Parallels Between Betting Contracts and Credit Derivatives:

Lessons Learned from FIFA World Cup 2006 Betting Markets

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Abstract

In this paper we notice similarities between betting contracts and credit derivatives. Specifically, we study very liquid betting markets on the FIFA World Cup 2006. We notice that betting contracts on events such as a win, draw or loss of a given team, or number of goals scored during the game can be viewed as particular cases of credit derivatives. A goal scored during the game plays a role of a default event, and the scoring intensity plays a role of the intensity to default. The betting market believes that the scoring intensity drops to about two thirds of the original level for the team which just scored, meaning additional goals (credit default events) of the scoring are perceived as less likely. This is justified by the fact that the team which just scored starts to play less offensively. In addition to the study of the scoring intensities implied by the market, we introduce a novel concept how to measure the excitement of a game. This could also be applied to other sports.

1 Introduction

Betting markets on the FIFA World Cup 2006 related events reached unprecedented efficiency and liquidity. It was possible to buy and sell futures type contracts on the outcome of the game or the number of goals scored, and trade them even during the actual game. Prices of all the traded events (win, draw or loss of a given team; or number of goals) were immediately influenced by a goal or a red card. One can view a goal or a red card as a credit event which affects the prices of the traded contracts, essentially upgrading some of them, and downgrading others. As opposed to markets which trade credit risk, soccer games experience a rather high and frequent number of credit events. Thus the betting market on soccer games can serve as an interesting parallel to credit markets, revealing some psychological factors which influence the traders. We should also mention one specific of the betting market, namely that the information feedback is one sided – the game influences the betting market, while the betting market is not supposed to influence the game.

We analyze data provided by tradesports.com to estimate the market implied scoring intensity of a given team as the game progresses. This can be viewed as the intensity of upgrading or downgrading the traded betting contracts. We observe that after a goal, the market experiences several minutes of price turmoil when some of the contracts are mispriced. After the market settles during the post-goal period, the implied intensity of the scoring team drops down in most cases, while the intensity of the second team remains unchanged. This effect is due to the fact that the scoring team typically starts to play more defensively with the intention to freeze the score. Such behavior referred to as "sabotage" has been documented by Garicano et al (2005) on data from Spanish professional soccer league.

We also note from the market data that the post-goal intensities are more realistic than the pre-goal intensities, and the goal itself is a natural point at which the market reevaluates the parameters. A similar effect is found with a red card, event where both a decrease in the scoring intensity of the penalized team, and an increase of the intensity of the opponent team follows.

We also quantitatively define the concept of fairness and excitement of a soccer game. Fairness can be measured by the probability that the better team wins (or does not lose the game), while excitement can be measured by the first variation of the winning probabilities. Dramatic changes in the winning chances make the game more exciting.

2 The Model

The betting market on a given match traded the following contracts:

- Team 1 to win,
- Draw,
- Team 2 to win,
- Two or more goals scored,
- Three or more goals scored,
- Four or more goals scored,
- Five or more goals scored.

These contracts expired at the end of the regular time of a given match (90 minutes + injury time). If a particular event happened, the payoff was $100, otherwise the contract expired worthless. It was possible to buy and sell the contract, even during the actual game.

Notice that if the score remains 0:0, only the contract written on Draw tends to appreciate, all other contracts tend to depreciate in value as time goes by without scoring. The other contracts typically appreciate only when there is a goal scored by one of the teams. Thus these betting contracts behave like credit derivatives, where the role of a credit event is represented by a goal. The intensity of scoring can be viewed as the default intensity if compared to credit modelling.

During the elimination round games, two more contracts were traded:

- Team 1 to advance,
- Team 2 to advance.

These contracts were traded even when the match went into overtime (in the case of draw during the regulation plus injury time).

For pricing the betting contracts, we use the Poisson model of the scoring. We further assume that the scores of the two teams are independent. This model is supported by previous research, such as Wesson (2002). All the contracts in this case depend only on two parameters: the scoring intensity of the first team λ_t and the scoring intensity of the second team μ_t at time t. It is reasonable to expect that the market views λ_t and μ_t as the expected number of goals scored by team 1 and team 2 respectively for the remainder of the match (time between the current time t and the end of the match time T.

Let the present score be $X_t : Y_t$. The theoretical prices of these contracts are given by the following formulas:

$$(1)\quad \frac{\text{Win Team 1}}{100} = \mathbb{P}(X_T > Y_T) = \sum_{k=0}^{\infty} \mathbb{P}(X_T = k - X_t, Y_T < k - X_t) = \sum_{k=0}^{\infty} \left(e^{-\lambda_t} \frac{\lambda_t^k}{k!} \cdot \sum_{i=0}^{k-X_t-Y_t-1} e^{-\mu_t} \frac{\mu_t^i}{i!} \right)$$

$$\text{(2)} \qquad \frac{\text{Draw}}{100} = \mathbb{P}(X_T = Y_T) = \sum_{k=0}^{\infty} \left(e^{-(\lambda_t+\mu_t)} \cdot \frac{\lambda_t^{(k+\max(X_t+Y_t)-X_t)}}{(k+\max(X_t+Y_t)-X_t)!} \cdot \frac{\mu_t^{(k+\max(X_t+Y_t)-Y_t)}}{(k+\max(X_t+Y_t)-Y_t)!} \right)$$

$$\text{(3)} \qquad \frac{\text{Win Team 2}}{100} = \mathbb{P}(Y_T > X_T) = \sum_{k=0}^{\infty} \mathbb{P}(Y_T = k - Y_t, X_T < k - Y_t) = \sum_{k=0}^{\infty} \left(e^{-\mu_t} \frac{\mu_t^k}{k!} \cdot \sum_{i=0}^{k-X_t-Y_t-1} e^{-\lambda_t} \frac{\lambda_t^i}{i!} \right)$$

$$\text{(4)} \qquad \frac{\text{Two+}}{100} = \mathbb{P}(X_T + Y_T \geq 2) = \sum_{k=(2-X_t-Y_t)^+}^{\infty} e^{-(\lambda_t+\mu_t)} \frac{(\lambda_t+\mu_t)^k}{k!}$$

