. Furthermore, hedonic pricing models are useful for welfare analysis and public policy design, as they allow the

valuation of non-marketable attributes such as environmental quality, safety, or accessibility, informing planning decisions and regulatory interventions.

However, the methodology also presents limitations. It requires highly detailed and extensive datasets containing accurate information on prices and the specific characteristics of goods or services. The results are sensitive to the functional form chosen (linear, logarithmic, or semi-logarithmic), which imposes restrictive assumptions on the estimation process. Moreover, hedonic models often face multicollinearity problems because many attributes are correlated, such as location and land value in housing markets, complicating the estimation of individual effects. Another important limitation is its reliance on the assumption that markets are in competitive equilibrium, which may not hold in the presence of market imperfections or rigidities. Finally, hedonic pricing struggles to account for unobservable or qualitative attributes that are not included in the dataset, potentially biasing estimations.

The methodology has been widely used in the real estate market to estimate the value of attributes such as square footage, neighborhood characteristics, and proximity to public transportation or environmental amenities, as exemplified by the seminal works of Rosen (1974) and J. N. Brown and Rosen (1982), as well as studies by Cheshire and Sheppard (1995). Applications extend to the airline industry, where it has been employed to assess the value of flight duration, stopovers, airlines, and schedules, as shown in the work of Pels et al. (2001). It has also been applied to the analysis of cultural and sporting event tickets, estimating the value of seat location, visibility, rivalry, or event prestige, as discussed by C. Shapiro and Varian (1999) and Humphreys and Johnson (2020). In addition to referencing Rosen's pioneering work, it is recommended to cite J. N. Brown and Rosen (1982) in this section to reinforce the theoretical and methodological foundations of hedonic price models. It is also important to establish a clear distinction between the concept of variable price and the hedonic price. The term variable price typically refers to the price changes arising from temporal factors, such as purchase timing, seasonality, or dynamic pricing strategies implemented by sellers to adjust prices based on demand fluctuations or inventory considerations. For example, airline ticket prices often vary depending on the date and time of purchase, as well as proximity to the departure date (Gallego and Van Ryzin 1994).

In contrast, hedonic price refers to the implicit value of the inherent characteristics of a good or service that contribute to its market price at any given moment. Hedonic pricing decomposes the total observed price into the marginal contributions of its attributes, such as size, quality, brand, or location in the case of housing markets (Rosen 1974). Therefore, while variable pricing focuses on when a good is purchased and how market dynamics influence its price, hedonic pricing focuses on what is being purchased, quantifying the monetary value of each characteristic embedded in the product or service.

This distinction is crucial for empirical analyses, as conflating temporal price variation with attribute-based price decomposition can lead to the misinterpretation of market behavior and the determinants of consumer willingness to pay (Lancaster 1966; Pels et al. 2001). Incorporating this conceptual clarification strengthens the methodological foundation of hedonic price models and their application in markets characterized by both time-based price variability and differentiated goods.

The ticket price represents the value assigned for enjoying a live football match at the stadium by a fan or consumer. Using a hedonic pricing model, the set of attributes associated with the good being enjoyed was decomposed. Authors like Kemper and Breuer (2016) conducted a study using the hedonic pricing method in the football domain, specifically analyzing Derby County in the Premier League during the 2013/2014 season. The methodology used was called dynamic ticket pricing (DTP). In other sports like baseball in the MLB, Mondello and Rishe (2005) and Drayer et al. (2012) explored this area of knowledge. The latter conducted a ticket study on the Colorado Rockies using a methodology called variable ticket pricing (VTP), taking into account variables such as the opposing team and the match date. Additionally, other authors developed software for price setting using the DTP system, as recorded in studies by Dunne (2012) and Moore (2010) on the San Francisco Giants.

The decomposition of attributes or variables for the calculation of ticket prices for sporting events is a common methodology for price setting. Gönsch et al. (2009) and Klein and Steinhardt (2008), using the dynamic pricing model (DPM), implemented a multi-price setting system based on numerous variables such as the day of the week the match was played, seat location, opponent evaluation, and league standing. Therefore, following this approach, our study considers that when a fan decides to purchase a ticket, several aspects are considered in the decision-making process. Some of these variables have been incorporated into this study, segmented into two groups: intrinsic variables related to the match and extrinsic variables unrelated to it. The intrinsic variables selected for this study are three: the valuation of team rosters, a team's position in the league standings, and the comparative valuation of the two teams prior to a match. For extrinsic variables, two were considered the elements of analysis: stadium comfort based on UEFA ratings and the attendance ratio at the stadiums.

Much has been written about the topic addressed here, both in relation to the methodology described and the variables included in the model. We aim to highlight the sources used for this study and previous authors who have made contributions to this topic. Regarding the variables, previous authors consider the quality of players to be the factor most appreciated by fans. To determine this value, this study relied on the evaluations provided by the website www.transfermarkt.com, which reports updated information on the market value of football players individually in case of a potential transfer. The data from Transfermarkt has been incorporated into this study, considering that the total value of a team's roster represents the sum of the individual evaluations of each player on the team. Many authors consider this German database one of the most reliable databases for player and team evaluations due to its regular updates. Authors such as Müller et al. (2017) utilized these evaluations, along with other referenced indicators such as salaries, game performance statistics, potential transfers, or interest from other teams in a hypothetical purchase. Other authors also incorporated Transfermarkt data into their work because the values provided are influenced by commentary from specialized magazines and newspapers, as mentioned in

the publication by Bryson et al. (2012). Furthermore, it has been observed that player evaluations are determined by incorporating certain correlation indices, such as the relationship between players' salaries and expert-assessed performance levels. Studies by Franck and Nüesch (2011) and Torgler and Schmidt (2007) included salary and performance variables in player evaluations. Müller et al. (2017) defended Transfermarkt.com as one of the best platforms for estimating market value. When focusing on team performance as a factor recognized by fans, league standings become a variable to include in the proposed model. Previous studies consider that fans are more likely to attend matches where teams are ranked at the top of the standings compared to teams in relegation positions. Bitran and Wadhwa (1996) included this variable in their study, finding that league position was a decisive factor in ticket pricing strategies.

