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# Making life difficult for others – an economic and financial insight into the networks of Spanish Soccer teams' yellow and red cards

# Complicarles la vida - una visión económica y financiera de las redes de tarjetas amarillas y rojas de los equipos de fútbol español

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**Abstract.** A soccer match without the exhibition of yellow or red cards is very uncommon in professional competition. Sanctions for bad behavior by players have ethical implications for the essential rules of healthy competition. On the other hand, the cards displayed are related to strategic factors of the game and they can have significant costs for the teams. The main objective of this work focuses on analyzing the interactions, patterns and determinants of the relationships that occur between the teams based on the disciplinary sanctions given and received. We study the seasons of the Spanish Professional Soccer League from 2010/2011 to 2018/2019, utilizing complex network analysis. We consider the value of the teams' transfers and the referee's profile as determining factors. Our major evidence suggests there has been a downtrend in the number of cards exhibited in the matches throughout the seasons, although there have been stable fee revenues for the organizer (RFEF). We also identify different profiles of referees able to increase the number of cards exhibited to some particular teams. We also observe that teams usually competing for the same rank tend to participate in matches with a higher number of exhibited cards, but financial similarities between the competing teams are not as significant for explaining the aggressiveness/exposure in the matches.
**Keywords:** Costs; Soccer; Fees; Network Analysis; Soccer sanctions

**Resumen.**
Un partido de fútbol sin exhibición de tarjetas amarillas o rojas es muy poco común en la competición profesional. Las sanciones por el mal comportamiento de los jugadores tienen implicaciones éticas para el correcto funcionamiento de la competición. Por otro lado, las tarjetas están relacionadas con factores estratégicos del juego y pueden tener costes importantes para los equipos. El principal objetivo de este trabajo se centra en analizar las interacciones, patrones y determinantes de las relaciones que se dan entre los equipos en función de las sanciones disciplinarias impartidas y recibidas. Estudiamos las temporadas de la Liga Española de Fútbol Profesional desde 2010/2011 a 2018/2019, utilizando análisis de redes complejas. Consideramos el valor de las transferencias de los equipos y el perfil del árbitro como factores determinantes. Nuestra principal evidencia sugiere que ha habido una tendencia a la baja en el número de tarjetas exhibidas en los partidos a lo largo de las temporadas, aunque ha habido ingresos estables por honorarios para el organizador (RFEF). También identificamos diferentes perfiles de árbitros capaces de incrementar el número de tarjetas exhibidas a algunos equipos en particular. Por otra parte, observamos que los equipos que normalmente compiten por el mismo rango tienden a participar en partidos con un mayor número de tarjetas expuestas, pero las similitudes financieras entre los equipos competidores no son tan significativas para explicar la agresividad/exposición en los partidos.
**Palabras clave:** Costes, Fútbol, Sanciones, Network Analysis, Faltas de fútbol

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## Introduction

The card system was created 35 years ago as a way to notify soccer players of fouls and misconduct. Today, the red and yellow card system is vital to the game of soccer and often decides significant match results (Almeida et al., 2022; Álvarez et al., 2020). Referee decisions can be essential to the team's prospects of winning championships, qualifying for lucrative European competition, or avoiding relegation. In this way, financial and economic elements of the teams are relevant impacts from a team's reception of cards, which increases the pressure on referees and on the soccer authorities (Buraimo et al., 2010; Dawson et al., 2007; Magel & Melnykov, 2014). On the other hand, the use of disciplinary sanctions for sabotage has also been identified (Deutscher & Schneedmann, 2017; Kempa & Rusch, 2019).

International literature has approached the study of the determinants of displayed cards from two areas. Firstly, authors such as Anders and Rotthoff (2010), Cho and Shin (2016), Gómez-Déniz and Dávila-Cárdenes (2017), Downward and Jones (2007), and Scoppa (2008) identify dimensions related to the interaction between players. Secondly, there is a dimension of study that analyzes the aspects that influence the referee's decisions, such as the reciprocity effect or referee bias (Kempa & Rusch, 2019; Zhang et al., 2022; Couto & Sayers, 2023; Audrino, 2020). On the other hand, other dimensions can be identified that have not been analyzed in depth and that may have relevance to the disciplinary sanctions given and received. Two of them are the financial and economic aspect of professional teams (Sapp et al., 2018; Audrino, 2020) and player transfer costs (Mourao, 2022, 2016).

In this way, the main objective of this work focuses on analyzing the interactions, patterns and determinants of the relationships that occur between the teams based on the disciplinary sanctions given and received. To achieve this objective, we have carried out an empirical analysis divided into three parts. First, networks analysis is used to explore the interaction between the various participating teams and to detail the cards transfer patterns. Next, we use a probabilistic model to deepen the analysis and identify the characteristics of the teams' aggressiveness and exposure in the cards' flows. Finally, we identifiy the determinants that influence the (red and yellow) cards – either given or received – using exponential random graph models (ERGMs)

We use La Liga (Spanish League) data from the 2010/2011 to 2018/2019 seasons to carry out the study. Two major reasons justify this focus on La Liga. First, La Liga is one of the top professional soccer leagues in the world; second, it has been found that La Liga has had significant changes in the exhibition of red and yellow cards during the last several seasons.

