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An Empirical Analysis of an Old Football Myth

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IMPRESSUM

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An Empirical Analysis of an Old Football Myth*

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Abstract

In this paper we investigate how the expulsion of a player influences the outcome of a football match. Common sense implies a negative impact for the affected team. However, an old football myth suggests that such an expulsion might also be beneficial since it increases the team spirit as well as the efforts of the affected team. We make use of a unique dataset containing all games played in a World Cup Championship between 1930 and 2002 and follow a twofold econometric strategy: We start with a conditional maximum likelihood estimator which is independent of the relative strength of the teams before we extend this estimator to take the relative strength of the teams and the minute of the expulsion into account. Our results indicate that the scoring intensities of both teams do not differ after the expulsion. Conducting scenario analysis reveals that the impact of a red card depends on the minute of the expulsion and does not have an impact at all if given at the end of the first half or later.

Keywords: Poisson Process, (Un)Conditional Likelihood, Football, Red Card Effect
JEL Classification:C40, Z00

*This is a short note on football and econometrics, the two passions of our mentor Reinhard Hujer to whom we dedicate this paper. The authors thank Carl-Axel Brandt, Joachim Frick, Peter Haan, Paulo Rodrigues, Florian Arun Täube and Oliver Wünsche for valuable comments.

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1 Introduction

Professional football (called soccer in the United States) is one of the most popular sports in the world. It has a long tradition in Europe and South America, and people are becoming increasingly interested in North America, Africa, and Asia. Every four years, a World Cup Championship tournament is organised by the *Federation International de Football Association* (FIFA) and attracts an enormous amount of attention, for example the 1998 tournament in France was viewed by an accumulated audience of over 37 billion people.

As the number of supporters grows, the number of football 'experts' is increasing as well, sharing an enormous basis of football knowledge.[1] Some football 'wisdom' is rather trivial, such as the famous statements by Sepp Herberger, a former coach of the German national team in the 1950s that "the ball is round" and "the game lasts 90 minutes." Other theories are more subtle and call for an empirical examination. For example, it is often suggested that referees favor the home team in tight situations. Garciano, Palacios-Huerta, and Prendergast (2005) and Dohmen (2005) analyse this statement for the Spanish and the German football leagues and indeed find some empirical support. Carmichael and Thomas (2005) pick up this question and analyse whether a home-field advantage exists due to larger support from the home audience and familiarity with the playing ground. Using data from the English Premier League, they provide evidence regarding the existence of such an effect. Additionally, they find that the expulsion of a player is less costly to an away team than to a home team, as this disadvantage may be better accommodated for by the away team, which is already playing more defensively.

Compared to games like basketball, football is a low-scoring game. In order to increase the number of goals scored, the rules have been revised frequently (we will say more on this issue in Section 2.1). Brocas and Carrilo (2004) analyse such two controversial changes, the "three-point victory" and the "golden goal." Using game-theoretical arguments, they show that contrary to common belief, the incentives to play more offensively are not increased by these changes. Another reform, introduced in 1993, is the rule that a second yellow card sends a player off the field. This rule was aimed not only to increase fair play but also to increase the number of goals and the attractiveness of the game.

[1] A collection of some funny and surprising scientific insights on football can be found in Wesson (2002).

The aim of our paper is to analyze the impact of such an expulsion of a player on the scoring intensity of both teams. A player can be sent off the field for illegal defensive actions or foul play. Whereas standard theory would suggest a negative impact for the team affected by the expulsion, an old football myth suggests that such an expulsion might also be beneficial, since team spirit and the affected team's efforts are increased. Inspired by several games in World Cup tournaments where some teams were able to win with only ten players, we try to answer the following question: "Is it true that a football team with one or more players warned off the field is able to mobilize last reserves, strengthen team spirit, and therefore win the game?" Or to put it differently: "Is a disqualification of a player really a disadvantage for the affected team, or can it turn to an advantage?"

Our study is related to a paper by Ridder, Cramer, and Hopstaken (1994), who analyse the effect of a red card during three seasons of the Dutch professional football league. We extend their analysis in two ways. First, we make use of an international dataset, containing all games played in a World Cup Championship tournament between 1930 and 2002. Second, in contrast to Ridder, Cramer, and Hopstaken (1994), our econometric modelling strategy takes into account the relative strength of the teams before the expulsion. Since there are some special rules for the World Cup tournaments (in contrast to league games), we take them into account as well.