$$\text{(5)} \qquad \frac{\text{Three+}}{100} = \mathbb{P}(X_T + Y_T \geq 3) = \sum_{k=(3-X_t-Y_t)^+}^{\infty} e^{-(\lambda_t+\mu_t)} \frac{(\lambda_t+\mu_t)^k}{k!}$$

$$\text{(6)} \qquad \frac{\text{Four+}}{100} = \mathbb{P}(X_T + Y_T \geq 4) = \sum_{k=(4-X_t-Y_t)^+}^{\infty} e^{-(\lambda_t+\mu_t)} \frac{(\lambda_t+\mu_t)^k}{k!}$$

$$\text{(7)} \qquad \frac{\text{Five+}}{100} = \mathbb{P}(X_T + Y_T \geq 5) = \sum_{k=(5-X_t-Y_t)^+}^{\infty} e^{-(\lambda_t+\mu_t)} \frac{(\lambda_t+\mu_t)^k}{k!}$$

Notice that we have 7 contracts which depend only on two parameters λ_t and μ_t, and thus the estimation of these parameters might not lead to consistent results. The market might even admit arbitrage (risk free profit) if the contract prices are not properly related to each other. For instance, the contracts on Win of Team 1, Draw, and Win of Team 2 should add up to 100. However, due to the inefficiencies of the market, such as bid-ask spread, asynchronous trading, no-shorting rules and such, it might be difficult to lock these opportunities.

In order to estimate λ_t and μ_t, we assume that

$$\text{(8)} \qquad \text{Traded Price} = \text{Theoretical Price} + \text{Error}.$$

We take the estimate which minimizes the absolute sum of these errors, namely find the minimizer of the following expression:

$$\text{(9)} \qquad \min_{\lambda_t,\mu_t} \sum_i \Big| [\text{Theoretical Price of Contract } i](\lambda_t,\mu_t) - [\text{Traded Price of Contract } i] \Big| .$$

Figure 2 shows the realized scoring intensity during the FIFA World Cup 2006. Figure 3 shows the market implied intensities for elimination round games. Figures 4, 5, 6 and 7 show the market implied intensities for the group games. We start our inference analysis at the beginning of the game (time $t = 0$), and finish when the game ends in the regulation (90 minutes) plus injury time. We indicate the break between the two periods, which lasts 15 minutes. We cannot infer the intensities for games which went into overtime (in the elimination round) since only the contracts on advancing from the given game were traded. They do not carry enough information about the scoring intensities.

2.1 Effect of the Goal

By analyzing the market implied intensities of scoring, we can notice a significant decrease of the scoring rate for the team which just scored. We can assume that there is a change of the scoring rate according to the following formula:

$$\lambda_{new} = \theta_1^g \cdot \lambda_{old} \tag{10}$$

for certain θ_1^g for the team which just scored, and

$$\mu_{new} = \theta_2^g \cdot \mu_{old} \tag{11}$$

for certain θ_2^g for the team which just received the goal.

From our analysis of 107 goals for which we can infer the scoring intensities (out of 143 total goals), we obtain that the mean for θ_1^g is 0.61 with standard deviation 0.32, and mean for θ_2^g is 1.01 with standard deviation 0.37. The histogram is given in Figure 9. Such drop of rates in not surprising due to the possible intention of the scoring team to freeze the score, as previously noted by Garicano et at (2005). What is interesting is that the effect seems to be one-sided, the drop of the rates affects only the team which just scored.

This effect seems to be rather significant, and it naturally leads to the question of whether the drop of the scoring rate is supported by the actual statistical data. We use two approaches to check this effect. One is to analyze the scoring time (exponentially distributed) and see whether the scoring rate drops between the two goals. The other is a financial approach, where we compare the performance of two trading strategies: one which buys a contract on number of goals at the beginning of the match, the other which buys a contract on number of goals right after the first goal.

For the statistical test of the decrease of the rates, we consider the time until the first goal, and the time between the first and the second goal of a given team. We estimate the intensities until the first goal and until the second goal using maximum likelihood estimation. The ratio of the intensities is 0.46. The drop could be explained by the fact that the team which just scored may not be as motivated to attack.

Financial interpretation reveals additional insight. If a decrease in rates were unsubstantiated, there would be a discrepancy between buying a contract on the number of goals at the beginning of the match as compared to buying the same contract right after the goal. A trader who purchases one contract on 2 or more goals at the beginning of the match pays \$3,860 in total for 55 games (the remaining 9 games not having enough liquidity for this contract). A trader who enters the same contract immediately after the first goal pays only \$3,542 in total (he would not enter the contract if there was no goal). However, both portfolios are close enough to the payoff on the actual portfolio, which would be \$3,600. The betting market displayed tendencies to overprice contracts on number of goals in the first place, expecting about 2.44 goals per game (regulation time) on average, where as the actual scoring rate was 2.23 (including overtime), lower than expected. The FIFA World Cup 2006 had one of the lowest scoring rates in the entire World Cup history, so this discrepancy was somewhat unexpected.

We get a similar picture for all other contracts on number of goals as well. This means that the value of a portfolio bought directly after the first goal is closer to the actual payoff on the contract than the value of a portfolio bought prior to that. A portfolio of contracts on 3 or more goals would cost \$2,788 if bought at the beginning of the match, and would cost \$2,731 if bought after the first goal (actual payoff \$2,500). Portfolio of contracts on 4 or more goals would cost \$540 if bought at the beginning of the match, and would cost \$730 if bought after the first goal (actual payoff \$800). Portfolio of contracts on 5 or more goals would cost \$35 if bought at the beginning of the match, and would cost \$82 if bought after the first goal (actual payoff \$100).

Statistically, there is an evidence that the scoring rate indeed dropped rather significantly by a factor of about 0.46 following a goal, for the team which scored. The market also tended to rethink rates after the first goal or a red card, and we observe that the new rate was more realistic than the old one, although it required compensation for the scoring team. Interestingly enough we find no evidence that the scoring rate for the non scoring team changed in any way.