The remaining structure of this paper is as follows. First of all, reviews the literature about the behavior of the players and the evaluation of the referees, as well as the determinants of red and yellow cards in football. Next, shows our empirical analysis. Third, we discuss cards' networks using exponential random graph models. The last section concludes and provides opportunities for further research.

***Literature Review***

The creation of the soccer cards had the function of preventing non-sports behaviors on the pitch. In this sense, previous studies have analyzed how suspension rules due to the accumulation of cards during a competition regulate the behavior of players and referees (Gomar et al., 2020). VanDerwerken et al. (2018) explain that suspension rules can generate different effects, namely direct effects and indirect effects. The direct effect is that the threat of suspension makes the player more cautious. In this sense, data show that professional soccer is becoming less aggressive (Sapp et al., 2018; VanDerwerken et al., 2018).

On the other hand, Lex et al. (2015) and VanDerwerken et al. (2018) explain that whether a player gets called for a foul or receives a penalty card depends not only on his/her behavior but also on the referee's profile. In this way, the referee's bias has been a topic increasingly studied in scientific literature (Vasilica, et al. 2022). The works of Lago-Peñas and Gómez-López (2016), Buraimo et al. (2010), Scoppa (2008), and Boyko et al. (2007) identify that the bias of the referee tends to favor the local team. Memmert et al. (2008) and Unkelbach and Memmert (2008) find that significantly fewer yellow cards are shown in the first minutes compared to the rest of the game. Also, Downward and Jones et al. (2007) and Kempa and Rusch (2019) show that more yellow cards tend to be awarded to the visiting team. Wunderlich et al. (2023) supports prior research regarding a crowd-induced referee bias, but they identify that the number of spectators is not the determining factor of the advantage of playing at home.

Previous studies find that the yellow and red card system also generates effects on the dynamics of the matches (indirect effects). Gómez-Déniz and Dávila-Cárdenas (2017) find that "the probability of showing cards is greater when the match is a 'derby,' because these games are often played with a greater intensity" (Gómez-Déniz & Dávila-Cárdenas, 2017, 642). Additionally, Bar-Eli et al. (2006) show that the chances of a sanctioned team scoring or winning were substantially reduced following the sanction. This effect could imply an indirect economic cost because it also influences the achievement of sports objectives. In addition, we can also expect moral costs from the cards' exhibition. An accumulated reputation of being an aggressive team increases the probability of future sanctions against that soccer team (Dawson et al., 2007) and a reputation of aggressiveness hardly rewards sporting teams with a sustainable path of victories along the seasons (Buraimo et al., 2010).

As authors like Anders and Rotthoff (2010) or Cho and Shin (2016) have observed, the display of yellow or red cards is not the sole responsibility of the team or of the player who committed fault, but rather the result of the interaction between the offending player's team and the opposing team. The literature on the determinants of cards exhibited in soccer matches has identified a common set of dimensions—ranging from the rank for both teams and a historical past of tight matches between the same teams to the differences in the budget size of the competing teams and the low sporting quality of the defense lines of the team (Zhao & Zhang, 2023; Gómez-Déniz & Dávila-Cárdenes, 2017; Scoppa, 2008; Downward & Jones, 2007).

Other dimensions found to be relevant are related to the financial values associated with each team – from the budget for the season to correlated values such as volume or balance of player transfers (Mourao, 2016). Traditionally, teams with greater financial resources can contract (defense) players who, due to their quality, are less likely to block the action of opponents through fouls punishable with yellow or red cards (Sapp et al., 2018). Another argument explored is related to the concept that in the world of professional sport, there is a space for "class struggle" between the wealthiest clubs and the least-wealthy clubs that would make certain clubs more concerned with this differentiation, and those with less financial resources traditionally become more aggressive in approaching the game (Vahed et al., 2002). Although there has been an approach to the effect that a team's financial position can have in relation to team dynamics, it has not been analyzed in depth.

A report from CIES Football Observatory (2020) also explored some promising correlations between the average number of exhibited cards and some socio-economic indicators of the country. This report concluded that "The wealthier the country or the higher its Human Development Index, the less the cards are given to players. Conversely, the higher the homicide rate and the greater the perceived corruption, the more likely the referees are to distribute cards."

Therefore, according to the most relevant literature for this research (Kempa & Rusch, 2019; Mourao, 2016; Scoppa, 2008; Baker et al., 2012), the following factors can enhance the exhibition of cards during a soccer match:

- Increases in transfers or budget differentials across teams (Mourao, 2016)

- Established reputation of hard matches constructed from previous cards' flows between the teams (Baker et al., 2012)
- Small differences in the standings' ranks/accumulated points in the league (Scoppa, 2008)
- Low quality of the team's defensive positions (Mourao, 2016)
- Reciprocity (Kempa & Rusch, 2019)
- The referee's profile (regarding the previous contact with each team, namely number of refereed matches and/or number of exhibited cards) (Hlasny & Kolaric, 2017)