The paper will proceed as follows. We will describe the basic rules of the game and the data used for the analysis in Section 2, where we will also present some preliminary descriptive results. Section 3 introduces our econometric strategies, before we present the estimation results in Section 4. Section 5 contains some simulation results and, finally, draws some conclusions.

2 Rules, Data, and First Descriptive Results

2.1 Rules of the Game

The basic rules of football have been rather stable over recent decades, though some refinements have been introduced (for a general overview see FIFA (2005)). Every team has 11 players, and the team who scores the most goals wins. The official duration of the match is 90 minutes, where the first and second halves last 45 minutes each. The clock is not stopped when the play is interrupted, e.g., by an injury of a player, but the referee can allow for lost time at the end of each half. This might result in a situation where the 45th and 90th minute last longer than sixty seconds.

Some special rules apply to World Cup tournaments. The mode of the tournament initially changed quite often, but has been pretty stable since 1986. Whereas in 1930 only 13 teams participated in the tournament, the number of participating teams was 32 in 2002. Common to all tournaments is a preliminary or group round. At this stage every team plays against each opponent in its group, and the best teams qualify for the next round. In most tournaments this is a knockout-round, where only the winning team advances further. In the group round draws are possible, but in the knockout round the game was either replayed (up to 1958) or went into a 30-minute overtime (two halves of fifteen minutes each). If this also results in a draw, the winner is decided by penalty shootout.

In the most recent rules of the game, there are several offences for which a player can be sent off the field. This occurs, for example, if he: (1) is guilty of serious foul play or violent conduct, (2) spits at an opponent or any other person, (3) denies the opposing team a goal or an obvious goalscoring opportunity by deliberately handling the ball, (4) denies an obvious goalscoring opportunity to an opponent moving towards the player's goal by an offence punishable by a free kick or a penalty kick, (5) uses offensive or insulting or abusive language and/or gestures, or (6) receives a second caution ("yellow card") in the same match. When we look at the number of red cards per tournament in the next subsection, we see an increasing trend reflecting a permanent tightening of these measures. Note that the rule that a second yellow card causes a player to be sent off the field was only introduced in 1993. The aim of these reforms was to introduce more fair play and partly to increase the number of goals and the attractiveness of the game.

2.2 Data and Some Descriptives

In the following we will present some first descriptive results.[2] Table 1 contains summarizing statistics for all 643 games played at the 17 World Cup Championships (1930-1938

[2]Our data was collected from the official FIFA Worldcup homepage.

and 1950-2002).[3] Whereas the number of teams and games increased remarkably over the last decades, the average number of goals per match dropped from 3.89 in 1930 to 2.52 in 2002. A second point to note is that the number of expulsions has increased substantially. Whereas in the early years a red card was an extremely rare event, spectators at the championship in 2002 witnessed a red card in every fifth match, and between 1990 and 1998 a red card occurred even in every fourth match.

Table 1: Descriptive Results for All World Soccer Championships

Year	Number of Teams	Number of Games	Number of Goals[1]	Number of Red Cards	Goals per Game[1]	Red Cards per Game
1930	13	18	70	1	3.89	0.06
1934	16	16	68	1	4.25	0.06
1938	15	18	84	2	4.67	0.11
1950	13	22	88	0	4.00	0.00
1954	16	26	140	1	5.38	0.04
1958	16	35	126	3	3.60	0.09
1962	16	32	89	3	2.78	0.09
1966	16	32	89	4	2.78	0.13
1970	16	32	95	0	2.97	0.00
1974	16	38	97	5	2.55	0.13
1978	16	38	102	1	2.68	0.03
1982	24	52	146	5	2.81	0.10
1986	24	52	132	7	2.54	0.13
1990	24	52	115	14	2.21	0.27
1994	24	52	141	13	2.71	0.25
1998	32	64	171	16	2.67	0.25
2002	32	64	161	13	2.52	0.20
Sum		643	1914	89		
Mean	19.35	37.82	112.59	5.24	3.24	0.11

[1] Goals scored during penalty shootouts are not included.

Eighty-nine, or 13.8 percent of 643 matches, were ‘red card’ matches, that is matches were at least one player was expelled. In 67 matches there was only one red card, and in 19 matches two players were expelled. Out of the 19 matches with two expulsions, in eleven games one player from each team was sent off the field, leaving eight games in which two players from one team were sent off. Finally, there are three matches with three red cards. Figure 1 shows the distribution of the minute of exclusion. Since we have

[3] 71 different countries participated at those world championships, some of which do not exist any longer (e.g., the German Democratic Republic, the Soviet Union, and Yugoslavia).

to account for group round and death round matches (where the latter case might result in overtime), we separate these two cases.