To see that the estimated rates after the goal are realistic, we consider the following portfolios of contracts bought right after the first goal: a team which just scored to win, draw of the game, and a team which received the goal to win. The value of the portfolio for the scoring team to win would cost $4,033 (actual payoff $3,900), the portfolio on draw would cost $1,030 (actual payoff $900), and the portfolio for the scoring team to lose would cost $635 (actual payoff $700). The discrepancies between the costs and payoffs are insignificant and are mostly due to the inefficiencies in the market.

The market also experiences price turmoil right after the goal. In principle, the prices of all contracts are related to each other, and thus after the goal they should find new price levels which are consistent. It usually takes several minutes before the price turmoil settles down. Figure 8 illustrates this concept for several selected games. We plot the difference between the theoretical and the realized price of each contract.

2.2 Effect of the Red Card

Similar effect on the scoring rates is visible when a player is sent off the field for an offense. The team is playing short handed for the rest of the match without the player who received the red card. During the FIFA World Cup tournament, 28 players were penalized in total. We can use a similar multiplicative model for the change of scoring rates:

$$\lambda_{new} = \theta_1^{rc} \cdot \lambda_{old} \tag{12}$$

for certain θ_1^{rc} for the team which was just penalized, and

$$\mu_{new} = \theta_2^{rc} \cdot \mu_{old} \tag{13}$$

for certain θ_2^{rc} for the opposite team.

Our analysis includes 18 instances of the change of rates after the red card. The remaining penalties happened in the overtime, or too late in the game to infer change of the rates. The estimated mean for θ_1^{rc} is 0.63 with standard deviation 0.2, the mean for θ_2^{rc} is 1.24 with standard deviation 0.31. The histogram is given in Figure 10.

The famous “headbutt” for which the French captain Zinedine Zidane was sent off in the final match between Italy and France happened in the 110th minute of overtime, so we cannot estimate the red card effect on the scoring rates. The two remaining contracts were influenced in the following way. Italy to win the World Cup appreciated from 50.60 to 59.50, while France to win the World Cup depreciated from 50 to 40. Italy eventually won the game on penalties.

The effect of the red card was previously studied by Ridder et al (1994) on data from the Dutch professional league. They concluded that the increase of the scoring rate for the team which is not penalized is statistically significant, which is in accordance with our findings. In contrast to our study, they have not observed statistically significant drop of the scoring rate of the penalized team.

3 Fairness and Excitement of the Game

In this section, we propose a novel way to measure the fairness and excitement of a game.

As a theoretical measure of fairness, we propose to use

$$\text{Probability that the better team wins,} \tag{14}$$

or

$$\text{Probability that the better team does not lose.} \tag{15}$$

If we knew the scoring intensities λ and μ at the beginning of the match, we can compute the fairness as a function of these two parameters. In principle we can never know these intensities for sure, so the concept of fairness is just theoretical.

While it is desirable to have a highly fair game, it might not necessarily lead to a game which would be exciting. If we knew that the better team would win, the outcome of the game would be predetermined, and thus not exciting. On the other hand, when the two teams are competing for the win to the last minute, that makes the game very exciting. Thus we propose the following measure for excitement:

$$\text{Excitement} = \text{Variability of the Probabilities of Winning for Each Team.} \tag{16}$$

Variability can be measured as the First Variation (FV):

$$FV(f) = \lim_{\max|t_{i+1}-t_i|\to 0} \sum |f(t_{i+1}) - f(t_i)|. \tag{17}$$

First variation can be viewed as the length of the graph of a given function f. The longer the path of winning probabilities for a given team, the more swings there are in the game, and thus the game is more exciting. Formally, we can define

$$\text{Excitement} = \text{FV(Probability of Team 1 Wins)} + \text{FV(Probability of Team 2 Wins)}. \tag{18}$$

This definition makes sense if draw is not an option, such as in the elimination round games. If draw is possible, we can use a modified version:

$$\begin{aligned}\text{Excitement} = {} & \text{FV(Probability that Team 1 Wins)} \\ & + \text{FV(Probability of Draw)} + \text{FV(Probability that Team 2 Wins)}.\end{aligned} \tag{19}$$

Table 1 orders the elimination round games according to the realized level of excitement, where we used the estimates of the probability of team 1 or 2 to win by the quotes given by the betting market. Team 1 column is the First variation of the Probability that Team 1 Wins, Team 2 column is the First variation of the Probability that Team 2 Wins, and the last column is the total. Notice that since

$$\text{Probability Team 1 Wins} = 1 \text{ - Probability Team 2 Wins,} \tag{20}$$

we should have in theory

$$\text{FV(Probability of Team 1 Wins)} = \text{FV(Probability of Team 2 Wins)}, \tag{21}$$

so the two columns should be close to each other, and any difference is due to the imperfections of the betting market.

Among the top 5 most interesting games, four of them went into the penalty shootouts (England vs. Portugal, Italy vs. France, Switzerland vs. Ukraine, and Germany vs. Argentina), and the fifth one was a game where 4 players were given a red card (Portugal vs. Holland). On the other hand, the least interesting games were one-sided, with the losing team scoring no goals.

A similar picture is visible in the group games ordered by the level of excitement in Table 2. Since the outcome of the group game could have ended in a draw, we use the modified definition of the excitement which includes the first variation of the probability of draw. Notice that the first variation measure indeed separates the most exciting games which had many turns in them (such as the game between England and Sweden), from games where the winner was a heavy favorite to start with and no surprises happened (such as the game between Saudi Arabia and Spain).

In general, the first variation of the probability of winning is mostly changed if there is a game deciding event close to the end of the game, if there are a number of events where the game lead is changed, or if the weaker team unexpectedly wins or draws the game. On the other hand, only small changes in the first variation of winning probabilities occur when the game is one sided, with an early lead from the favorite team.

Interestingly enough, we can compute expected level of excitement as a function of scoring rates λ and μ. See Figure 11. Notice that there is an absolute maximum for the expected level of excitement, peaking at around $\lambda = \mu = 7$. Thus the most exciting matches would occur with play against two equally strong teams, each of them scoring an average of 7 goals per match. From this perspective, soccer games are on average less exciting than hockey games, since hockey enjoys higher scoring rates than soccer. However, it seems suboptimal to have more than 7 goals scoring per game since the probabilities of winning the game would not change as much as lower scoring games.