Table 1.
Descriptive Statistics (33 teams, 2010/2011-2018/2019)

| Variables | Observations | Mean | Standard Deviation | Max | Min |
|---|---|---|---|---|---|
| Transfers balance (Millions, €) | 17490 | -0,50 | 12,87 | 14,45 | -61,11 |
| Points (end season) | 17490 | 56,73 | 10,07 | 92,11 | 47,44 |
| Rank | 17490 | 9,79 | 2,95 | 13,44 | 1,33 |
| Gols Against | 17490 | 48,99 | 13,10 | 76,33 | 22,33 |
| Refereed Matches_a1 | 17490 | 2,39 | 2,11 | 6,00 | 0,00 |
| Refereed Matches_a2 | 17490 | 9,18 | 6,57 | 23,00 | 0,00 |
| Refereed Matches_a3 | 17490 | 4,94 | 3,71 | 14,00 | 0,00 |
| Refereed Matches_a4 | 17490 | 0,12 | 0,33 | 1,00 | 0,00 |
| Refereed Matches_a5 | 17490 | 1,15 | 1,37 | 4,00 | 0,00 |
| Refereed Matches_a6 | 17490 | 1,09 | 1,42 | 5,00 | 0,00 |
| Refereed Matches_a7 | 17490 | 8,70 | 6,16 | 19,00 | 0,00 |
| Refereed Matches_a8 | 17490 | 1,15 | 1,12 | 4,00 | 0,00 |
| Refereed Matches_a9 | 17490 | 4,73 | 4,43 | 12,00 | 0,00 |
| Refereed Matches_a10 | 17490 | 9,30 | 7,49 | 21,00 | 0,00 |
| Refereed Matches_a11 | 17490 | 4,30 | 3,23 | 11,00 | 0,00 |
| Refereed Matches_a12 | 17490 | 0,06 | 0,24 | 1,00 | 0,00 |
| Refereed Matches_a13 | 17490 | 8,48 | 7,64 | 23,00 | 0,00 |
| Refereed Matches_a14 | 17490 | 10,64 | 7,79 | 25,00 | 0,00 |
| Refereed Matches_a15 | 17490 | 8,24 | 6,14 | 25,00 | 0,00 |
| Refereed Matches_a16 | 17490 | 2,12 | 1,90 | 5,00 | 0,00 |
| Refereed Matches_a17 | 17490 | 11,03 | 7,56 | 25,00 | 0,00 |
| Refereed Matches_a18 | 17490 | 0,06 | 0,24 | 1,00 | 0,00 |
| Refereed Matches_a19 | 17490 | 7,97 | 5,49 | 20,00 | 0,00 |
| Refereed Matches_a20 | 17490 | 0,12 | 0,42 | 2,00 | 0,00 |
| Refereed Matches_a21 | 17490 | 10,58 | 6,72 | 22,00 | 0,00 |
| Refereed Matches_a22 | 17490 | 1,85 | 1,89 | 6,00 | 0,00 |
| Refereed Matches_a23 | 17490 | 5,88 | 4,01 | 14,00 | 0,00 |
| Refereed Matches_a24 | 17490 | 0,12 | 0,33 | 1,00 | 0,00 |
| Refereed Matches_a25 | 17490 | 0,06 | 0,24 | 1,00 | 0,00 |
| Refereed Matches_a26 | 17490 | 6,76 | 6,02 | 18,00 | 0,00 |
| Refereed Matches_a27 | 17490 | 0,36 | 0,60 | 2,00 | 0,00 |
| Refereed Matches_a28 | 17490 | 10,27 | 8,86 | 30,00 | 0,00 |
| Refereed Matches_a29 | 17490 | 2,00 | 2,02 | 7,00 | 0,00 |
| Refereed Matches_a30 | 17490 | 5,18 | 4,70 | 15,00 | 0,00 |
| Refereed Matches_a31 | 17490 | 0,18 | 0,64 | 3,00 | 0,00 |
| Refereed Matches_a32 | 17490 | 3,36 | 3,13 | 11,00 | 0,00 |
| Refereed Matches_a33 | 17490 | 5,03 | 4,07 | 12,00 | 0,00 |
| Refereed Matches_a34 | 17490 | 1,06 | 1,20 | 3,00 | 0,00 |
| Refereed Matches_a35 | 17490 | 2,67 | 2,61 | 7,00 | 0,00 |
| Refereed Matches_a36 | 17490 | 0,06 | 0,24 | 1,00 | 0,00 |
| Refereed Matches_a37 | 17490 | 3,21 | 2,79 | 9,00 | 0,00 |
| Refereed Matches_a38 | 17490 | 5,27 | 4,54 | 13,00 | 0,00 |
| Refereed Matches_a39 | 17490 | 4,55 | 3,44 | 11,00 | 0,00 |
| Refereed Matches_a40 | 17490 | 1,21 | 1,43 | 5,00 | 0,00 |
| Refereed Matches_a41 | 17490 | 0,91 | 1,07 | 3,00 | 0,00 |
| Refereed Matches_a42 | 17490 | 4,94 | 3,86 | 13,00 | 0,00 |
| Refereed Matches_a43 | 17490 | 7,00 | 4,88 | 14,00 | 0,00 |
| Refereed Matches_a44 | 17490 | 4,58 | 3,26 | 10,00 | 0,00 |
| Refereed Matches_a45 | 17490 | 2,21 | 2,16 | 6,00 | 0,00 |
| Refereed Matches_a46 | 17490 | 2,55 | 2,32 | 8,00 | 0,00 |
| Refereed Matches_a47 | 17490 | 10,82 | 7,49 | 26,00 | 0,00 |
| Refereed Matches_a48 | 17490 | 6,52 | 5,66 | 18,00 | 0,00 |
| Refereed Matches_a49 | 17490 | 2,30 | 2,30 | 7,00 | 0,00 |

Source: Authors' elaboration upon RFEF data. Note: Refereed matches axx relate to refereed matches by referee xx'.