Other authors have contributed to their valuation models by incorporating direct matchups between two teams. Typically, a fan of a team ranked high in the standings during a league season will prefer and value matches against teams competing for similar goals, such as winning a championship or securing a Champions League spot, more than matches against lower potential teams. Conversely, fans of traditionally lower ranked teams have different expectations and valuations compared to the other group. In a league format where all teams play each other twice, a peculiarity emerges that can be defined as the "rich fan vs. poor fan paradox." The same match analyzed by a fan of a lower ranked team will be rated higher and bring greater satisfaction than by a fan of a higher ranked team facing a weaker opponent. Therefore, this peculiarity lies in the fact that the same match is valued differently depending on the type of fan watching it. Rosen (1974) conducted his study based on a set of heterogeneous goods, as is the case with matches in the Spanish League. This heterogeneity stems from the differing team rankings, usually influenced by economic budgets. While the match remains the same in terms of intrinsic variables (player quality, rankings, and match value), extrinsic variables such as the stadium where the match takes place alter the match's valuation depending on the type of fan. García et al. (2020) in their study on ticket pricing identified variables like home team value, match outcome uncertainty, and the day of the week as determinants of price.

As an innovative aspect, this study has included variables related to the physical, environmental, and psychological surroundings, referred to as extrinsic variables. According to previous studies by Álvarez Cano and Ospina Galindez (2020), it has been tested that fans value the type of stadium where they will watch a match. Factors like accessibility, seating comfort, and entertainment and dining services make attending a football match a complementary experience. As a reference, UEFA's stadium classification has been used, which is published on UEFA's official website under its stadium infrastructure regulations. The classification ranges from 1 to 5 stars based on parameters like field dimensions, maximum spectator capacity, seating type and proximity, VIP areas, lighting, media zones, public address systems, and video scoreboards. Ferrand's (1996) research on fan motivation based on match type and club affiliation variables established a correlation between loyalty and fan behavior. Rothschild (1984) also argued that a sense of belonging induces specific behaviors, including product searches, information processing, and decision-making. This is why this study includes stadium attendance ratio as an extrinsic variable, as it reflects fans' loyalty and attachment to their teams. Both studies mentioned earlier found a direct correlation between attendance ratio and team standings in a given season. This variable is also referred to as fans' "loyalty ratio." Naturally, when a team has a strong league position, it demonstrates that its players are competing at a high level, which increases stadium attendance. The publication by Samra and Wos (2014) also explored loyalty in sports fans across different disciplines in the United Kingdom, using a diverse society as a model to examine factors determining fan categories. Palmquist (1984) also focused on pricing through hedonic variables based on tangible and intangible attributes. In this study, tangible variables include those that can be objectively obtained, such as league standings, stadium type, and attendance ratio. However, this attendance ratio also has an intangible component, reflecting team loyalty. Intangible or subjective variables include team evaluations, which are influenced by player valuation fluctuations and impact the data derived from direct matchups between teams.

Another initial aspect of this study is its practical utility for professional football clubs in decision-making for ticket pricing. One question to consider is the following: who sets football ticket prices? To address this, we consider that a Spanish first-division club offers a sports event in a monopolistic competitive market since there is likely no other club in the same city offering an equivalent product. The product is selective, as is the case in most Spanish cities, where only one team is in the top division. Exceptions include cities like Madrid (Real Madrid/Atlético Madrid), Barcelona (Barça/Espanyol), or Seville (Sevilla/Betis), where more than one team is in the top tier. However, fans are loyal to their team and would never attend a rival team's match due to loyalty. Therefore, football ticket prices in a monopolistic competitive market are determined not by price-accepting variables typical of perfect competition but by hedonic variables based on tangible and intangible attributes, as Palmquist (1984) described. Thus, demand determines the variables influencing a fan's decision to purchase a ticket, as football matches are not essential products but rather differentiating ones. Referring to the study by García et al. (2020), they classified the variable "team quality" as a luxury good.

This underscores the importance of this study, which will analyze fans' preferences when consuming this intangible product composed of various attributes and the existing gap between club-set prices and fans' desired prices. This aspect was explored as a research area by S. L. Shapiro and Drayer (2012) and Kemper and Breuer (2016), who analyzed fan satisfaction with football ticket prices, considering multi-tiered pricing based on factors such as same-day purchase, purchase 1 day before, or 2 weeks in advance.

2 | Research Methods

The methodology used is based on a hedonic pricing model (DTP), inspired by Rosen's (1974) study, which developed a supply-side model of maximizing heterogeneous goods according to their attributes, subject to consumer budgets. Similarly, García et al. (2020) developed the same model with the difference of considering the good (football match) as the weighted sum of

three intrinsic variables explained earlier, but without including extrinsic variables that could enhance the final data obtained.

The innovative and differentiating element lies in the fact that this study proposes a model based on fan preferences, that is, a demand-driven model. Within the discipline of microeconomics, consumer theory is the most commonly used to understand consumer preferences. Therefore, the model is based on maximizing a utility function of two main variables. These two variables are those previously described as intrinsic and extrinsic. To give it a mathematical format, we will choose a Cobb–Douglas utility function with constant returns, where each variable will represent the intrinsic and extrinsic attributes of the matches. The weighting of fan preferences will be represented by their exponents so that the sum of the two exponents equals one. This unit will represent 100% of preferences. To this preference model, we must add the economic or budgetary constraint of the fans. The budget line will be represented by the ticket price set by the club. The ticket price will be composed of the two variables mentioned earlier, intrinsic and extrinsic, and each variable will be assigned a value.

We would like to highlight the influence on our study of the use of the Cobb–Douglas function by authors like Fan et al. (2010), where these authors described in their study the preferences of web service consumers. This study provides a method for selecting a web service using uncertain subjective weights, employing the method of marginal substitution with the Cobb–Douglas preference indifference curve. Similarly, in our study, but with a focus on the preferences of football fans, the same model is implemented to calculate the qualitative evaluation of preferences when purchasing a football ticket. These authors represented convex preference curves on a preference map, signifying the different demand options regarding the valuation of web services. We would also like to highlight Faro's (2013) study in which the author demonstrates that the expected utility of a consumer is perfectly represented by a Cobb–Douglas function. Her analysis is interesting in affirming that an expected utility contradicts a behavior pattern averse to a situation of uncertainty, meaning the preference curves represent consumers with a conservative profile in their decisions. This aligns with this research, where fans demonstrate high loyalty to their teams.

