Yellow Cards: Do They Matter?

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Abstract

Using data from the Bundesliga, the top German football league (American 'soccer'), we analyze the effects of yellow and red cards on the probability of victory for a team. For the team receiving the cards, we find that yellow and red cards decrease the probability of victory. However the number of fouls called increases the probability of victory for that team. We therefore find that aggressive play is valuable, but pushing too hard is detrimental. We also find that the probability change is different for the home and away teams.

Keywords: European Football (Soccer), yellow cards, red cards, fouls, referee bias

JEL codes: L22, L83

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I. Introduction

The use of fouls, and foul calling, has been exploited in studies for many reasons. Price and Wolfers (2009) use referee calls to measure racial bias in the NBA while Dohmen (2008) and Buraimo, Forrest, Simmons (2010) use foul calls to measure home team favoritism in European Football. Although many have used fouls to explain biases, this paper expands the literature by explaining the effects of yellow and red cards (i.e. foul calling) on a team's ability to win games.

Jewel (2009) acknowledged this gap in the literature and estimates the demand for aggressive play in the English Primer League, finding aggressive play is negatively associated with the probability of winning. Our study expands upon this by separating out the effects of offside calls, fouls called, yellow cards, and red cards as aggressive behavior, while controlling for offensive statistics like corner kicks and shots on goal.

The next section discusses the model set-up. Section three presents the data and results, including two robustness checks. The last section concludes.

II. Methodology

To analyze the effects of yellow and red cards we use data from the Bundesliga, the top German football league (American 'soccer').[1] We look at the effect of yellow and red cards on the performance of teams in the league from fall 2004 to spring 2009, a span of five seasons. We use rich data from the league to examine yellow cards awarded, yellow to red cards (a result of one player receiving two yellow cards), red cards awarded (direct red cards for flagrant fouls), total fouls committed by each team, shots on goal, corner kicks, game outcome, and a proxy for overall talent (a dummy variable for top five

[1] Found at www.Bundesliga.de

ranked teams the previous season). These data are for all 306 games of each season and are described below in table I.

Table I:

Variable	Description
Season	2004/2005 - 2008/2009 season
Game	In-season game week, 1-34
HYellowC (AYellowC)	Yellow Cards given to the home (away) team
HYellowRed	Yellow to Red cards given to the home team
HRedC	Red cards given to the home team
HFouls	Fouls called on the home team
HCKick	Home team corner kicks
HOffs	Home team offside calls
HShots	Home team shots on goal
HWin	Home team win
Tie	Tie game
HLWin	Home team was ranked (top 5) at the end of the previous season
TopGame	Both teams playing were ranked at the end of the previous season

In football there are three possible outcomes: a win, tie, or loss. Following the practice of many European football leagues, in the Bundesliga points are awarded for both a win and a tie. We focus on the probability of the home team winning, using a probit model, and on the overall effects using an ordered probit.

$$\begin{aligned} \text{GameOutcome}_i = {} & \alpha + \beta_1 \text{HYellowC} + \beta_2 \text{HYellowRed} + \beta_3 \text{HRedC} + \beta_4 \text{HFouls} \\ & + \beta_5 \text{HCKick} + \beta_6 \text{HOffs} + \beta_7 \text{HShots} + \beta_8 \text{HLwin} + \beta_9 \text{AYellowC} + \beta_{10} \text{AYellowRed} \\ & + \beta_{11} \text{ARedC} + \beta_{12} \text{AFouls} + \beta_{13} \text{ACKick} + \beta_{14} \text{AOffs} + \beta_{15} \text{AShots} \\ & + \beta_{16} \text{ALwin} + \beta_{17} \text{TopGame} + \varepsilon \end{aligned} \quad (1)$$

Equation 1 is run separately for the home team's probability of winning and as an ordered probit, where GameOutcome equals 0 for the away team's victory, 1 for a tie,

and 2 for a home team's win. We expect the signs on home yellow cards, home yellow to red cards, and home red cards to be negative, whereas the away team's cards should have positive signs. We predict that if a home team receives any card, yellow or red, it will decrease the probability of victory. This occurs because receiving a red card garners a player ineligible for the remainder of the game. Although receiving a yellow card shows a player is aggressive, after receiving a yellow card the player will decrease their aggressive play due to a fear of a second yellow card (a red card).