## *Data and methodology*

*Data*

The database has the data of red and yellow cards given to and received by each La Liga team from the 2010/2011 through 2018/2019 seasons. In addition, a series of variables was constructed. This series of variables follows the literature discussed in Literature Review section. The variables shown below will be used as determinants/attributes in the third part of the empirical analysis (table 1 shows the descriptive statistics of these attributes):

- Transfers' balance (as an available proxy of team's budget)
- Standings' ranks
- Standings' points
- Historical median rank at the competition (since 2010/2011)
- Historical average number of points at the end of the season (since 2010/2011)
- Goals against in the season
- Number of matches refereed by each referee for each team (since 2010/2011).

### *Methodology – formal aspects*

We have developed to three steps for the development of empirical analysis. First, we have done a descriptive analysis of the observed networks to explore the interaction between the various participating teams and to understand the card transfer patterns and their determinants. As Lee and Wilkinson (2018) explain, network analysis offers an additional methodological advantage that involves the complementary role that this plays in the common statistical and traditional econometric methods. Specifically, authors such as Giuffre (2013) or McLeod et al. (1996) explain that the study of social networks to gain insight into the sports industry is a promising field.

Next, we used probabilistic models to delve into the analysis of the patterns that occur between teams in relation to cards. As argued, in a soccer match, a team can either receive cards from other teams or give to the latter. These connections can be reciprocal if the two teams, in the same period, give and receive cards. These patterns can be analyzed by a probabilistic model (p1), following Uddin and Hossain (2013). Following Uddin and Hossain (2013), we can classify all matches between teams i and j (i, j) as mutual ($x_{ij} = x_{ji} = 1$), asymmetric ($x_{ij}$ not equal to $x_{ji}$), or null ($x_{ij} = x_{ji} = 0$).

The probabilities of each type of dyad are modeled as a function of three sets of parameters: capacity of giving cards to the other teams because it is a team more likely to suffer hard faults (which we identify as "exposure"), capacity of mainly receiving cards because the teams' players tend to injure the opponents (which we identify as "aggressiveness"), and reciprocity (capacity to simultaneously receive and provoke cards). The probabilities of mutual, asymmetric and null dyads, denoted $m_{ij}$, $a_{ij}$, and $n_{ij}$, respectively, are modeled as follows:

$$m_{ij} = \lambda_{ij} \exp^{(\rho+2\theta+\alpha_i+\alpha_j+\beta_i+\beta_j)}$$
(Equation 1)

$$a_{ij} = \lambda_{ij} \exp^{(\theta+\alpha_i+\beta_j)}$$
(Equation 2)

$$n_{ij} = \lambda_{ij}$$
(Equation 3)

In Equations 1-3, the $\alpha$ parameters are interpreted as "exposure" measures for each node (in our case, for each team). The $\beta$ parameters are interpreted as "aggressiveness" measures. The $\rho$ parameter is related to a general measure of the tendency toward "reciprocity" in the network. The $\theta$ parameter is a function of the density of the network, reflecting the total number of observed arcs in the observed matches (an arc is defined as a directed path in a network). Finally, the $\lambda$ parameters are normalizing constants used to guarantee that the modeled probabilities add to one for any given dyad.

Following Holland and Leinhardt (1981), positive values for each parameter provide statistical evidence of how the studied effects favor establishing relationships between teams. A positive $\theta$ indicates that if the density of the net increased (i.e., as the number of connections between teams grows), it can be expected that any particular team may establish a greater number of connections with other teams (suggesting the existence of a latent trend for more aggressive matches in the league). In contrast, when $\theta$ is negative, the interpretation of Holland and Leinhardt (1981) suggests that the number of connections in the net does not help to explain the density of connections between a team and the remaining teams.

Finally, it is relevant to explore the reasons—in addition to the explanatory dimensions—for the observed structure of the movements of cards, dimensions such as arcs, the simultaneous presence of bidirectional moves (i.e., teams retributing cards–especially red cards–to the teams that were also responsible for received cards), or even the effects of certain exogenous variables such as the attributes already listed.

Therefore, we will turn to exponential random graph models (ERGMs) for testing the suggested attributes as explanatory dimensions of the revealed edges. In this way, exponential random graph models (ERGMs) represent the third methodological tool used in the study.