On average, the first expulsion in group round matches occurs during minute 59.2 (SD = 23.7), with a minimum of 1 and a maximum of 90 minutes. In death round matches the earliest expulsion took place during the 14th minute and the latest during the 103rd minute, leading to an average of 69.5 (SD = 22.9). It is quite interesting to note that 33 percent of the 643 games were death round matches, but nearly 40 percent of the red cards were delivered in these death round matches. Hence, it seems that in these important games it is more likely that a player will be expelled.

Insert Figure 1 about here

Finally, to get a first impression of the effects of a red card, we check how the success of the affected team ('red card' team henceforth) changes after the expulsion.[4] Before the exclusion, three different outcomes of the match are possible: the red card team can lead, the match might be drawn, or the red card team could be losing. After the exclusion the same three outcomes are possible, yielding nine different transition possibilities (see Figure 2).

Insert Figure 2 about here

Table 2 shows how the 86 red card matches are distributed among these possibilities.

Table 2: Final Results and 'Red Card' Team's Pre-Expulsion Status

	Final Result for the Red Card Team							
Status before	Number of Games				In % of All Games			
the expulsion	Lag	Draw	Lead	Sum	Lag	Draw	Lead	Sum
Lag	32	2	1	35	37.2	2.3	1.2	40.7
Draw	16	16	11	43	18.6	18.6	12.8	50.0
Lead	1	0	7	8	1.2	0.0	8.1	9.3
Sum	49	18	19	86	57.0	20.9	22.1	100.0

[4] Since in three games a red card was given simultaneously to both teams, we drop them from the analysis.

Looking at the the diagonals of Table 2 shows that in most games the result stays the same. In 37.2 percent the team who gets the red card already lags and loses also in the end, whereas in 18.6 percent of the games the result is drawn at the time of the expulsion and stays like this until the end. Finally, in 8.1 percent of the matches the red card team leads at the expulsion and wins. Hence, in 63.9 percent the result does not change after the expulsion. The numbers below the diagonal show, that the result of the red card team deteriorates in 19.8 percent of the matches, whereas the upper part indicates that the result improves in 16.3 percent of the games. Note that the red card is given in 40.7 percent of the games to the team which is already losing and only in 9.3 percent of matches to the leading team. Therefore, it seems important to take the relative strength of the teams at the time of the expulsion into account to model the red card effect consistently.

3 Econometric Modelling

3.1 Conditional Maximum Likelihood Estimation

We start our econometric analysis by estimating a model proposed by Ridder, Cramer, and Hopstaken (1994) (called the RCH model hereafter). They analyze the goals scored by red carded versus non-red carded teams before and after the expulsion of a player and define K_{10} (K_{11}) as the number of goals scored by the red card (non-red card) team before the expulsion. Likewise, M_{10} and M_{11} denote the number of goals scored by the red card and non-red card teams after the expulsion. RCH assume that the number of goals scored by both teams follow two independent Poisson processes which depend on the relative strength of the teams (γ_j, measured by the relative scoring intensity of team j at time t as compared to the average scoring intensity at time t), the time of the expulsion (τ), the average scoring intensity at minute t ($\lambda(t)$) and the effect of the red card itself (θ_j). More formally, using the notation by RCH and skipping the observational index i for convenience:

$$K_j \sim P\left(\gamma_j \int_0^{\tau} \lambda(t)dt\right) \qquad M_j \sim P\left(\theta_j \gamma_j \int_{\tau}^{90} \lambda(t)dt\right) \quad \text{for} \quad j = 10, 11. \tag{1}$$

Basically, the RCH model states that the number of goals scored by team j before the expulsion at time τ is equal to the average number of goals scored until τ times the relative strength of team j. After the expulsion, the average number of scored goals changes according to the multiplicative effect θ_j.

RCH develop a conditional maximum likelihood estimator which is independent of the relative strength of the teams, γ_j. More precisely, they consider the fraction of goals scored after the red card which is independent of any team-specific effects.