We expect the signs on the home team's fouls, corner kicks, off-side calls, and shots on goal to all be positive (with the inverse for the away team). These should have positive effects on the home team's ability to win because receiving foul calls, without getting carded, is a proxy for playing hard. In addition, corner kicks allow for a free kick close to the goal, off-side calls are a proxy for an offensive play, and shots on goal are necessary for scoring goals, and therefore winning. The dummy variables for lagged ranking and TopGame are a proxy for high quality teams.

We present the results of two regressions for the dependent variable of home team win (binary) as well as two with an ordered probit model. Further expanding the models, both are specified as equation 1 (above) and equation 1 with squared terms on yellow cards, fouls, corner kicks, off-sides, and shots on goal. Each regression controls for time dependent effects, both across seasons and within season, with fixed effects. We ran these regressions for AWin (Away wins, binary) and tie games but did not include the output. General results are discussed. [2]

Two different robustness tests are also included. We test the effect of corner kicks, which could be correlated with shots on goal, and other fixed effect models.

[2] Please contact the authors for these data output.

III. Data and Results

Table II shows data combining both home and away teams and table III shows the data separately. The data are from the 2004/2005 season to the 2008/2009 season, for all 34 weeks. There are 18 teams in the league each year. The home team wins 46% of the time, the away team wins 28% of the time, and 26% of the time games are tied. This home field bias in winning is consistent with other football data (Jewel 2009).

Table II:

All Data				
Variable	Mean	Std. Dev.	Min	Max
Season	2006	1.415	2004	2008
Week	17.5	9.814	1	34
HWin	0.459	0.499	0	1
Tie	0.258	0.438	0	1
AWin	0.282	0.45	0	1

Table III:

Home					Away				
Variable	Mean	Std. Dev.	Min	Max	Variable	Mean	Std. Dev.	Min	Max
HYellowC	1.714	1.188	0	6	AYellowC	2.070	1.276	0	6
HYellowRed	0.031	0.174	0	1	AYellowRed	0.062	0.247	0	2
HRedC	0.031	0.176	0	2	ARedC	0.063	0.249	0	2
HFouls	18.112	4.923	3	40	AFouls	19.696	5.163	3	41
HCKick	5.900	3.021	0	20	ACKick	4.486	2.518	0	14
HOffs	3.492	2.375	0	21	AOffs	3.209	2.302	0	14
HShots	15.270	4.925	3	35	AShots	12.194	4.645	1	33
HGoals	1.625	1.306	0	8	AGoals	1.215	1.124	0	6
HLWin	0.278	0.448	0	1	ALWin	0.278	0.448	0	1

The maximum amount of yellow cards given in a game is six and this occurs individually for home and away teams. The maximum number of red cards is two for the away team, but only one for the home team. To test if yellow and red cards have an effect on the probability of victory for the home team we control for the number of fouls called per game (averaging 19 per game), the number of corner kicks each team receives, shots

on goal, and a dummy variable for if the team finished in the top five of the league the previous year.

As seen in table IV (marginal effects reported), when the home team receives a yellow card it significantly decreases their probability of winning. With an average of two yellow cards issued to each team, the first yellow card decreases the probability of victory by more than the second card. Recall that when a player receives a red card, that player is ineligible for the remainder of the game and his team has to play with one less player for the rest of that game. There are two ways to receive a red card; if a single player receives two yellow cards, the second yellow, by rule, is a red card, or a flagrant foul. The effects of these two ways are estimated separately; one player receiving two yellow cards decreases the probability of the home team winning by 22 to 27 percent, on the binary probit and ordered probit models, respectively, both significant at the one percent level (remember the ordered probit ranges from zero to two). Receiving a direct red decreases the probability of victory by 44 to 48 percent, on the ordered probit and binary porbit models, respectively, again both significant at the one percent level.

When the home team receives a yellow card, the probability of victory decreases by 13 to 15 percent in the binary probit and ordered probit models, respectively. These results are significant at the one percent level.

Table IV: Equation 1. Probit regression of home team wins and ordered probit.