According to Shumate and Palazzolo (2010), a general ERGM model is described as follows:

$$P(X = x) = \frac{\exp\{\theta' z(x)\}}{k(\theta)}$$
(Equation 4)

In Equation 4, we model the probability of a given network *P(x)* depending on the estimation of a vector of model parameters $\theta$. The term *z(x)* refers to a vector of network statistics, and *k* is a normalizing function whose role is to guarantee a certain probability distribution across the random networks. Given the relevance of red cards for synthesizing the flow of cards among teams in a competing league, we will focus on the distribution of red cards along La Liga's seasons between 2010/2011 and 2018/2019 (for yellow cards, we can show our estimates if requested).

For the estimation of Equation 1, we usually use maximum pseudolikelihood estimations (MLE). This method fits a logistic regression for the vector of network statistics. Therefore, we will work with the following maximum pseudolikelihood estimation:

$$PL(\theta) = \prod_{i \neq j} \prod_{m=1}^{r} P(X_{ijm} = 1 | X_{ijm}^{C})^{X_{ijm}} P(X_{ijm} = 0 | X_{ijm}^{C})^{1-X_{ijm}}$$
(Equation 5)

Following Shumate and Palazzolo (2010), the maximum pseudolikelihood estimation for each parameter is computed as a product of the log-odds ratio of two probabilities: the probability of observing each tie, *P(X=1),* and the probability of not observing that tie in the network, *P(X=0)*. Additional features—such as the use of pseudolikelihood ratio statistics, discussion of the independence assumptions, and robustness in small samples—are discussed by authors including Shumate and Palazzolo (2010) and Robins et al. (1999). Let us also observe that the attributes can be analyzed considering the values characterizing each node of origin and each node of destination and the differences or similarity between the values characterizing each node of origin and each node of destination (Caimo & Friel, 2013).

Given the nature of our sample, we opted to estimate Equation 5 by Bayesian procedures (Caimo & Friel, 2013). We follow Caimo and Friel (2013) and we used the software MPNET which use to the Bayesian estimation algorithm proposed by Caimo and Friel (2009). The parameter settings for our estimates were the following: Parameter burn-in: 500; Proposal scaling: 0.009; Multiplication factor: 33; MCMC Sample Size: 15000; Max estimation runs 1000; Do GOF at convergence 700; Maximum lag (SACF): 100 (at Scaled Identity Matrix). We will also analyze the most-frequently cited indices for goodness of fit of ERGMs estimated by Bayesian procedures in Table 4. According to Shumate and Palazzolo (2010), if the estimated posterior mean parameters have significant values, i.e., are higher than twice the estimated standard deviation, then this is an indication of a good fit.

For our ERGM, we explored a set of variables used as determinants/attributes for the flow of cards between La Liga's teams. These attributes were explained in the Data subsection and Table 1 shows the descriptive statistics of these attributes. However, from the first estimations, we preferred the historical mean/median of these variables for explaining the exhibition of cards. Therefore, in the final estimations of Equation 5, we will only consider the historical mean/median of these variables as attributes for each team. Let us also notice that each attribute will be observed in four interaction terms: match, mismatch, match and reciprocity, and mismatch and reciprocity. This procedure follows Baker et al. (2012), and it will allow us to realize, for instance, whether significant differences between teams' ranks tend to increase or reduce the number of exhibited cards.

### *Empirical Section – A Network Analysis of La Liga's Red Cards*

*Descriptive analysis of the networks along the 2010/2011-2018/2019 seasons*

To explore this interaction between the offending player's team and the opposing team and to understand the card transfer patterns and the determinants of this probability, we will turn to network analysis.

For the observed period (2010/2011-2018/2019), the network of red cards had 33 nodes (the number of playing teams) and 478 edges/ties. This network comprised three strong components (meaning three groups of teams provoked among themselves the most red card exhibitions). For the same period, the network of yellow cards had the same 33 nodes, but the number of edges was significantly higher at 867 (as expected because there have been significantly more yellow cards exhibited than red cards). The number of components was two, which means there was a higher probability of more yellow cards between two random teams of La Liga.

The average clustering coefficient is 20.517 for the whole network of yellow cards. This value is 1.361 for the network of red cards. Following Watts and Strogatz (1998), the "clustering coefficient of an actor is the density of its open neighbourhood," which we can simplify by stating that it is a measure of the concentration of neighbors of a given team in the network. The presented values suggest that a team in the yellow cards' network has many more neighbors (teams and edges) than in the red cards' network.

The average path length is 1.126 for the network of yellow cards and 1.513 steps for the network of red cards, which also reflects the high connectedness in these networks. Next we will detail the intensity of cards sent by a team (outdegree) and the intensity of received cards (indegree).

For the observed network of red cards (all matches of La Liga between 2010/2011-2018/2019), the top three teams in terms of outdegree are composed of Athletic Bilbao (57 red cards sent to other teams), Barcelona (56 red cards sent), and Sevilla (56 red cards sent). The respective bottom three teams in terms of outdegree are composed of Girona (3 red cards sent), Hercules (3 red cards sent), and Huesca (0 red cards sent), also explained by the small number of seasons played in La Liga.