Denoting

$$A(\tau) = \int_0^\tau \lambda(t)dt \quad \text{and} \quad B(\tau) = \int_\tau^{90} \lambda(t)dt, \tag{2}$$

as the average number of goals scored before and after the exclusion, the conditional distribution of M_j given the total number of goals scored by team j, N_j, follows a binomial distribution $M_j|N_j \sim B(N_j, g_j(\theta_j))$ with

$$g_j(\theta_j) = \frac{\theta_j B(\tau)}{A(\tau) + \theta_j B(\tau)} \qquad \text{for } j = 10, 11. \tag{3}$$

The log-likelihood function is then given by

$$\log L = \sum M_j \log\left(g_j(\theta_j)\right) + (N_j - M_j)\log\left(1 - g_j(\theta_j)\right). \tag{4}$$

Applying this estimator to a sample of red card and non-red card teams yields the multiplicative effect of an expulsion on the average scoring intensity of the red card team, θ_{10}, and the non-red card team, θ_{11}.[5]

3.2 Estimating the Average Scoring Intensity

The log-likelihood function in (4) depends on the average number of goals scored until the time of expulsion, $A(\tau)$, and after the expulsion, $B(\tau)$, which have to be estimated first. Table 3 shows how the goals in all matches are distributed among 15-minute-intervals. It can be seen that the number of goals is higher in the second half (compared to the first half) and highest in the last quarter of the matches.

[5]Note that observations where $N_j = 0$ must be omitted before estimation, since the conditional distribution is only defined for $N_j \geq 1$.

Table 3: Scoring Intensity by 15-Minute Intervals in All Matches

	Number of Goals[1]	
Time Interval	abs.	in %
0-15	260	13.60
16-30	295	15.43
31-45	259	13.55
46-60	322	16.84
61-75	343	17.94
76-90	382	19.98
91-105	27	1.41
105-120	24	1.26

In order to obtain an estimate for the average scoring intensity, we ran the following regression using all matches in our dataset:

$$\text{Average number of goals per team and match} = \beta_0 + \beta_1 \text{Minute of the goal} + \epsilon$$

Estimation yields (standard errors in parentheses and $R^2_{adj} = 0.98$):

$$\hat{\beta}_0 = .013526\ (.013986) \qquad \hat{\beta}_1 = .014167\ (.000204),$$

which means that the average number of goals scored by a team in a match increases from 0.014 in the first minute to 1.29 by the 90th minute.

3.3 Unconditional Maximum Likelihood Estimation

Next we will conduct an unconditional analysis of the number of goals scored by the red card team and the non-red card team before and after the expulsion. More specifically, we will include a proxy for the relative strength of both teams measured by the difference between the goals scored at the time of expulsion. Additionally, we will include other control variables as well, such as death round match and home advantage.[6] Table 4 shows the underlying model structure. Similar to the RCH model, we assume that the average number of goals scored by both teams before and after the expulsion follow independent Poisson distributions. The intensity parameters for the red card team before and after the expulsion are denoted by λ_{10}^K and λ_{10}^M and, accordingly, the intensity parameters for the non-red card team by λ_{11}^K and λ_{11}^M.

[6]It should be clear, that home advantage is a rather rare event. Only in 87 out of the 643 total matches one team had a home advantage (13.5%). This is true for 13 out of 89 (14.6%) 'red card' matches.

Table 4: Unconditional Poisson Regression Model

	Before the Expulsion	After the Expulsion
Red Card Team	$K_{10} \sim P(\lambda_{10}^K)$	$M_{10} \sim P(\lambda_{10}^M)$
Non-Red Card Team	$K_{11} \sim P(\lambda_{11}^K)$	$M_{11} \sim P(\lambda_{11}^M)$

The average number of goals scored before and after the expulsion for both teams are then given by

$$K_j = \lambda_j^K \qquad M_j = \lambda_j^M \qquad \text{for } j = 10, 11. \tag{5}$$

The Poisson regression model assumes that the intensity parameter depends linearly on a set of explanatory variables. Since λ_i must be greater than zero, a log-linear specification is chosen. We include the following covariates in our empirical analysis: Minute of the exclusion, relative strength (measured as the difference between the goals scored by the red card team and the non-red card team at the time of the expulsion) and dummy variables for a home advantage and a death round match.

We define two outcome variables to measure the impact of a red card being issued at time τ. Similar to the RCH approach, we start by considering a simple before-after estimator (BAE) defined as

$$\theta_j^{\text{BAE}} = M_j - K_j \quad \text{for j = 10,11} \tag{6}$$

which compares the average scoring intensity after the expulsion at time τ with the average scoring intensity before the expulsion for team j. If $\theta_j^{\text{BAE}} > 0$, a red card has a positive impact on the scoring intensity of team j.