Variables	HWin		Game Outcomes	
HYellowC	-0.056	-0.152	-0.125	-0.356
	(4.40)**	(4.49)**	(4.40)**	(4.62)**
HYellowC2		0.024		0.055
		(3.04)**		(3.18)**
HYellowRed	-0.21	-0.22	-0.491	-0.541
	(2.64)**	(2.75)**	(2.79)**	(3.04)**
HRedC	-0.488	-0.479	-0.917	-0.885
	(4.71)**	(4.56)**	(4.98)**	(4.76)**
HFouls	0.007	0.015	0.023	0.021
	(2.26)*	(1.01)	(3.22)**	(0.65)
BCKick	-0.043	-0.047	-0.094	-0.127
	(7.87)**	(2.83)**	(7.87)**	(3.61)**
HOffs	0.017	0.047	0.037	0.102
	(2.84)**	(3.22)**	(2.75)**	(3.22)**
HShots	0.014	0.024	0.032	0.067
	(4.11)**	(1.79)	(4.12)**	(2.22)*
AYellowC	0.024	0.054	0.062	0.137
	(2.10)*	(1.58)	(2.41)*	(1.79)
AYellowC2		-0.007		-0.016
		(0.98)		(1.06)
AYellowRed	0.099	0.104	0.313	0.32
	(1.71)	(1.78)	(2.41)*	(2.45)*
ARedC	0.192	0.199	0.496	0.506
	(3.40)**	(3.50)**	(3.80)**	(3.86)**
AFouls	-0.007	-0.001	-0.021	-0.016
	(2.35)*	(0.09)	(3.14)**	(0.47)
ACKick	0.012	-0.005	0.041	0.027
	(2.02)*	(0.26)	(2.90)**	(0.66)
AOffs	-0.019	-0.036	-0.048	-0.074
	(3.18)**	(2.12)*	(3.56)**	(1.94)
AShots	-0.007	-0.011	-0.025	-0.078
	(1.85)	(0.84)	(3.12)**	(2.68)**
Lagged Winning Controls	Yes	Yes	Yes	Yes
In-Season FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R2	0.1352	0.1442	0.0990	0.1060
Observations	1520	1520	1520	1520

Absolute value of z statistics in parentheses

* significant at 5%; ** significant at 1%

When the away team receives a yellow card it increases the probability that the home team wins by 5 to 6 percent, although these estimates are insignificantly different from zero. Jointly tested they have a chi-square of 4.38, with a p-value of .1117. However we continue to find the first card has a larger effect than additional yellow cards. A yellow to red card for the away team has an insignificant impact in the binary probit, but increases the home team's chances of winning by 16 percent in the ordered probit, significant at the five percent level. Receiving a flagrant foul (red card) increases the home team's chances of winning by 20 to 25 percent for the binary probit and ordered probit, respectively, both significant at the one percent level.

The other controls in this regression are jointly significant and come out as expected, except corner kicks. The coefficient on home team fouls increases the probability of winning as do offside calls and shots on goal, with the inverse on away team's coefficients. The corner kicks have a negative impact on the home team winning. However this could be driven by the fact that those teams who are more likely to receive corner kicks are also the same teams that are likely to receive offside calls and shots on goal. These results are controlling for in-season fixed effects (week of play), yearly fixed effects, and winning controls (lagged team ranking and top games – both teams were ranked last season).

The regressions of the away team's probability of winning, although not shown for brevity, show the same general conclusion. When looking at ties, there are virtually no significant predicators of a team's probability to tie the other team.

Robustness

We conduct two forms of robustness checks. First, we separate out variables that could be correlated and second we use different fixed effects – controlling for team level fixed effects in addition to across seasons and within season fixed effects . The first robustness test deals with the issue noted about corner kicks above. It is possible that corner kicks could be serially correlated with other independent variables in the regression. For example, the number of corner kicks is expected to be highly correlated with the number of shots on goal and offside calls, and thus winning. To measure if the results found above are driven by this multicollinearity, we run the binary probit model with and without corner kicks, shots on goal, and offside calls.

As seen in table V the effects of yellow and red cards are not affected by the different models with and without corner kicks, offside calls, and shots on goal. Also, the coefficients on corner kicks, offside calls, and shots on goal do not change with the different specifications of the model.