References

[1] Garicano, L., I. Palacios-Huerta, “Sabotage in Tournaments: Making the Beautiful Game a Bit Less Beautiful. Working Paper, 2005.

[2] Ridder, G., J. S. Cramer, P. Hopstaken, “Down to Ten: Estimating the Effect of a Red Card in Soccer,” *JASA,* Vol. 89, No. 427, 1994.

[3] Wesson, J., *The Science of Soccer,* IoP, 2002.

4 Appendix

Figure 1: Total realized intensity of scoring in World Cup FIFA 2006 games.

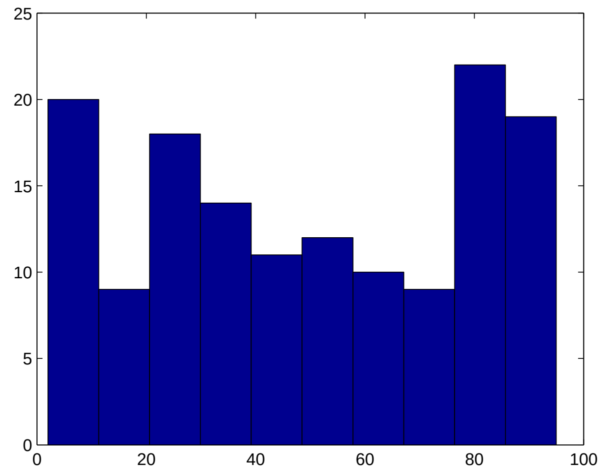

Figure 2: The corresponding histogram of scoring as a function of time in World Cup FIFA 2006 games.

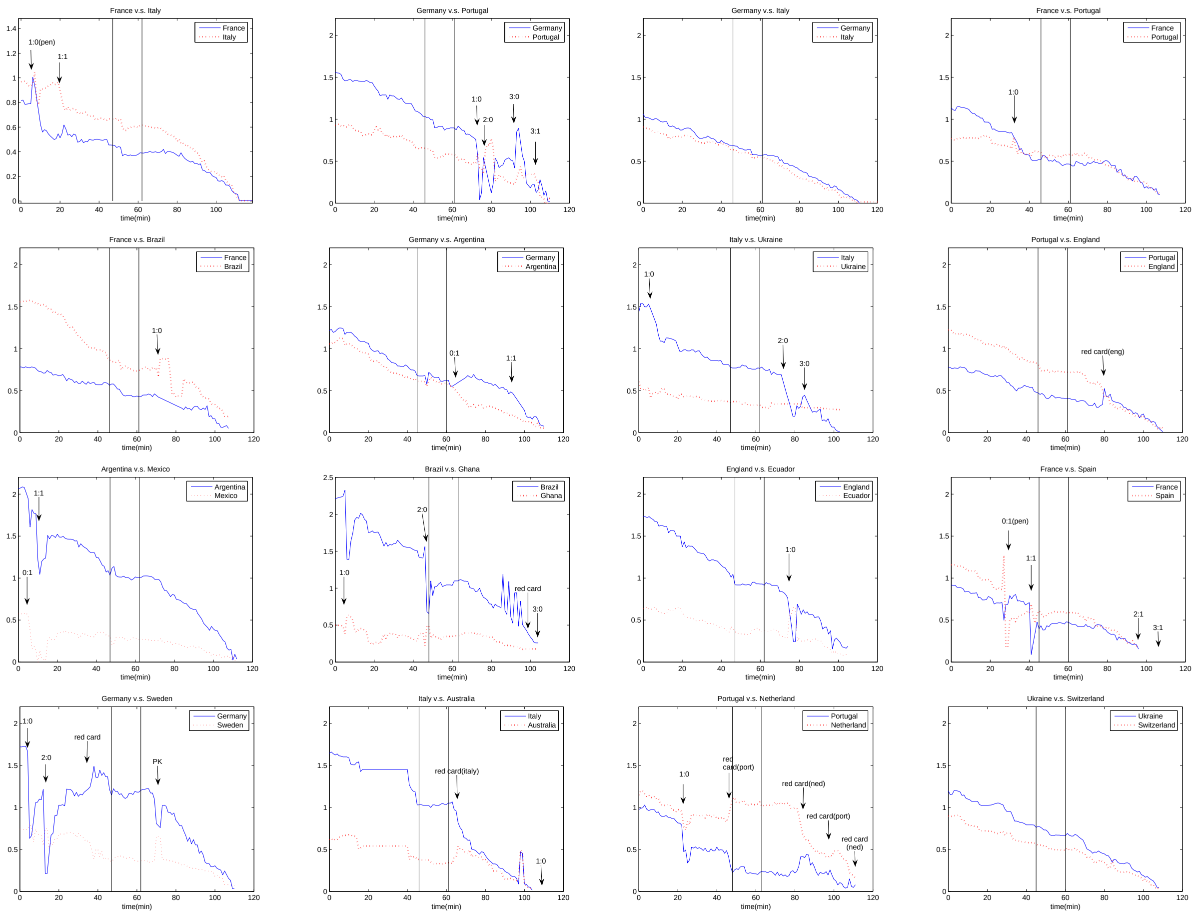

Figure 3: Implied intensities of scoring in World Cup FIFA 2006 games, elimination round games.