Therefore, we propose a problem of efficiency in preferences regarding the attributes of a football match, resulting from the sum of intrinsic variables "match value/standings/team quality" (x_1) and extrinsic variables (x_2) "stadium value/loyalty ratio." The construction of the approach is based on formulating a linear programming problem, where the objective is to optimize a Cobb–Douglas utility function with constant returns. Consequently, this function will be represented by two variables: x_1, which defines fans' intrinsic variables, and x_2, which represents extrinsic variables. At the same time, this function will be constrained by fans' budget, where M will be the ticket price. Fans will distribute their valuation between the price assigned to consumed intrinsic variables ($x_1 p_1$) and extrinsic variables ($x_2 p_2$).

The approach would be as follows:

$$\begin{aligned} &\max U(x_1, x_2) = x_1^{\alpha} x_2^{1-\alpha}, \\ &s.a. : M = x_1 p_1 + x_2 p_2, \end{aligned} \tag{1}$$

Based on the construction of this model, it will be demonstrated how the equality (RMS x_1/x_2) $= -\frac{p_1}{p_2}$ allows the consumer to obtain the quantities x_1 y x_2 that maximize their utility. To achieve this, it will be essential to use tools provided by both algebra and calculus to arrive at what is known as "Consumer Optimization." Using these two elements, the next step is to find the consumer's optimum.

There are various ways to find the consumer's optimum. One method involves expressing x_2 as a function of x_1 and substituting it into the MRS equation. Another method employs a technique known as the Lagrange multiplier method. For the purposes of this research, the second method will be used. The most accessible and straightforward approach to understand is the one used in Varian (1995), which will be detailed below:

$$L = x_1^{\alpha}\, x_2^{1-\alpha} - \lambda\,(x_1 p_1 + x_2 p_2 - M)\,. \tag{2}$$

The first-order conditions would be given by:

$$\frac{dL}{dx_1} = \alpha x_1^{\alpha-1}\, x_2^{1-\alpha} - \lambda\; p_1 = 0, \tag{3}$$

$$\frac{dL}{dx_2} = (1-\alpha)\, x_1^{\alpha}\, x_2^{-\alpha} - \lambda\; p_2 = 0, \tag{4}$$

$$\frac{dL}{d\lambda} = -x_1 p_1 - x_2 p_2 + M = 0. \tag{5}$$

By operating, it would result in:

$$\alpha x_1^{\alpha-1} x_2^{1-\alpha} p_2 = (1-\alpha)\, x_1^{\alpha} x_2^{-\alpha} p_1. \tag{6}$$

This means that by grouping terms, we obtain a system of equations to solve for all the terms:

$$\begin{aligned} &(1-\alpha)\cdot x_1 p_1 = \alpha x_2 p_2 \\ &M = x_1 p_1 + x_2 p_2. \end{aligned} \tag{7}$$

In this way, the quantities consumed by the fans of the intrinsic and extrinsic variables when breaking down the ticket price would be as follows, configuring the demand functions of the fans in relation to each of the variables:

$$x_1 = \frac{\alpha M}{p_1}, \tag{8}$$

$$x_2 = \frac{(1-\alpha)\, M}{p_2}. \tag{9}$$

With the aim of finding the optimal ticket price, we will calculate the marginal rate of substitution (RMS x_1/x_2) of the two variables, equating it to the slope of the budget, which is composed of the ratio between the prices of both variables (p_1/p_2). From this, we will obtain the relationship between x_1 and x_2 to later break down a preference map by type of variable, where we will compare preferences according to whether they are intrinsic or extrinsic variables and the breakdown of the ticket price. In this

map, we will design the utility curve for each fanbase and observe the position of each curve relative to the origin point (0,0). The farther this utility curve is from the origin, the higher the utility level of that fanbase. This will allow us to establish a classification of fanbases based on their level of satisfaction, based on the variables and ticket prices.

The calculations of the exponents of the utility function, α associated with intrinsic variables in relation to x_1 and $(1-\alpha)$ associated with extrinsic variables x_2, were obtained from a study by Navarro-García et al. (2014), which addressed a similar topic based on perceived quality and satisfaction of football spectators of a club in Spain's La Liga. With a framework identical to this study, being a team from the Spanish league and with a temporal proximity to the season analyzed, we incorporated the results obtained by these authors into our study as fixed reference indices. In this way, the level of satisfaction of the same intrinsic variables, that is, the match quality variables, was associated with the extrinsic variables related to the quality of the facilities and services. For data collection, the reference study conducted a satisfaction survey on a sample of 700 fans using a Likert scale evaluation from 1 to 5 points (1: very good, most preferred, [...] 5: very bad, undesirable). The results indicated that fans almost equally split their preferences between the value of their team and the quality of the stadium. Therefore, in our study, to refine the satisfaction indices, the exponent α associated with intrinsic variables x_1 was assigned a value of 0.54, and the exponent $(1-\alpha)$ associated with extrinsic variables x_2 was assigned a fixed value of 0.46.

The calculation of the prices (p_1, p_2) was carried out based on the records calculated for the analyzed intrinsic and extrinsic variables. To determine the price of the intrinsic variables, we obtained data from the 2018/2019 season, based on three variables that define fan satisfaction with the quality of a team: final season ranking (D_1), squad value (D_2), and the value of the home matches throughout the season (D_3). As for the extrinsic variables related to stadium quality, atmosphere, and environment, we selected two variables: attendance ratio (D_4), which indicates the level of fan loyalty to their team, and (D_5) the stadium rating according to the star rating given by UEFA. In all variables, to obtain a homogeneous evaluation, the value was calculated based on the weight each variable represents for each team. Finally, each group of intrinsic and extrinsic variables was grouped by summing their weights, such that the average representation of each group determined the percentage of the ticket price breakdown for each team by each variable group.

Regarding the definition of the values of the variables that are part of the optimization model, we will now proceed to define the calculation of each one:

1. - Variable: Final ranking position (D_1).