This simple before-after strategy suffers from its implicit assumption that the scoring intensity is time invariant. The estimates in Section 3.2 have shown, however, that the scoring intensity increases linearly over time, yielding upward-biased estimates of θ_j^{BAE}.

In order to account for this bias, we extend the simple before-after estimator to a difference-in-differences (DID) estimator, which eliminates common time trends by subtracting the before-after change in scoring intensities for the non-red card team from the before-after change of the red card team according to:[7]

$$\theta^{\text{DID}} = \theta_{10}^{\text{BAE}} - \theta_{11}^{\text{BAE}}. \tag{7}$$

[7]For a more thorough discussion of evaluation estimators like the BAE and DID, see Heckman, LaLonde, and Smith (1999).

If $\theta^{\text{DID}} > 0$, an expulsion actually favors the red card team, whereas $\theta^{\text{DID}} < 0$ means, that we have found evidence that an expulsion is more beneficial, or at least less harmful, to the non-red card team. In the final section we will analyze how both estimators evolve over time.

4 Estimation Results

4.1 Conditional Maximum Likelihood Estimation

We first apply the conditional maximum likelihood estimator from equation (4) to all 89 red card matches played in a World Cup championship. As mentioned above, in three matches, red cards were given simultaneously to both teams. In order to estimate the impact of an expulsion on the affected team, we excluded the three matches from the estimation. Additionally, due to the conditional maximum likelihood estimator we have to exclude matches where one of the teams has not scored at all, leaving us, finally, with a total of 68 observations.[8]

Table 5: Conditional Maximum Likelihood Estimation Results

	All Matches		Death Round Matches		Matches After 1986	
	Estimator	Std. Err.	Estimator	Std. Err.	Estimator	Std. Err.
$\hat{\theta}_{10}^{\text{CML}}$	0.91	0.24	0.73	0.30	0.99	0.30
$\hat{\theta}_{11}^{\text{CML}}$	0.80	0.15	0.64	0.20	0.90	0.20

We obtain the following estimation results (see Table 5). According to the CML results, scoring intensities decrease after an expulsion by 9% for the affected team and by 20% for the non-affected team. However, both effects are not significantly different from one. Separating death round matches and excluding matches played before 1986 enables us to investigate whether the results are stable. Compared to all matches, an expulsion in a death round match has an even stronger negative impact on the scoring intensities of both teams. However, again both impacts do not significantly different from each other. The same holds true for matches played after 1986. Ridder, Cramer, and Hopstaken (1994) found that an expulsion increases the scoring intensity of the non-affected team by 88% while leaving the scoring intensity of the red card team unchanged. In contrast,

[8]Note also, that we excluded goals scored during penalty shootouts from the number of goals scored after the expulsion.

we find that for the World Cup championship a red card does not deteriorate the scoring intensity for the affected team compared to the non-affected team.

4.2 Unconditional Maximum Likelihood Estimation

Table 6 contains the estimation results separated for the red card and the non-red card team before and after the expulsion. Several points are notable. First of all, the timing of the red card has important implications on scoring intensities for both teams.

Table 6: Estimation Results of the Poisson Regression Model

	Before the Exclusion		After the Exclusion	
Variable	Coefficient	p-Value	Coefficient	p-Value
		Red Card-Team		
Intercept	-2.45	0.00	0.35	0.37
Minute of Exclusion	0.02	0.01	-0.02	0.00
Relative Strength	0.67	0.00	0.08	0.64
Home Advantage	-0.10	0.84	-1.63	0.11
KO Round	0.49	0.16	0.06	0.89
		No Red Card-Team		
Intercept	-1.69	0.00	1.16	0.00
Minute of Exclusion	0.01	0.03	-0.03	0.00
Relative Strength	-0.72	0.00	-0.32	0.01
Home Advantage	-0.03	0.95	0.29	0.36
KO Round	0.17	0.49	-0.20	0.51

[1] Notes: Excluding penalty goals.

Of course, the average number of goals before the exclusion increases with the minute of the exclusion. Accordingly, the later the exclusion, the less time both teams have to score, and thus the scoring intensity after exclusion decreases with each increasing minute before exclusion. Relative strength has no impact on the scoring intensity after exclusion of the red card team. On the other hand, the stronger the red card team at the time of the exclusion, the smaller the scoring intensity of the non-red card team after the exclusion. Neither home advantage nor whether the match was a death round match has an impact on the scoring intensity. In the following section, we will demonstrate how these estimation results can be used to assess the impact of a red card.