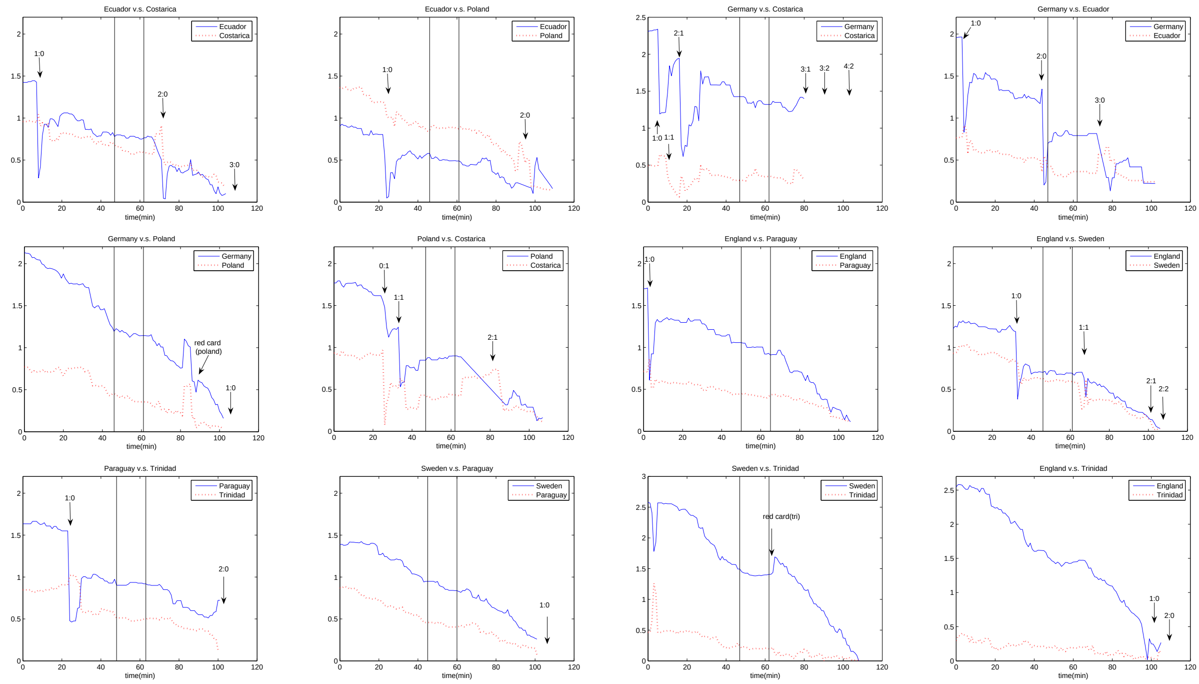

Figure 4: Implied intensities of scoring in World Cup FIFA 2006 games, group A and B games.

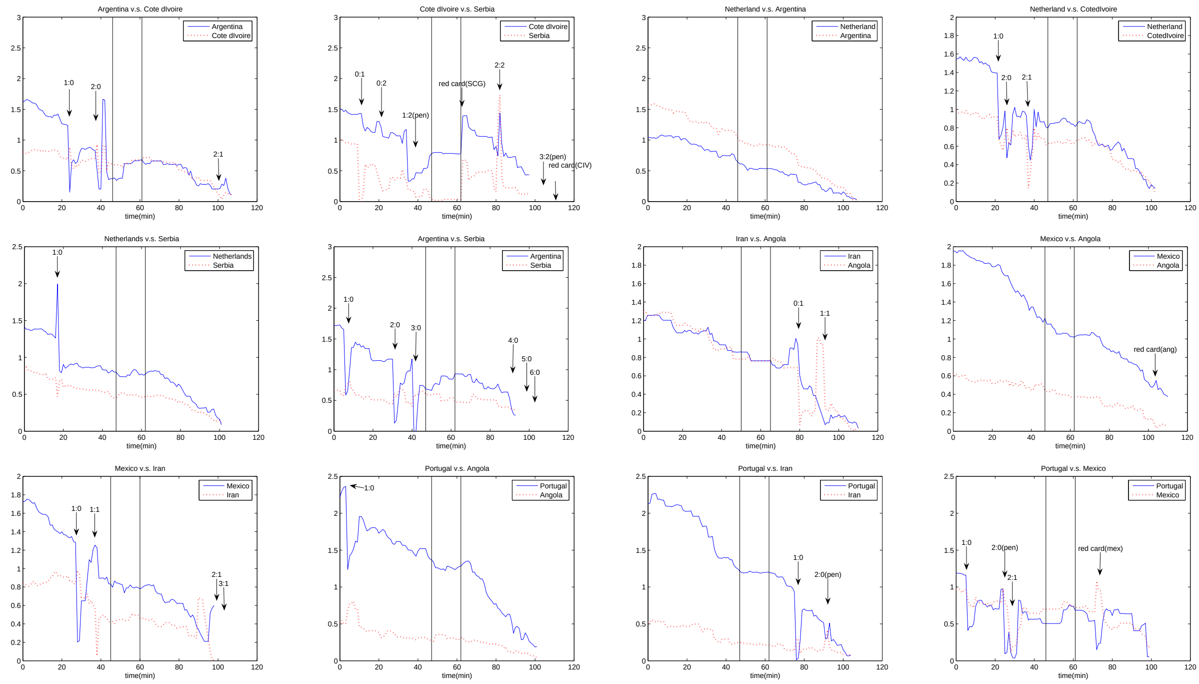

Figure 5: Implied intensities of scoring in World Cup FIFA 2006 games, group C and D games.