If we move to the indegree indicator, the top three include Malaga (59 cards received), Sevilla (54 red cards received), and Valencia (54 red cards received). The respective bottom three are composed of Real Valladolid (5 red cards received), Girona, and Huesca (both with no red cards received). The values of centralization (out and in) are 0.0198 and 0.0211, respectively, which means that the presence of "hubs" in these networks is not likely, i.e., teams controlling the distribution of red cards.

For the network of yellow cards along these seasons, the top three for outdegree are Real Sociedad (948 yellow cards sent), Atletico Bilbao (938 yellow sent), and Real Madrid (924 yellow sent). The bottom three are composed of Girona (115 yellow sent), Hercules (99 yellow sent), and Huesca (0 yellow sent). For the indegree indicators, the top three are composed of Espanyol (925 yellow received), Valencia (923 yellow received), and Sevilla (889 yellow received). The bottom three are composed of Girona (105), Hercules (101), and Huesca (0). The values of centralization are 0.0025 for outdegree and 0.0024 for indegree, again suggesting the absence of few teams responsible for most of the cards' flows.

Although we obtained very small values for the overall centralization in both networks, we also wanted to analyze the betweenness centrality measure, which provides insight regarding the "bridges" in the network (i.e., teams that tend to simultaneously give and receive a significant number of cards). For the network of yellow cards, the teams with the most significant scores for betweenness centrality are Atletico Bilbao, Atletico Madrid, Barcelona, Coruna, Espanyol, Getafe, Levante, Malaga, and Real Madrid (score of 7.046). For the network of red cards, the teams with the most significant scores for betweenness centrality are Valencia (56.13), Malaga (55.50), and Sevilla (38.43). As we will detail in next subsections, these teams have a particular responsibility for the flow of cards in La Liga.

Lastly, in this subsection in which we described the networks of yellow cards and of red cards, we will also use the notion of a clique. At the most general level, a clique is a subset of a network in which the actors are more closely and intensely tied to one another than they are to other members of the network. In our cases, cliques are composed of teams that generate especially hard matches when they compete.

For the observed network of red cards, the most important clique has been generated by the following teams: Athletic Bilbao, Atletico de Madrid, Espanyol, Levante, Malaga, Real Sociedad, and Sevilla. Therefore, we can expect that any match between two of these teams will have a higher probability of having red cards exhibited. For the network of yellow cards, the most relevant clique is composed of the following teams: Almería, Athletic Bilbao, Atletico de Madrid, Barcelona, Celta Vigo, Deportivo Coruna, Espanyol, Getafe, Granada, Levante, Malaga, Mallorca, Osasuna, Rayo Vallecano, Real Betis, Real Madrid, Real Sociedad, Real Valladolid, Real Zaragoza, Sevilla, Valencia, and Villarreal.

### *Deepening the teams' aggressiveness and exposure in the cards' flows*

From the results obtained in the networks analysis we are going to delve into the identified patterns and study the characteristics of the teams' aggressiveness and exposure in the cards' flows. Considering data for all the teams playing between the 2010/2011 and 2018/2019 seasons, we have Table 2 and Figure 1 showing these estimates for the observed sample.

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Let us also state that we are able to provide separate estimates for each season. To avoid redundancy, we will omit figures and tables for yellow cards, but these figures and tables will be available if requested.


Figure 1. Exposure (xx-axis) versus Aggressiveness (yy-axis), Red Cards
Source: Authors' elaboration upon RFEF data

Table 2.
Exposure x Aggressiveness

| Teams | Exposure | Aggressiveness | Teams | Exposure | Aggressiveness |
|---|---|---|---|---|---|
| Alaves | -1,261 | -1,289 | Leganes | -1,274 | -1,092 |
| Almeria | -0,035 | -0,078 | Levante | 1,169 | 1,615 |
| Athletic Bilbao | 1,637 | 0,767 | Malaga | 1,576 | 1,83 |
| Atletico de Madrid | 0,113 | 0,832 | Mallorca | -1,093 | -0,735 |
| Barcelona | 0,847 | 0,251 | Osasuna | -0,58 | 0,474 |
| Celta de Vigo | 0,65 | 0,623 | Racing de Santander | -1,755 | -0,7 |
| Cordoba | -2,235 | -1,916 | Rayo Vallecano | 0,662 | 0,257 |
| Deportivo Coruna | 0,668 | 0,079 | Real Betis Balompie | 1,443 | 0,231 |
| Eibar | 0,139 | -0,083 | Real Madrid | 0,833 | 0,615 |
| Elche | -1,261 | -1,289 | Real Sociedad | 1,023 | 0,608 |
| Espanyol | 1,36 | 1,843 | Real Valladolid | -0,646 | -2,017 |
| Getafe | 1,576 | 1,83 | Real Zaragoza | -0,746 | -0,053 |
| Girona | -0,802 | -2,649 | Sevilla | 1,36 | 1,843 |
| Granada | 1,418 | 0,777 | Sporting Gijon | -0,203 | -0,249 |
| Hercules | -3,116 | -1,408 | Valencia | 1,145 | 2,119 |
| Huesca | -2,565 | -2,538 | Villarreal | 0,662 | 0,257 |
| Las Palmas | -0,712 | -0,755 | | | |

Note: ϴ = -0.3565; ρ = 0.3749

The negative value found for the ϴ parameter is interpreted as suggested in the methodological section; the trend of this network is to not have random flows of cards among the teams. This means the existing arcs are defined by exogenous dimensions (as we will study in the next subsection).