5 Simulation Results and Conclusions

We can use the estimation results in Table 6 to analyze the impact of an expulsion on the subsequent scoring intensities of both teams. Figure 3 contains the before-after estimator, as defined in equation (8), as well as the difference-in-differences estimator given in equation (9). Figure 3 assumes that at the time of the expulsion the match is drawn, neither team has a home advantage, and that the match takes place in the group round.

Insert Figure 3 about here

Looking at the before-after estimators for both teams shows that the impact of a red card decreases with each increasing minute before expulsion. If, for example, a player is sent off the field in the thirtieth minute, the subsequent scoring intensity of the affected team increases compared with its scoring intensity before the expulsion. However, such an expulsion increases the scoring intensity of the non-red card team even stronger, implying a negative overall impact of a red card at this point in time.

The later the expulsion, the more similar the before-after estimators for both teams become. As a result, a late red card, i.e., from the sixtieth minute on, does not change the final result of the match. Thus, an early expulsion increases the winning probability of the non-affected team considerably. If the red card is given in the fifteenth minute, the average number of goals scored increases by 2.7, but the red card team will score one goal less than the 'non-red' card team. However, if the red card is given after half-time, its impact on the final outcome of the match can be disregarded. Thus, we can conclude, that ten do not do it better. If the red card is given at the beginning of the second half, however, at least they do not worse. Hence, the old football myth can not be supported statistically and remains a myth.

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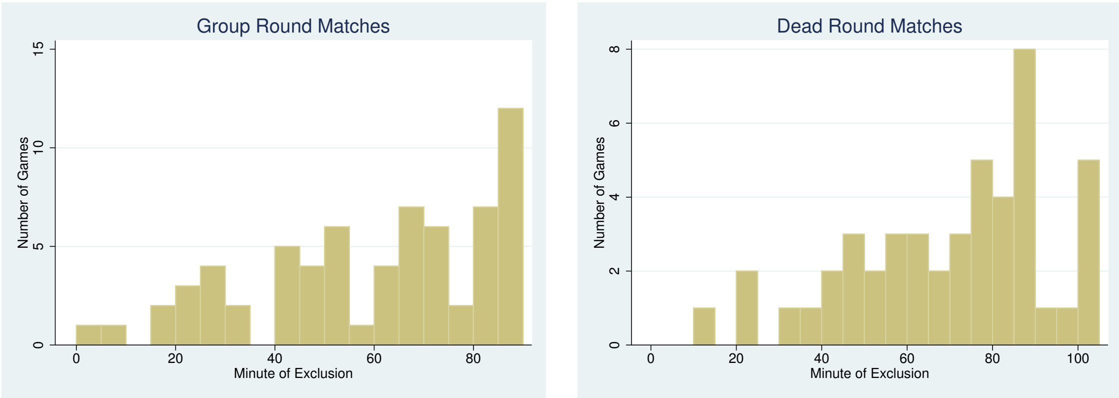
A Figures

Figure 1: Distribution of the Number of Red Cards by Time - Group Round and Death Round Matches



212 (32.97%) of all games were death round matches.
Out of the 89 red card matches, 39.33% occurred during a death round match.

Figure 2: Transition Probabilities for the Red Card Team

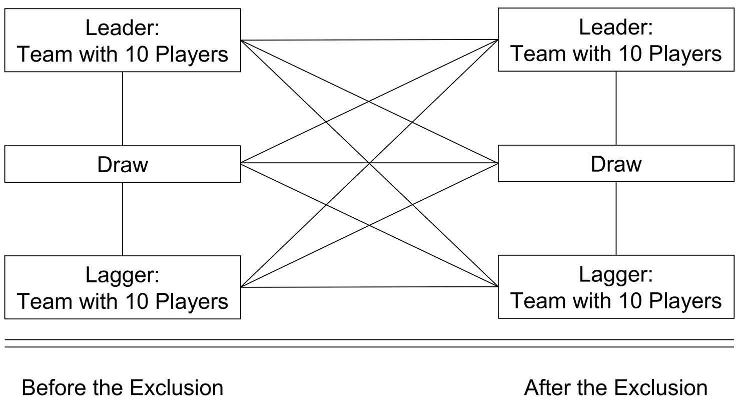


Figure 3: Match is Drawn at the Time of the Expulsion, Neither Team has a Home Advantage, Group Round Match