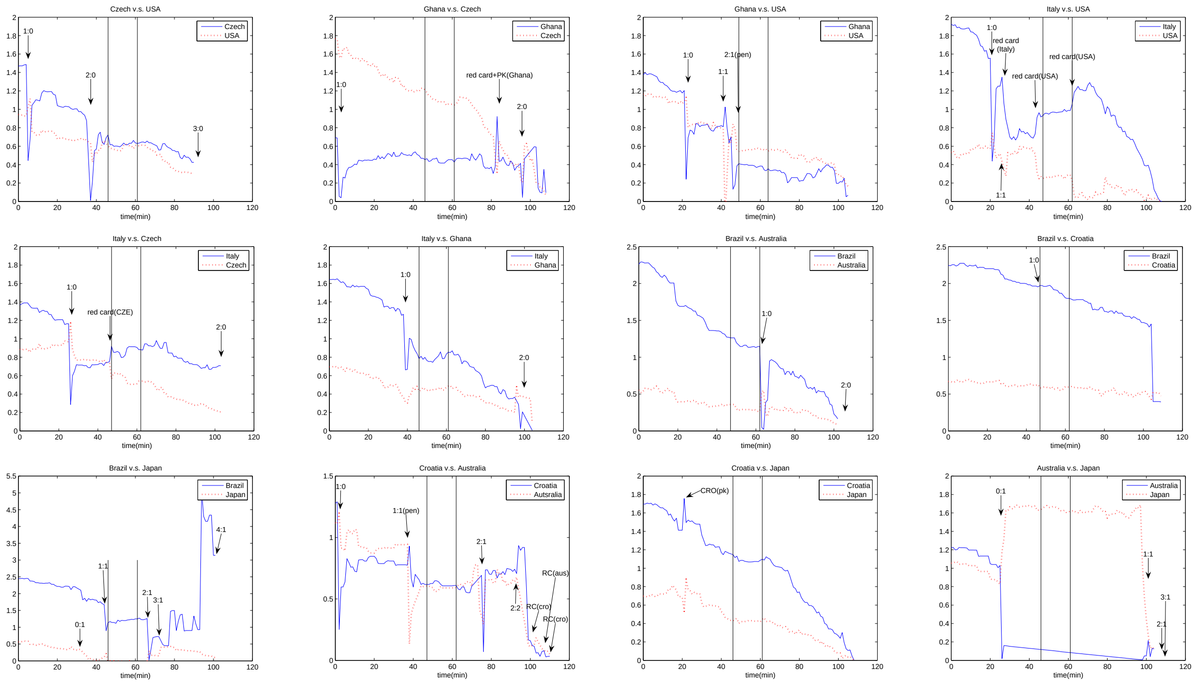

Figure 6: Implied intensities of scoring in World Cup FIFA 2006 games, group E and F games.

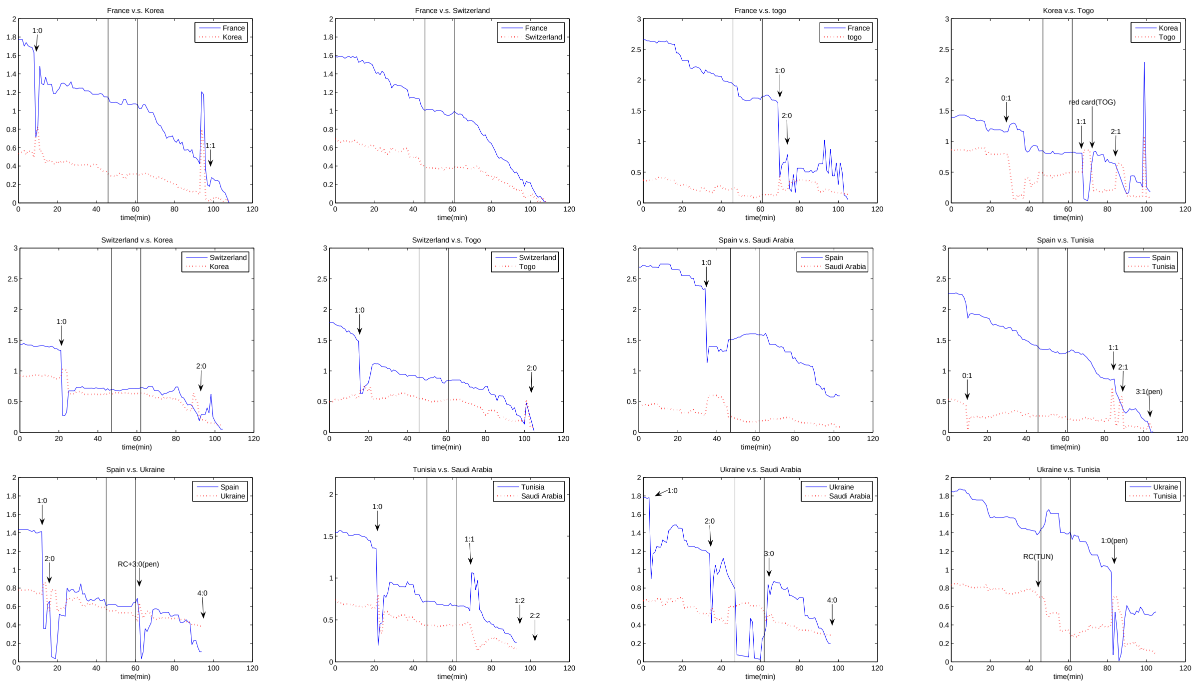

Figure 7: Implied intensities of scoring in World Cup FIFA 2006 games, group G and H games.