However, the positive value for the ρ suggests that when a card is given by a team to another, it is also expected there will be cards from the first recipient's team to the original one; therefore, we can conclude for a certain trend of reciprocity. This reciprocity has already been discussed in the work of Alves et al. (2023). From Table 2, we observe how the estimated parameters change for the Spanish teams. We observe teams that simultaneously exhibit positive and high estimates for the parameter of "exposure," suggesting a higher capacity of suffering faults and giving cards to the other teams, but also high values of "aggressiveness," i.e., a high capacity of making faults. The most notorious cases were those of Sevilla, Getafe, and Malaga.

Their position (located in the quadrant characterized by positive values of "exposures" and "aggressiveness") shows the central position of these teams for the flow of red cards in La Liga. Reversely, teams with negative values in both these dimensions shall be interpreted as cases of teams relatively isolated in the red cards' network that we are observing. The most notorious of these "isolated" cases were Huesca, Hercules or Cordoba in these ten seasons. Comparing these groups, we can confirm the heterogeneity of the observed Spanish teams in the described network of red cards along the ten seasons between 2010/2011 and 2018/2019. P1 estimates also allow for computing the probability of a red card between any two teams. Table 3 and Figure 2 show the mean value of each team's probability of participating in a match with red cards exhibited.

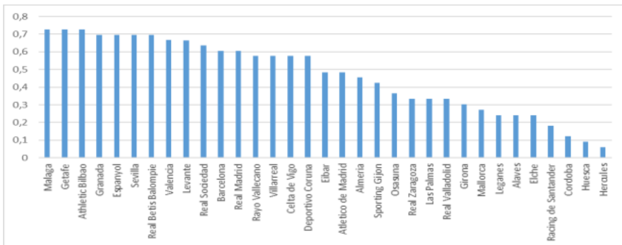


Figure 2. Probability of playing in a match with red cards (La Liga, 10/11-18/19)

Table 3.
Probability of playing in a match with red cards (La Liga, 10/11-18/19)

| Teams | Probability | Teams | Probability |
|---|---|---|---|
| Malaga | 0,728 | Atletico de Madrid | 0,483 |
| Getafe | 0,728 | Almeria | 0,455 |
| Athletic Bilbao | 0,727 | Sporting Gijon | 0,425 |
| Granada | 0,697 | Osasuna | 0,364 |
| Espanyol | 0,697 | Real Zaragoza | 0,335 |
| Sevilla | 0,697 | Las Palmas | 0,334 |
| Real Betis Balompie | 0,696 | Real Valladolid | 0,333 |
| Valencia | 0,667 | Girona | 0,303 |
| Levante | 0,665 | Mallorca | 0,272 |
| Real Sociedad | 0,636 | Leganes | 0,242 |
| Barcelona | 0,606 | Alaves | 0,242 |
| Real Madrid | 0,606 | Elche | 0,242 |
| Rayo Vallecano | 0,576 | Racing de Santander | 0,181 |
| Villarreal | 0,576 | Cordoba | 0,122 |
| Celta de Vigo | 0,576 | Huesca | 0,090 |
| Deportivo Coruna | 0,576 | Hercules | 0,060 |
| Eibar | 0,485 | | |

Without surprise, the teams with high values characterizing their dimensions of exposure and aggressiveness tend to have significant probabilities of participating in matches with red cards.

***Why these cards? Discussing cards' networks using exponential random graph models***

In the last part of the empirical analysis we show the result of the analysis of the determinants of the cards using exponential random graph models. In Table 4, we only exhibit the final model (named "combined model," according to Shumate and Palazzolo, 2010). In Table 4, we only exhibit the variables for which we found overall significant estimates. The remaining variables and estimates will be exhibited if requested.

Table 4.
ERGM estimates for red cards' flows (20010/2011-2018/2019)

| Acceptance Rate: 0.61 | PostMean | Stddev |
|---|---|---|
| Arc | -1.094* | 0.148 |
| Reciprocity | 0.2321* | 0.109 |
| Transf_Match_Reciproc. | -0.2872* | 0.160 |
| Transf_Mismatch_Reciproc. | -0.0214 | 0.127 |
| Points_Match_Reciproc. | 0.2199* | 0.076 |
| Points_Mismatch_Reciproc. | -0.1956 | 0.203 |
| Rank_Match_Reciproc. | -0.2774 | 0.222 |
| Rank_Mismatch_Reciproc. | 0.5078* | 0.205 |
| Golsuf_Match_Reciproc. | 0.2552* | 0.093 |
| Golsuf_Mismatch_Reciproc. | 0.1286 | 0.113 |