This intrinsic variable regarding fan satisfaction has been calculated by assigning a higher score for better ranking positions. Each team (P_i), where $i = 1, ..., 20$, has been scored with the inverse of their ranking position so that the first-place team receives the highest score and the last-place team the lowest:

$$D_{1,i} = \frac{P_i}{\sum_{i=1}^{n=20} P_i}; P_i = \frac{1}{i}. \tag{10}$$

To determine the weight of this score for each team, the weight each team represents in relation to the total number of teams has been assigned. A scoring system based on the historical rankings of the teams in Spain's La Liga was created by García et al. (2020), grouping the teams into four major groups and assigning them different weights based on their historical rankings.

2. - Variable: Team quality (D_2).

This variable has been calculated based on the value obtained from the database www.transfermarkt.com, which provides the updated value of the squads for all teams. The squad values of all teams are represented by the variable TM, where $i = 1..., 20$. Therefore, the final value assigned to this variable will be obtained by calculating the weighted arithmetic mean of the total value of all the teams in the league.

$$D_{2,i} = \frac{TM_i}{\sum_{i=1}^{n=20} TM_i}. \tag{11}$$

3. - Variable: Match value (D_3).

The evaluation of a team's matches will be considered a quality variable sensitive to fans, as it will represent the perceived quality of the set of matches a team plays at home throughout a season. The calculation of this evaluation (VE_i) has been determined based on the value of the matchups for all teams when playing as the home team during the entire season. Therefore, the value of the home team's squad (TM_i) is multiplied by the value of the visiting team's squad (TM_K). The records obtained for each team have been grouped, taking into account that each team plays 19 home matches (TM_K), where $k = 1, ...19$. The value obtained for each team will represent a weight in relation to the total set of matchups, and this will be the value for this variable:

$$D_{3,i} = \frac{VE_i}{\sum_{i=1}^{20} VE_i}; \quad VE_i = \sum_{k=1}^{19} TM_i \times TM_K. \tag{12}$$

4. - Variable: Attendance ratio or fan loyalty ratio $(D4)$.

To determine the value of this extrinsic variable related to fan loyalty to their teams, the attendance ratio (ATT_i) of each team as the home team has been calculated. Attendance at the stadium is considered an act of loyalty to the team, and it is a sensitive index because the decision to attend a match is influenced by the social support of the fanbase. Therefore, for this calculation, the average attendance during the season has been considered in relation to the maximum spectator capacity of the stadiums $(\max cp_i)$. The resulting index will give us the weight of each team in relation to the total average attendance of the other teams in the competition.

$$D_{4,i} \frac{\frac{ATT_i}{\max cp_i}}{\sum_{i=1}^{n=20} \frac{ATT_i}{max\ cp_i}}. \tag{13}$$

5. - Variable: UEFA stadium ranking (D_5).

Finally, the quality of the stadiums in terms of access, amenities, architectural aesthetics, dimensions, and services is considered an extrinsic variable for the fans. For its evaluation, the UEFA stadium classification criterion has been used. This classification determines the quality of the stadium by stars, based on criteria such as accessibility, field dimensions, number of seats, and services offered, such as press areas, catering, and boxes. The UEFA stadium classification assigns a rating of 1–5 stars ($U*_i$). Currently, in its latest classification, UEFA rates Spanish stadiums between 3 and 4 stars. To standardize this index in relation to the other variables, the representation ratio of each stadium has been calculated based on the average ratings compared to the other stadiums.

$$D_{5,i}\frac{U*_i}{\sum_{i=1}^{n=20} U*_i}. \tag{14}$$

Once all the ratios for each variable by team have been obtained, we perform the distribution and grouping of these variables, according to whether they are intrinsic or extrinsic, with the aim of breaking down the ticket price by characteristics, following the hedonic price criteria of Lancaster (1966) and Rosen (1974). For the intrinsic variables, we group them by summing the ratios (D_1, D_2, D_3), which will represent the prices of the intrinsic variable x_1. On the other hand, we perform the same operation with the extrinsic variables (D_4, D_5), where the sum of their weights will correspond to the price of the extrinsic variables x_2. Since all the variables have been standardized according to their representation ratio, we finally calculate for each team the influence of the quality variables, ranking, and matchups on one side, and on the other side, the variables of loyalty and stadium quality.

$$p_1 = \frac{\sum_{i=1}^{3} D_i}{\sum_{i=1}^{5} D_i} M, \tag{15}$$

$$p_2 \frac{\sum_{i=4}^{5} D_i}{\sum_{i=1}^{5} D_i} M. \tag{16}$$

Once the prices for each variable are known, the quantities consumed by each variable (x_1, x_2) can be determined. By applying Equations (7) and (8), we obtain these valuations, considering the criterion implemented in this study of establishing fixed preference indices for each type of variable represented by α and $(1-\alpha)$, in relation to the study conducted by Navarro-García et al. (2014).

To finalize the set of formulations, we are now in a position to determine the utility level of each fanbase in the Spanish League. With the values x_1, x_2, corresponding to the quantities consumed by each type of variable, and the preference levels for each type of variable α and $(1-\alpha)$, we solve the Cobb–Douglas utility function.

The assertion regarding weighting each player's market value by their effective participation during the season is not included in the present analysis for methodological and data availability reasons. First, the objective of this study is to capture the team's potential market value as an aggregate indicator of its perceived sporting quality, regardless of the specific distribution of playing time throughout the season. This approach is consistent with the literature on efficiency analysis in professional football clubs, which uses the sum of market values as a proxy for the "available competitive capacity" (Barros et al. 2010; Haas 2003).

Second, incorporating effective participation would require a higher level of data disaggregation, including minutes played by each player, their position, tactical contribution, and availability across the season. Such data are not always available in a complete and homogeneous manner for all leagues and seasons included in the analysis. This limitation could reduce the comparability of the sample and increase model complexity without necessarily yielding substantially different results (Espitia-Escuer and García-Cebrián 2010).

Finally, although it is recognized that actual participation influences a player's economic and sporting value, this effect tends to be reflected, at least partially, in their updated market valuation. Therefore, and to maintain methodological consistency with previous studies, the sum of market values has been used as a global measure of team strength, while acknowledging this limitation in the discussion section for consideration in future research.