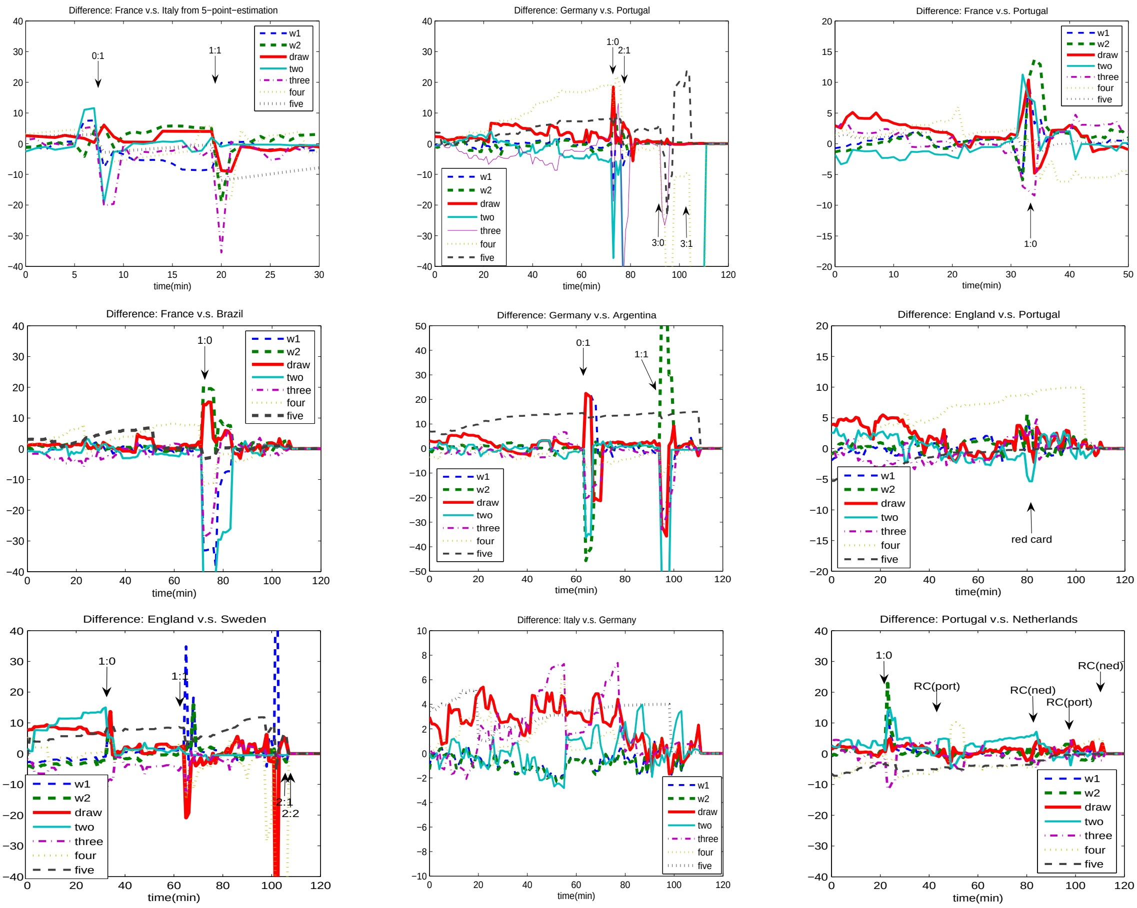

Figure 8: Price turmoil after the goal for selected games.

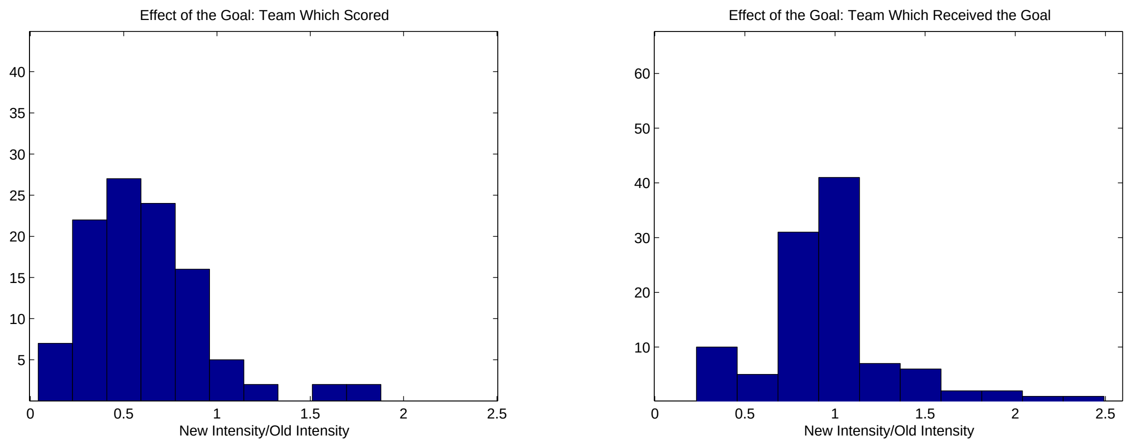

Figure 9: Comparison of the pre-goal and post-goal intensities for the scoring team (left), and the team which received the goal (right).

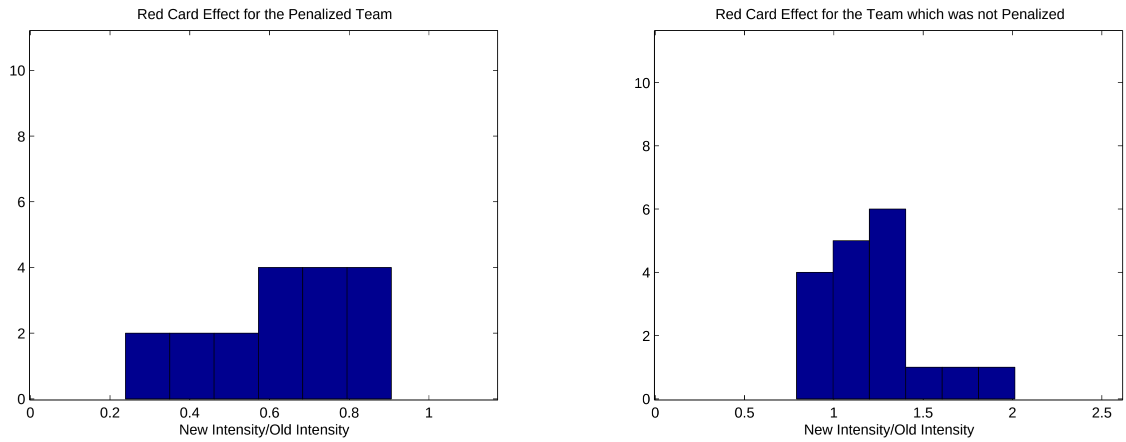

Figure 10: Comparison of the pre-red card and post-red card intensities for the scoring team (left), and the team which received the goal (right).

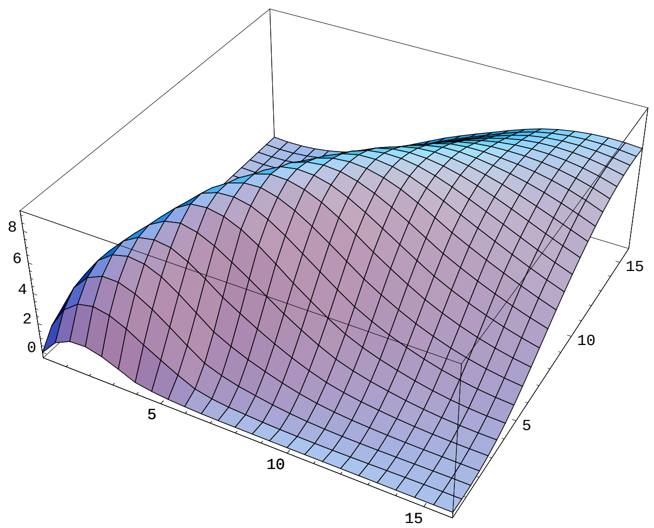

Figure 11: Expected excitement as a function of intensities of scoring.