Legend: Transf_Match_Reciproc – Same Means of transfers' balances of the teams in the match & both teams have red cards; Transf_Mismatch_Reciproc – different means of transfers' balances of the teams in the match, and both teams have red cards; Points_Match_Reciproc.–same means of total season's points of the teams in the match, and both teams have red cards; Points_Mismatch_Reciproc.–Different total season's points of the teams in the match, and both teams have red cards; Rank_Match_Reciproc.–same medians of ranks of the teams in the match along the seasons, and both teams have red cards; Rank_Mismatch_Reciproc.–different medians of ranks of the teams in the match along the seasons, and both teams have red cards; Golsuf_Match_Reciproc.–same means of goals against the teams in the match along the seasons, and both teams have red cards; Golsuf_Mismatch_Reciproc.–different means of goals against the teams in the match along the seasons, and both teams have red cards

The negative estimated values for the arc parameters in Tables 4 shall be interpreted following Frank and Strauss (1986); this indicates that ties are not random. This finding suggests an additional incentive to search for dimensions to explain the existence of the observed ties. The reciprocity parameter's estimate (0.2321, statistically significant at 0.01) reinforces the idea that there exists a simultaneous red card in a match in which one of the teams has first received one red card.

In Table 4, we have a combined model with structural parameters and attributes. The structural parameters found to be significant were the arc and reciprocity. The attributes followed our literature and were related to the referees' effect and to the sporting determinants. The acceptance rate is high (0.60) for the estimated parameters, which, following van der Pol (2019), shows a high capacity of the estimated model to explain the found ties between the teams.

Regarding the referees' effect, some estimates deserve comments. First, certain referees tend to exhibit more red cards in matches played by teams already sanctioned by these referees in the past. They can be divided into two groups: referees showing cards for both teams and referees only showing red cards for one of the teams. There are also other referees who tend to exhibit red cards independent of having already exhibited red cards in past matches of the teams they have refereed. However, most of the observed referees were not associated with significant estimated effects in the expected number of red cards exhibited in the matches they refereed. We observe that, besides referees' effects, the number of red cards tends to increase if there is a significant difference between the historical median positions of the teams. Additionally, tight matches–characterized by the same number of goals for both teams–tend to be characterized by a higher number of red cards exhibited. If the historical mean of points is close between the competing teams, there tends to be a higher number of exhibited red cards too, which reinforces the hypothesis of latent aggressiveness between teams usually competing for the same ranks. Reversely, there tends to exist a lower probability of red cards in matches played by teams characterized by a close balance of transfers in the previous season.

## Conclusion, Implications and Further Challenges

This paper discusses the interactions, patterns and determinants of red and yellow cards given and received by each La Liga team in the period from 2010 to 2019. These sanctions are applied for the display of yellow and red cards, as has been happening in the world of soccer for more than 50 years. Our empirical study has allowed a deep analysis using network analysis, probabilistic models and exponential random graph models (ERGMs).

As analyzed for the last decade, there has been a decrease in the number of cards displayed in La Liga, as well as in most European leagues. However, as no team receives cards for playing alone, this field of analysis requires greater detail of the sporting relationships that are established in the games. Thus, we resort–in an unprecedented way in the sciences of sports economics–to a network analysis between the teams in question.

In summary, we can conclude that the distribution of red cards in the various editions of La Liga obeys some standards that the network analysis allows us to observe. Attributes range from economic and financial dimensions, namely the ability to generate player transfers, to the traditional competitiveness profiles of each team in competition. As analyzed, teams that historically dispute the same places tend to find themselves in matches most likely to have red cards displayed. Also, teams with the same defensive quality–visible in the same number of goals conceded–tend to have more red cards displayed than when there is a significant difference in that number. Finally, a significant number of referees tend to show red cards in matches involving teams that have already been cautioned for them previously. We recognize the importance of the dimension of reciprocity, which shows how significantly the display of a red card for one team tends to increase the probability that the opposing team will also receive red cards; this is consistent with the hypothesis of propensity for the balance (Dawson et al., 2007) that certain referees and competitive and sporting contexts can promote.

Thus, recognizing that cards–especially red cards–tend to be a source of costs for professional clubs (or revenue for the professional competitions' organizational institutions), this work has shown how certain dimensions resulting from the interaction between clubs can determine a greater or lesser number of cards displayed and associated fines. If it is true that neither team receives a yellow or red card for playing alone (which justifies the use of network analysis), it is also evident that many cards result from games between two teams specifically. Our values showed how the weight of a competitive past can explain the sharing of red cards. Thus, it becomes necessary to transform this historical competitiveness into relationships built on a paradigm of valuing fair play, where the ambition for victory is combined with respect for all colleagues and spectators. Second, the dispute for ranks that cannot be shared (since only one team finishes in each position of the championship, not sharing it "ex aequo") also requires a culture of constructive involvement in favor of the quality of sport and sustainability of ethical values that each competition must promote. Finally, if the referees are professionally prepared to rigorously judge the moves, especially those involving the punishment of the offending players with yellow or red cards, then the heterogeneity found in our results demonstrates the heterogeneous reading of sports regulations performed by the referees who work in La Liga.

Three challenges emerge from some of the limitations of this work. First is the extent of the observed sample of seasons, including seasons before 2010/2011. Second is the possibility of extending the observation to secondary leagues in Spain to confirm the (decreasing) evolution in the cards and to test the robustness of the results achieved here. Third is to study the network of costs' transfers, considering not only the volume of the fees but also their share in each team's budget.

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