3 | Results and Findings

The time frame for this study was conducted for the three seasons from 2016 to 2019. It was observed that the results were virtually identical across the three seasons analyzed, with the only difference being that each season incorporated three new teams from the second division, with their own pricing rates different from the relegated teams. Therefore, for the presentation of the results, we have selected the 2018/2019 season as the most representative, being the most up-to-date of the three.

In Table 1, the intrinsic variables are broken down by final ranking position, team quality, and match value. The sum of the three ratios reports the total ratio of these variables and their corresponding weight (D_1, D_2, D_3), along with the weight that represents the total set of intrinsic variables. As shown in the chart, there is a correlation between ranking position and fan valuation, meaning that fans of higher ranked teams are those who value their team's quality variables the most. Regarding the distribution of squad valuations, it is observed that the best players are in the highest ranked teams. Additionally, there is a notable finding that the top four ranked teams account for 60% of the total valuation of a team's intrinsic preferences.

Regarding team quality calculated based on their budgets, we observe consistency with previous studies by Kemper and Breuer (2016), Paul and Weinbach (2013), S. L. Shapiro and Drayer (2012), and García et al. (2020). Another significant finding comes from the study of the market typology of the Spanish League. If we apply the concentration ratio C4-classified to the team quality variable, we see that the top four teams account for 63.62% of the total quality player concentration (Table 1, column D2 "team quality attributes"). This ratio is typical of oligopoly markets

TABLE 1 | Valuation of intrinsic variables.

Teams	P_i	D_1	TM_i (millon €)	D_2	Ve_i (millon €)	D_3	$D_1+D_2+D_3$	Weights
F.C. Barcelona	1.000	0.278	1,160	0.206	5,184,980	0.186	0.670	0.223
At. de Madrid	0.500	0.139	872	0.155	4,149,782	0.149	0.443	0.148
Real Madrid C.F.	0.333	0.093	1.090	0.194	4,948,393	0.178	0.464	0.155
Valencia C.F.	0.250	0.069	443	0.079	2,296,096	0.082	0.231	0.077
Getafe C.F.	0.200	0.056	70	0.012	386,442	0.014	0.082	0.027
Sevilla FC SAD	0.167	0.046	269	0.048	1,439,512	0.052	0.146	0.049
R.C.D. Espanyol	0.143	0.040	82	0.015	456,560	0.016	0.071	0.024
Athletic Club	0.125	0.035	209	0.037	1,132,428	0.041	0.113	0.038
Real Sociedad	0.111	0.031	196	0.035	1,066,598	0.038	0.104	0.035
Real Betis B. S.	0.100	0.028	180	0.032	982,705	0.035	0.095	0.032
C.D. Alavés	0.091	0.025	71	0.013	394,950	0.014	0.052	0.017
S.D. Eibar	0.083	0.023	54	0.010	299,989	0.011	0.043	0.014
C.D. Leganés	0.077	0.021	92	0.016	511,003	0.018	0.056	0.019
Villarreal C.F.	0.071	0.020	222	0.039	1,202,089	0.043	0.102	0.034
Levante U.D.	0.067	0.019	73	0.013	402,905	0.014	0.046	0.015
Real Valladolid	0.063	0.017	189	0.033	1,025,687	0.037	0.088	0.029
RC Celta de Vigo	0.059	0.016	182	0.032	989,922	0.036	0.084	0.028
Girona F.C.	0.056	0.015	80	0.014	444,805	0.016	0.046	0.015
S.D. Huesca	0.053	0.015	38	0.007	212,766	0.008	0.029	0.010
Rayo Vallecano	0.050	0.014	59	0.010	327,300	0.012	0.036	0.012
	3.598	1.000	5630	1.000	27,854,912	1.000	3.000	1.000

Resource: Own elaboration.

or monopolistic competition. Previous studies, such as those by Rottenberg (1956) and Neale (1964), discussed the natural tendency in professional sports to encounter inefficiencies and power accumulation, where teams with the best players always win competitions. In previous literature, authors like Michie and Oughton (2004) studied the concentration of points for the top four ranked teams in the competition. The study by Barajas and Sánchez Fernández (2013) asserts that according to the European Commission, a dominant position exists when a company's market share is between 40% and 45% (or higher). A market share of 50%–80% would be considered a medium-concentrated market or monopolistic competition. If the market share is below 40%, we would be dealing with a perfectly competitive market.

In Table 2, similarly, the extrinsic variables of the fans are broken down, taking as a reference the variables of attendance ratio in relation to stadium capacity and the UEFA valuation of stadium quality (D_4, D_5). For the calculation of the weight of these variables, it has been determined in relation to the average representation of each, and then grouped in order to determine their final index.

It is worth noting that the average attendance in Spanish League stadiums is 73%, and there is no direct correlation between ranking position and fan loyalty ratio. It can be stated that fans of Spanish teams, regardless of their ranking position, the quality of their team, or the type of match, have a notably high percentage of attendance at the stadium. Furthermore, we observe that teams in the lower ranks have the same attendance ratio as those in the higher ranks, therefore demonstrating that the sense of belonging and loyalty to a team is not correlated with the league standings.

This homogeneity of the data across all teams in the league has been one of the key factors in this study, reaffirming that the behavior of fans in the Spanish League is homogeneous. Therefore, it has been one of the reasons why the study applied the results obtained by Navarro-García et al. (2014) to the preference variables α and $(1-\alpha)$. Given the homogeneity in fan behavior, the results for one team in La Liga have been extended to the rest of the teams. Thus, it was a correct decision to standardize a preference allocation of 54% to intrinsic variables and 46% to extrinsic variables.

Regarding the breakdown of ticket prices by intrinsic and extrinsic variables, following the hedonic price criterion, it is observed that on average for all teams in the Spanish League, fans value intrinsic variables at 49% of the ticket price and extrinsic variables at 51%, with the average ticket price in La Liga being 53€. Continuing with the distribution of the variables in relation to ticket price, we highlight how fans of teams positioned at the top of the rankings consider match-related variables to represent a value of 86%–70% of the ticket price, while this value drops between 22% and 35% for teams in the middle and lower sections of the table (see Table 4).