However, in these specifications, and all previous specifications, the model is only predicting 10 to 14 percent of the reason on why teams win. Although we have interesting predictions on the effects of yellow cards, the overall predictive power is relatively low. For that reason we do a second robustness test to see if different forms of fixed effects can increase our predictive powers. In table VI we present the in-season fixed effects (week of play), yearly fixed effects, and winning controls (lagged team ranking and top games – both teams were ranked last season), all of which are in the original equation. We also add a team level fixed effect to test if different teams have different effects on the variables of interest.

Table V: Equation 1, excluding variables correlated with corner kicks. Probit regression on home team wins.

Variables	HWin			
HYellowC	-0.152	-0.155	-0.157	-0.153
	(4.49)**	(4.67)**	(4.65)**	(4.57)**
HYellowC2	0.024	0.024	0.024	0.023
	(3.04)**	(3.14)**	(3.12)**	(3.00)**
HYellowRed	-0.22	-0.229	-0.231	-0.234
	(2.75)**	(2.98)**	(2.98)**	(3.03)**
HRedC	-0.479	-0.468	-0.504	-0.516
	(4.56)**	(4.62)**	(4.83)**	(4.97)**
HFouls	0.015	0.014	0.011	0.01
	(1.01)	(0.94)	(0.74)	(0.70)
BCKick	-0.047		-0.034	-0.031
	(2.83)**		(2.21)*	(2.04)*
HOffs	0.047	0.039	0.047	
	(3.22)**	(2.79)**	(3.22)**	
HShots	0.024	0.014		
	(1.79)	(1.08)		
AYellowC	0.054	0.054	0.058	0.062
	(1.58)	(1.61)	(1.70)	(1.83)
AYellowC2	-0.007	-0.006	-0.007	-0.008
	(0.98)	(0.91)	(1.03)	(1.15)
AYellowRed	0.104	0.104	0.129	0.117
	(1.78)	(1.83)	(2.23)*	(2.03)*
ARedC	0.199	0.201	0.219	0.228
	(3.50)**	(3.58)**	(3.86)**	(4.05)**
AFouls	-0.001	-0.002	-0.002	-0.003
	(0.09)	(0.11)	(0.15)	(0.20)
ACKick	-0.005		-0.016	-0.018
	(0.26)		(0.89)	(1.05)
AOffs	-0.036	-0.032	-0.035	
	(2.12)*	(1.95)	(2.05)*	
AShots	-0.011	-0.004		
	(0.84)	(0.30)		
Lagged Winning Controls	Yes	Yes	Yes	Yes
In-Season FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R2	0.1442	0.1084	0.1337	0.1230
Observations	1520	1520	1520	1520

Absolute value of z statistics in parentheses

* significant at 5%; ** significant at 1%

Table VI: Equation 1. Using different types of Fixed Effects.