No.	Game	Result	Team 1	Team 2	Total
59	England vs. Portugal *	0 - 0	1.47	1.53	3.00
52	Portugal vs. Holland	1 - 0	1.24	1.16	2.40
64	Italy * vs. France	1 - 1	1.10	1.16	2.26
54	Switzerland vs. Ukraine *	0 - 0	1.14	1.02	2.16
57	Germany * vs. Argentina	1 - 1	1.06	1.04	2.10
56	Spain vs. France	1 - 3	1.00	0.92	1.92
53	Italy vs. Australia	1 - 0	0.74	0.76	1.50
60	Brazil vs. France	0 - 1	0.71	0.70	1.41
50	Argentina vs. Mexico	2 - 1	0.67	0.55	1.22
61	Germany vs. Italy	0 - 2	0.57	0.56	1.13
63	Germany vs. Portugal	3 - 1	0.40	0.49	0.89
62	Portugal vs. France	0 - 1	0.48	0.40	0.88
51	England vs. Ecuador	1 - 0	0.41	0.38	0.79
58	Italy vs. Ukraine	3 - 0	0.26	0.26	0.52
49	Germany vs. Sweden	2 - 0	0.22	0.20	0.42
55	Brazil vs. Ghana	3 - 0	0.11	0.18	0.29

Table 1: Elimination round games ordered by the excitement level.

No.	Game	Result	Team 1	Team 2	Draw	Total
35	Sweden vs. England	2 - 2	0.52	2.57	2.21	5.30
40	Ivory Coast vs. Serbia & M'gro	3 - 2	1.82	1.52	1.25	4.60
9	Australia vs. Japan	3 - 1	1.34	1.36	1.65	4.35
44	Croatia vs. Australia	2 - 2	1.79	1.16	1.21	4.16
26	Italy vs. United States	1 - 1	1.96	0.65	1.20	3.81
7	Mexico vs. Iran	3 - 1	1.77	0.65	1.38	3.80
32	Spain vs. Tunisia	3 - 1	1.89	1.01	0.84	3.73
16	Tunisia vs. Saudi Arabia	2 - 2	1.20	1.04	1.38	3.62
12	Korea Republic vs. Togo	2 - 1	1.37	1.02	0.86	3.26
17	Germany vs. Poland	1 - 0	1.51	0.11	1.33	2.95
34	Costa Rica vs. Poland	1 - 2	0.80	1.33	0.70	2.83
38	Iran vs. Angola	1 - 1	0.30	1.23	1.07	2.60
25	Ghana vs. Czech Republic	2 - 0	1.37	0.63	0.58	2.58
20	Sweden vs. Paraguay	1 - 0	1.09	0.24	1.22	2.55
37	Portugal vs. Mexico	2 - 1	1.23	0.43	0.84	2.50
42	Ghana vs. United States	2 - 1	1.22	0.80	0.34	2.36
29	France vs. Korea Republic	1 - 1	1.11	0.17	1.04	2.32
19	England vs. Trinidad & T'go	2 - 0	1.04	0.06	1.05	2.14
46	Ukraine vs. Tunisia	1 - 0	0.92	0.21	0.86	1.98
22	Holland vs. Ivory Coast	2 - 1	0.99	0.39	0.53	1.91
4	Trinidad & T'go vs. Sweden	0 - 0	0.11	0.92	0.80	1.83
43	Japan vs. Brazil	1 - 4	0.39	0.86	0.52	1.77
27	Japan vs. Croatia	0 - 0	0.21	0.74	0.70	1.64
2	Poland vs. Ecuador	0 - 2	0.47	0.81	0.34	1.62
5	Argentina vs. Ivory Coast	2 - 1	0.78	0.29	0.41	1.48
1	Germany vs. Costa Rica	4 - 2	0.54	0.19	0.73	1.46
23	Mexico vs. Angola	0 - 0	0.58	0.08	0.70	1.36
41	Czech Republic vs. Italy	0 - 2	0.30	0.71	0.34	1.35
39	Holland vs. Argentina	0 - 0	0.23	0.42	0.69	1.33
13	France vs. Switzerland	0 - 0	0.55	0.10	0.66	1.31
24	Portugal vs. Iran	2 - 0	0.64	0.07	0.60	1.30
28	Brazil vs. Australia	2 - 0	0.55	0.13	0.53	1.21
48	Switzerland vs. Korea Republic	2 - 0	0.57	0.23	0.40	1.20
18	Ecuador vs. Costa Rica	3 - 0	0.57	0.28	0.29	1.14
6	Serbia & M'gro vs. Holland	0 - 1	0.24	0.49	0.34	1.07
30	Togo vs. Switzerland	0 - 2	0.17	0.49	0.40	1.06
10	United States vs. Czech Republic	0 - 3	0.23	0.51	0.28	1.02
11	Italy vs. Ghana	2 - 0	0.46	0.18	0.33	0.97
15	Spain vs. Ukraine	4 - 0	0.48	0.19	0.29	0.97
14	Brazil vs. Croatia	1 - 0	0.52	0.14	0.29	0.96
36	Paraguay vs. Trinidad & T'go	2 - 0	0.50	0.23	0.12	0.85
21	Serbia & M'gro vs. Argentina	0 - 6	0.12	0.42	0.26	0.79
31	Saudi Arabia vs. Ukraine	0 - 4	0.08	0.39	0.24	0.71
33	Ecuador vs. Germany	0 - 3	0.35	0.12	0.23	0.70
47	Togo vs. France	0 - 2	0.09	0.36	0.21	0.67
3	England vs. Paraguay	1 - 0	0.35	0.12	0.13	0.60
8	Angola vs. Portugal	0 - 1	0.06	0.18	0.13	0.37
45	Saudi Arabia vs. Spain	0 - 1	0.03	0.15	0.11	0.29

Table 2: Group games ordered by the excitement level.