TABLE 2 | Valuation of extrinsic variables.

Teams	$ATT_i/\max cp_i$	D_4	U^*_i	D_5	D_4+D_5	Weights
F.C. Barcelona	0.77	0.053	4	0.058	0.111	0.055
At. de Madrid	0.82	0.056	4	0.058	0.114	0.057
Real Madrid C.F.	0.76	0.053	4	0.058	0.110	0.055
Valencia C.F.	0.82	0.056	4	0.058	0.114	0.057
Getafe C.F.	0.65	0.045	4	0.058	0.103	0.051
Sevilla FC SAD	0.65	0.045	4	0.058	0.103	0.051
R.C.D. Espanyol	0.58	0.040	4	0.058	0.098	0,.049
Athletic Club	0.76	0.052	4	0.058	0.110	0.055
Real Sociedad	0.57	0.039	3	0.043	0.083	0,.041
Real Betis B. S.	0.73	0.050	4	0.058	0.108	0.054
C.D. Alavés	0.86	0.059	3	0.043	0.103	0.051
S.D. Eibar	0.60	0.041	3	0.043	0.085	0.042
C.D. Leganés	0.82	0.056	3	0.043	0.100	0.050
Villarreal C.F.	0.71	0.049	3	0.043	0.092	0.046
Levante U.D.	0.80	0.055	3	0.043	0.099	0.049
Real Valladolid	0.69	0.047	3	0.043	0.091	0.045
RC Celta de Vigo	0.59	0.041	3	0.043	0.084	0.042
Girona F.C.	0.73	0.050	3	0.043	0.094	0.047
S.D. Huesca	0.84	0.058	3	0.043	0.102	0.051
Rayo Vallecano	0.79	0.054	3	0.043	0.098	0.049
	14.55	1.000	69,000	1000	2.000	1.000

Resource: Own elaboration.

The results suggest that the possible direct correlation between the average ticket price and the league position is not very high. In other words, teams with better league standings do not always set a higher average ticket price for the entire season compared to lower ranked teams. The correlation coefficient is 0.60 (see Table 5). This indicates that the pricing strategy followed by clubs is more related to variables that we cannot determine. Frequently uses the term "correlation" without specifying its precise numerical interpretation within the text. While the narrative mentions the existence or strength of correlations, it does not always clarify whether these refer to Pearson's *r*, Spearman's rho, or another measure, nor does it define the thresholds for categorizing them as weak, moderate, or strong. This lack of specification may limit the reader's ability to accurately interpret the statistical relationships described and assess the robustness of the findings. Therefore, it is recommended that each mention of "correlation" be accompanied by its numerical value, the type of coefficient used, and a brief interpretation consistent with standard statistical conventions (e.g., Cohen 1988).

Likewise, it is particularly striking how there is significant price disparity, as the difference between the highest and lowest ticket prices reaches nearly 300%. This means that despite being a homogeneous product—where all fans can enjoy all teams in the same way—prices vary according to each club's strategy.

For the correlations mentioned above, a Pearson statistical test was used, with a null hypothesis (H_0) stating that there is no relationship between the variables, versus an alternative hypothesis (H_1) indicating the existence of a relationship. The confidence level of the test is 95%, with a probability threshold below 5%. In this case, the hypothesis is to reject H_0 when there is no correlation between the variables and accept H_1 when a relationship is found. In both cases, the alternative hypothesis is valid, as there is evidence of a relationship between the compared variables.

Finally, one of the key findings of this study is the level of utility or fan preference. A difference in satisfaction levels is observed between Villarreal C.F. fans, who registered the lowest score, and F.C. Barcelona fans, who had the highest. The difference between these two records is 33.77%, which is not particularly excessive considering that the price difference between the highest and lowest ticket prices reaches almost 300%.

The graphical representation of the different levels of fan satisfaction is shown in Figure 1, designed as a preference map, where the variables that make up ticket prices are contrasted on both axes. The theory of indifference curves was developed by Edgeworth (1881) in his book *Mathematical Psychics: An Essay on the Application of Mathematics to the Moral Sciences*, while Pareto (1906) first drew them in his book *Manuale di economia politica*

TABLE 3 | Breakdown of ticket prices by type of variables and utility value.

Teams	p_1 (€)	p_2 (€)	α	1-α	M (€)	x_1	x_2	$U(x_1,x_2)$
F.C. Barcelona	69.950	11.550	0.54	0.46	81.50	0.629	3.246	1.338
At. de Madrid	83.497	21.503	0.54	0.46	105.00	0.679	2.246	1.177
Real Madrid C.F.	80.765	19.235	0.54	0.46	100.00	0.669	2.391	1.202
Valencia C.F.	31.777	15.723	0.54	0.46	47.50	0.807	1.390	1.036
Getafe C.F.	23.262	29.238	0.54	0.46	52.50	1.219	0.826	1.019
Sevilla FC SAD	21.980	15.520	0.54	0.46	37.50	0.921	1.111	1.004
R.C.D. Espanyol	38.803	53.697	0.54	0.46	92.50	1.287	0.792	1.030
Athletic Club	35.354	34.646	0.54	0.46	70.00	1.069	0.929	1.002
Real Sociedad	20.885	16.615	0.54	0.46	3750	0.970	1.038	1.001
Real Betis B. S.	29.283	33,217	0.54	0.46	62.50	1.153	0.866	1.010
C.D. Alavés	14.297	28.203	0.54	0.46	42.50	1.605	0.693	1.091
S.D. Eibar	10.176	19.824	0.54	0.46	30.00	1.592	0.696	1.088
C.D. Leganés	13.502	23.998	0.54	0.46	37.50	1.500	0.719	1.069
Villarreal C.F.	15.783	14.217	054	0.46	30.00	1.026	0.971	1.000
Levante U.D.	16.677	35.823	0.54	0.46	52.50	1.700	0.674	1.111
Real Valladolid	19.667	20.333	0.54	0.46	40.00	1.098	0.905	1.005
RC Celta de Vigo	17.491	17.509	0.54	0.46	35.00	1.081	0.920	1.003
Girona F.C.	14.724	30.276	0.54	0.46	45.00	1.650	0.684	1.100
S.D. Huesca	6.115	21.385	0.54	0.46	27.50	2.429	0.592	1.268
Rayo Vallecano	10.769	29.231	0.54	0.46	40.00	2.006	0.629	1.177

Resource: Own elaboration.