Variables	HWin				
HYellowC	-0.152	-0.145	-0.147	-0.151	-0.152
	(4.49)**	(4.33)**	(4.36)**	(4.38)**	(4.41)**
HYellowC2	0.024	0.021	0.022	0.022	0.023
	(3.04)**	(2.81)**	(2.84)**	(2.86)**	(2.90)**
HYellowRed	-0.22	-0.244	-0.241	-0.236	-0.233
	(2.75)**	(3.11)**	(3.06)**	(2.96)**	(2.90)**
HRedC	-0.479	-0.447	-0.442	-0.484	-0.478
	(4.56)**	(4.35)**	(4.29)**	(4.54)**	(4.48)**
HFouls	0.015	0.017	0.017	0.015	0.015
	(1.01)	(1.15)	(1.17)	(1.00)	(1.01)
BCKick	-0.047	-0.046	-0.047	-0.049	-0.05
	(2.83)**	(2.85)**	(2.89)**	(2.92)**	(2.95)**
HOffs	0.047	0.048	0.046	0.049	0.047
	(3.22)**	(3.21)**	(3.08)**	(3.24)**	(3.11)**
HShots	0.024	0.024	0.025	0.025	0.026
	(1.79)	(1.78)	(1.84)	(1.81)	(1.87)
AYellowC	0.054	0.049	0.049	0.055	0.055
	(1.58)	(1.44)	(1.43)	(1.58)	(1.57)
AYellowC2	-0.007	-0.006	-0.006	-0.007	-0.007
	(0.98)	(0.84)	(0.85)	(0.95)	(0.97)
AYellowRed	0.104	0.113	0.113	0.116	0.116
	(1.78)	(1.94)	(1.94)	(1.97)*	(1.96)*
ARedC	0.199	0.193	0.193	0.208	0.209
	(3.50)**	(3.45)**	(3.46)**	(3.64)**	(3.64)**
AFouls	-0.001	0.005	0.005	-0.001	-0.001
	(0.09)	(0.35)	(0.30)	(0.04)	(0.08)
ACKick	-0.005	-0.002	-0.002	-0.003	-0.004
	(0.26)	(0.13)	(0.14)	(0.19)	(0.19)
AOffs	-0.036	-0.031	-0.033	-0.036	-0.038
	(2.12)*	(1.82)	(1.93)	(2.09)*	(2.20)*
AShots	-0.011	-0.012	-0.011	-0.012	-0.011
	(0.84)	(0.94)	(0.87)	(0.89)	(0.82)
Lagged Winning Controls	Yes	Yes	Yes	Yes	Yes
In-Season FE	Yes	No	No	Yes	Yes
Year FE	Yes	No	Yes	No	Yes
Team FE	No	Yes	Yes	Yes	Yes
Pseudo R2	0.1442	0.1334	0.1349	0.1495	0.1511
Observations	1520	1520	1520	1520	1520

Absolute value of z statistics in parentheses

* significant at 5%; ** significant at 1%

Using the different fixed effects we have pseudo R-squares ranging from 13 to 15 percent. Given the different models tested, and the different fixed effects controlled for, we conclude that although the model has a relatively low predictive power, the estimates give an accurate measure of the effects of yellow and red cards in football matches given the data available.

IV. Conclusion

We find that yellow and red cards negatively impact the probability of winning games. We also find that the number of fouls positively impact the probability of winning. This shows that being aggressive is valuable, but only those teams that are aggressive enough without crossing the line to be carded are the teams that will win most often. This data show that aggression is valuable, even though it is hypothesized that aggressive teams get carded at different rates (Jones, Paull, and Erskine 2002).

We also think it is interesting that, on average, the away team is given twice as many red cards as the home team. Dawson et al. (2007) claim there are more yellow cards for away teams because they are typically the underdogs. It is important to note that the affect of a yellow, or red, card on the home team is different than the effect of a card on the away team. Receiving a red card can also change the strategy of the game, especially depending on the timing of the card (Ridder, Cramer, and Hopstaken 1994 and Caliendo and Radic 2006). We hope this study encourages continued research on these topics.

V. Works Cited

Buraimo, Babatunde, David Forrest, and Robert Simmons, 2010, The Twelfth Man? Refereeing Bias in English and German Soccer *Journal of the Royal Statistical Society* Volume 173 Issue 2 , Pages 279 - 468

Caliendo, M. and D. Radic, 2006, Ten Do It Better, Do They? An Empirical Analysis of an Old Football Myth *Discussion Paper 2158 Institute for the Study of Labor*, Bonn.

Dawson, P., Dobson, S., Goddard, J. and Wilson, J., 2007, Are football referees really biased and inconsistent? Evidence from the English Premier League. *Journal of the Royal Statistical Society, Series A*, 170, 231-250.

Dohmen, T., 2008, The influence of social forces: Evidence from the behavior of football referees. *Economic Inquiry*, 46, 411-424.

Jewell, R. Todd, 2009, Estimating Demand for Aggressive Play: The Case of English Premier League Football *International Journal of Sport Finance* Vol. 4, Is 3

Jones, M. V., G. C. Paull and J. Erskine, 2002, The Impact of a Team's Aggressive Reputation on the Decisions of Association Football Referees *Journal of Sports Sciences* 20, pp. 991-1000

Price, Joseph and Justin Wolfers, 2009, Racial Discrimination Among NBA Referees *NBER Working Paper 13206*

Ridder, G., J. S. Cramer and P. Hopstaken, 1994, Down to Ten: Estimating the Effect of a Red Card in Soccer *Journal of the American Statistical Association* 89, pp. 1124-1127