TABLE 4 | Descriptive statistic.

	Squads value (MM€)	Attendance (%)	UEFA stadium	Ticket price (€)
Promedium	281	73	3.45	53.33
Desv tp	345	9	0.51	24.02
Max	1160	86	4.00	105.00
Min	38	57	3.00	27.50

Resource: Own elaboration.

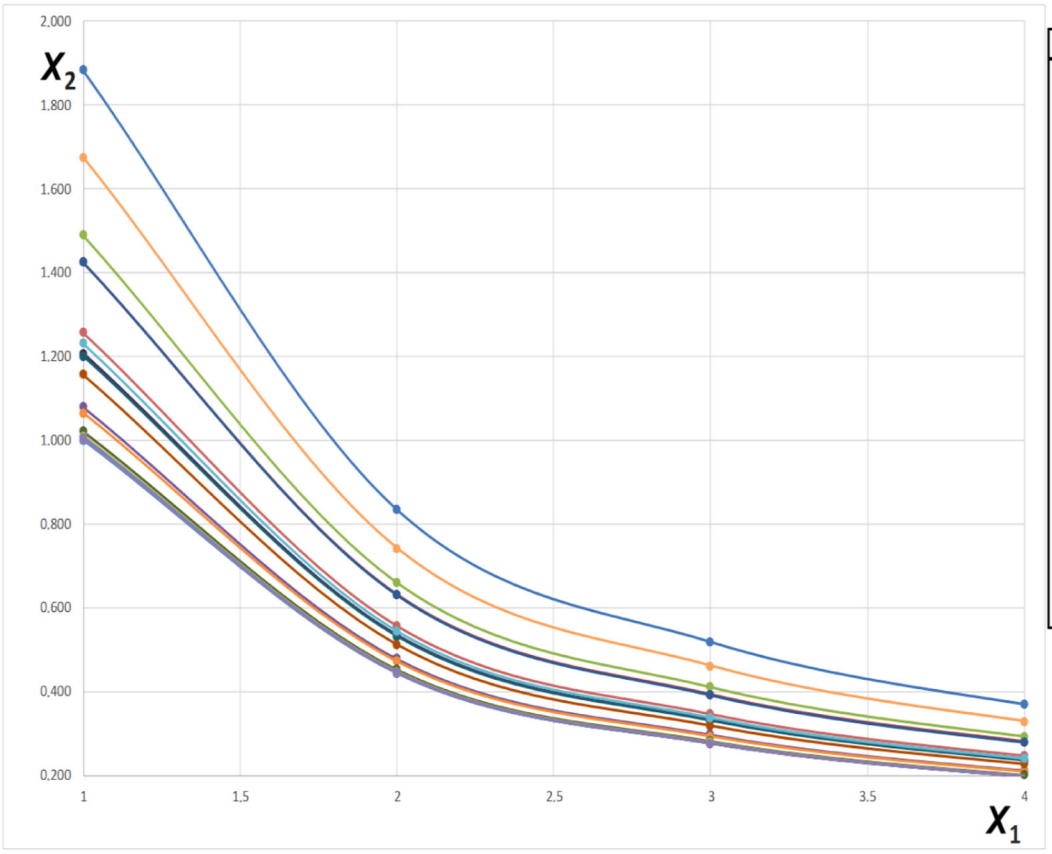
TABLE 5 | Correlation index.

Ticket price vs. final position table		
	Pi	*M* (€)
Pi	1	
M (€)	0.606868	1

con una introduzione alla scienza sociale in the early 20th century. This theory is derived from ordinal utility theory, which assumes that individuals can always rank any combination of goods in order of preference. Its origins trace back to the work of Jevons (1934).

In this study, the utility level in Table 3 confirms the existence of a correlation between fan satisfaction levels and ticket prices in teams occupying the top positions in the league standings. However, paradoxically, the second most satisfied fanbase belongs to the team ranked second-to-last, despite being in the relegation zone. It is a confirmed fact that fans exhibit homogeneous behavior, as evidenced by the relatively low dispersion in satisfaction indices, even though ticket prices vary significantly. Each fanbase's utility level is represented by a set of convex curves originating from the graph's origin, with curves further from the origin corresponding to fans with higher satisfaction levels, typically associated with lower ranked teams. The characteristics of these preference curves align with regular consumer theory preferences, adhering to principles such as completeness and non-satiation (Pindyck and Rubinfeld 1995), transitivity (Nicholson 2005), and convexity (Schotter 1996).

Teams with the highest utility levels are positioned further from the graph's origin, and as seen in Figure 1, only six teams have notably higher utility levels, while the rest remain highly concentrated. Additionally, budget slopes are steeper for teams



Teams	$U(x_1,x_2)$
F.C. Barcelona	1.338
At. de Madrid	1.177
Real Madrid C.F.	1.202
Valencia C.F.	1.036
Getafe C.F.	1.019
Sevilla FC SAD	1.004
R.C.D. Espanyol	1.030
Athletic Club	1.002
Real Sociedad	1.001
Real Betis B. S.	1.010
C.D. Alavés	1.091
S.D. Eibar	1.088
C.D. Leganés	1.069
Villarreal C.F.	1.000
Levante U.D.	1.111
Real Valladolid	1.005
RC Celta de Vigo	1.003
Girona F.C.	1.100
S.D. Huesca	1.268
Rayo Vallecano	1.177

Resource: Own elaboration.

FIGURE 1 | Preference map ordered by utility level.

with better league standings, as their intrinsic variable price is proportionally higher than their extrinsic variable price. As previously mentioned, graphical representation of preference maps using convex curves is a common practice in studies such as Fan et al. (2010), aimed at illustrating consumer preferences.

4 | Implications

The contribution of microeconomics to the field of sports economics serves as a valuable tool for improving efficiency analysis in decision-making within sports settings. In sport economics, efficiency criteria are used to evaluate how effectively professional football clubs convert their available resources into desired outputs. The concept of efficiency typically encompasses technical efficiency, which refers to a club's ability to maximize sporting outputs (e.g., points won, goals scored, wins achieved) given its inputs (e.g., player salaries, squad value, training resources), and allocative efficiency, which measures whether the club uses its resources in optimal proportions to minimize costs for a given level of output (Farrell 1957).

For decision-making in professional football clubs, efficiency analyses—often conducted using data envelopment analysis or stochastic frontier analysis—provide benchmarks that allow managers to identify underperformance relative to competitors with similar resources (Barros and Leach 2006; Haas 2003). For example, a technically efficient club converts its budget and squad characteristics into points effectively, while an inefficient club obtains fewer points despite similar or superior resources.

Applying efficiency criteria helps clubs. It is possible to assess the productivity of inputs, such as wage bills or transfer expenditures, in relation to sporting outcomes. Also benchmark against best-practice clubs, identifying gaps in resource utilization and management practices. Another contribution, it can be to inform strategic decisions, including player acquisition (Megía-Cayuela 2025), wage negotiations, or investments in facilities and staff, by prioritizing actions that improve efficiency rather than merely increasing expenditure. Finally, we can ensure financial sustainability, as efficient resource use maximizes sporting success within budgetary constraints, which is critical under Financial Fair Play regulations (UEFA 2018). Overall, incorporating efficiency criteria into management decisions enables professional football clubs to achieve competitive success (Megía-Cayuela 2023a) while maintaining financial discipline, thereby aligning sporting objectives with economic sustainability.

In particular, this kind of study focuses on determining fan satisfaction levels based on ticket prices. To optimize satisfaction, clubs must set optimal pricing strategies, thereby improving the efficiency of club management. The findings show that behind the price of an intangible good, the behavior of fans is defined through the analysis of ticket attributes. Each fan experiences a different level of satisfaction depending on their expectations,

which are directly related to their team's budget level and league position. Fans of higher budget teams, which generally have better league performances, tend to report higher satisfaction levels overall. However, this behavior is not always uniform, leading to the paradox that some lower performing teams have fanbases with satisfaction levels comparable to those of top-ranked teams. One possible explanation for this heterogeneity is the strength of social capital among a team's supporters. Social capital, defined as the networks, shared norms, trust, and social cohesion within a community (Putnam 2000), influences how fans perceive and evaluate their team's performance and management decisions. Higher levels of social capital among fans can lead to greater tolerance toward poor performance, stronger loyalty despite adverse results, and a higher sense of belonging that moderates dissatisfaction (A. Brown et al. 2008). Therefore, it is recommended that the author mention the concept of social capital as an underlying factor affecting the variability of fan satisfaction across different clubs. This finding supports the theory of García et al. (2020), which argues that football is a luxury good, where price does not always influence consumption. For lower budget teams with high satisfaction levels, fans tend to value non-performance-related aspects, such as simply participating in the league and enjoying direct matches against stronger teams. This demonstrates a certain homogeneity in satisfaction levels. Regarding the analysis of demand preferences in relation to pricing, new models and methodologies such as DTP (Kemper and Breuer 2016) and VTP (Drayer et al. 2012; García et al. 2020) have been developed, based on consumer theory. The contribution of this research includes innovative improvements not previously applied, such as the use of the Cobb–Douglas function with constant returns to solve an optimization problem related to fan satisfaction levels.

By calculating intrinsic variables (match-related factors) and extrinsic variables (ticket pricing factors), we can analyze fan behavior and uncover that price is not a barrier to access. Instead, football consumption is driven by affiliation, belonging, and loyalty to teams. This allows us to better understand the emotional and behavioral profile of fans and how to interpret the "rich versus poor fan paradox"—where the perceived value of the same good differs depending on the consumer's perspective and circumstances. For example, in a La Liga match between Barcelona and Eibar, two teams with opposing financial and ranking positions, each fanbase perceives the value of the match differently. Eibar fans, supporting a smaller club, accept lower ticket prices and prioritize extrinsic variables (affordability) over intrinsic ones (team quality). In contrast, Barcelona fans pay higher prices at their home stadium, justifying the expense as an act of loyalty, knowing their financial contribution helps sustain the club and attract top-tier players. This aligns with García et al.'s (2020) findings, who classify player quality as a luxury good, particularly for elite teams.

Another key finding is that fan loyalty is strong and consistent across all teams, but perspectives differ. Average attendance rates exceed 73% of stadium capacity, demonstrating a stable commitment from supporters. Notably, fans of Huesca, Rayo Vallecano, and Levante—despite their clubs' modest budgets, limited infrastructure, and lower league standings—report higher satisfaction levels than other teams. These fanbases are among the most loyal and appreciative. However, ticket pricing remains the primary factor influencing satisfaction levels. This highlights a significant area for improvement in terms of efficiency. Clubs must work to increase attendance rates and strengthen fan loyalty through optimized pricing strategies, ultimately maximizing ticket revenue. Many clubs fail to maximize profits because they do not set prices optimally, often ignoring fan preferences. There is a clear discrepancy between the prices set by clubs and the prices desired by fans. The key to profit maximization lies in finding a balance between these two figures. The study by Megía-Cayuela (2023a) successfully optimized ticket prices using the same framework and 2018/2019 season data, applying a hedonic pricing methodology to improve pricing efficiency. The recommendation is related to the importance within the literature on ticket pricing optimization in professional football due to its methodological and practical contributions. Unlike prior research, which predominantly examined the descriptive association between ticket prices and match characteristics (e.g., Buraimo and Simmons 2008; García and Rodríguez 2002) applied a hedonic pricing methodology within an optimization framework to directly improve pricing efficiency. Specifically, the study estimated fans' willingness to pay based on intrinsic and extrinsic match attributes and integrated these estimates to adjust ticket prices in a manner that maximized club revenue while maintaining demand stability. Compared to similar findings, such as those by Fernández et al. (2021) who analyzed determinants of ticket prices without implementing optimization strategies, Megía-Cayuela (2023b) advances the field by moving from explanatory modeling to actionable pricing decisions. This applied approach is essential for professional clubs aiming to translate econometric insights into revenue management strategies, making it one of the most relevant recent contributions to the area of pricing efficiency in football.

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