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Do Football Victories Affect Social Unrest? Evidence from Africa

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Abstract

Exploiting the quasi-random nature of football matches outcomes and their timing, I study the short-term causal impact of victories of national football teams on social unrest events in Africa. I find that victories reduce social unrest events whereas defeats do not. I document that victories appear to mainly affect violent events and mixed evidence in relation to government-targeted events. Victories report a heterogeneous impact depending on the ethnic fractionalization of countries and the level of autocracy of regimes, showing larger impact for more ethnically diverse and less autocratic countries. Studying the role of expectations, I report a stronger impact of victories when they are unexpected. Evidence suggests that the main channel at play is the national unity produced by victories, but I cannot reject the role of mood changes.

Keywords: Collective Action, Political Participation, Protests, Football, Africa.

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I. Introduction

Social unrest events have a profound impact on societies. One channel is through political change, as rally attendance affects voting behaviour and public policy (Madestam et al., 2013), by shifting voters' preferences and revealing their distribution (see Lohmann (1993, 1994)). Even the perception of threat of social unrest can lead to democratization and political transition (Acemoglu and Robinson, 2000; Aidt and Franck, 2015). An alternative channel through which unrest may play a role is by affecting economic outcomes. Indeed, non-violent social unrest episodes may alter income and food consumption (Dupas and Robinson, 2010) whereas violent conflict can affect people's discount rates, which in turn affect saving and investment decisions and can thus have a long-run impact (Voors et al., 2012).

Given its importance, previous work has focused on understanding the sources of social unrest. Many explanations have been proposed, such as the type of electoral institutions (Fjelde and Höglund, 2016), the strength of institutions (Dunning et al., 2011), fiscal adjustments (Ponticelli and Voth, 2011), grievance and political opportunities (Schock, 1996; Chenoweth and Ulfelder, 2017), and increases in food prices (Arezki and Bruckner, 2011; Berazneva and Lee, 2013; Bellemare, 2015). This paper studies the role played by seemingly irrelevant events as determinants of social unrest: games played by national football teams in Africa. Following a difference-in-difference strategy, I compare the number of social unrest events between countries whose team wins and countries whose team loses or ties before and after each match. Using data from the Social Conflict Analysis Database (Salehyan et al., 2012), a news-based dataset of social conflict events for the period 1990-2013, I show that victories in high-stake matches reduce the intensity and prevalence of social unrest events the following days. On the contrary, I find no evidence that losing matches leads to an increase in unrest.

My identification strategy relies on the exogeneity of football match results to local conditions and that the calendar for matches is set at a world-level in advance, making timing exogenous as well. One may think that matches could generate a strategic behaviour of agents. However, I show that the impact of victories remains significant regarding expected close matches and that results are not driven by pre-trends, supporting the exogeneity of treatment.

Match results could affect social unrest at least through two channels. First, it could increase national unity and reduce ethnic tensions. Depetris-Chauvin and Durante (2017) find that people reduce their reported ethnic identification and increase their trust in another ethnicity after a victory of their national football team, in sub-Saharan African. They also report a decrease in violence after the qualification of the national team to the Africa Cup of Nations for the 6 following months. Second, football outcomes can affect people's mood, which in turn affects their perceptions and behaviour.

Healy et al. (2010) shows that a boost in the sense of well-being of people generated from sport outcomes increases the voting share and improves the perception of incumbent. Correspondingly, Carvalho and Zilberman (2017) show that a big deception driven by a defeat had a negative impact on incumbent reelection.[1] I expect victories reduce the number of social unrest events through these two channels, and defeats increase the number of events only through the mood channel. The fact that only victories appear to be relevant would thus be supportive of the "national unity" hypothesis.

In line with Hendrix and Salehyan (2012), in this paper events are classified as: violent or non-violent, and as government-targeted or non-government-targeted. In relation to government-targeted and non-government targeted events, I find mixed evidence of its impact between the extensive and intensive margin, making results inconclusive. These findings do not provide clear evidence supporting the hypothesis of changes in mood affecting perception of incumbent. On the contrary, I find strong evidence that violent events are significantly reduced after victory, in line with both channels.

I also explore the heterogeneous impact of victories by ethnic fractionalization of countries. Ethnic fractionalization impacts institutions' quality, economic outcomes and policy of countries (Alesina et al., 2003), as well as on conflict via rent-seeking behavior of groups (Easterly and Levine, 1997). Via the national unity channel, I expect conflict to be reduced more in countries with higher ethnic fractionalization, which are likely to have more ethnic conflicts. Indeed, I report that countries with high ethnic fractionalization have a strong reduction of events after victories, and countries with low ethnic fractionalization present no effect on the number of events after victories.

Additionally, one may expect that the decrease on social unrest may be particularly weak in autocratic regimes if the channel at play is national unity and people's identification with the country as a whole is affected by regime type. Also, the willingness to protests of citizens of autocratic regimes, in spite of the higher costs involved, could show that participants are more involved which could make them less affected by the treatment. I document that victories do not reduce social unrest in countries with high levels of autocracy, but reduce the number of events in countries with less autocratic regimes.

Finally, I explore whether the ex-ante probability of winning associated with each match increases or decreases the effect of the treatment since there is evidence that shocks in expectations can induce changes in behaviour via mood changes. Card and Dahl (2011) show that defeats when the American football local team was expected to win lead to 10% increase in violence from men to their partners the same day, while victories in expected loss matches do not reduce this kind of violence. Their results are explained by a model of gain-loss utility based on the deviation from an

[1]They focus on the effect of the defeat of Brazil 1-7 in the World Cup of 2014 against Germany, on the presidential election of the same year.

expected rational reference point (see Koszegi and Rabin (2006)), that in this case corresponds to sport games outcomes. Munyo and Rossi (2013) find that a victory in an expected loss match, by one of the two most popular Uruguayan teams, strongly reduces violent property crime the hour after the end of the match (in 42%) and they also report an increase in violent property crime (in 70%) after losing a match that was expected to be won. Given this evidence via the mood change channel, I expect that victories decrease the number of social unrest events more profoundly after unexpected ones. Using Elo Rating System method, I constructed probabilities of winning and used them as a proxy of expectations of winning for population. I find that victories in expected loss matches have a stronger impact, but no statistically significant effect of defeats on expected win matches. Thus, euphoria and mood changes may be at play as well.

This paper is part of the vast literature of determinants of political participation. Networks affect protest behavior (González, 2016) and, by pressuring voters, political participation (Mutz, 2002). Papers of the impact of mass media include Aker et al. (2017), McLeod et al. (1999) and Tolbert and McNeal (2003). Evidence of the effect of personality traits on political participation include Vecchione and Caprara (2009). At the theoretical level, Brady et al. (1995) argue a positive relation between resources (i.e., time, money and “civic skills") and political participation. My contribution to this literature is to provide first estimates of the impact of patriotic and mood shocks on political participation. In order to avoid the reverse causality problem, I follow a simple identification strategy, exploiting the exogenous change produced by a football match.

The rest of the paper is organized as follows. Section II. presents the econometric model used, describes data and its sources, presents baseline results and robustness checks. Section III. presents the heterogeneous impact of victories depending on event type, country characteristics and ex-ante expectations. Section IV. concludes.

II. Empirical Strategy

II.A Econometric Model

In order to identify the causal relation between victories and social unrest I follow a difference-in-differences approach, comparing the difference in the change of the number of social unrest events before and after won matches (treated) with the change before and after ties or lost matches (control). I exploit the quasi-random nature of the result of football matches and the exogenous timing of the date, fixed in advance by the Fédération Internationale de Football Association (FIFA), which makes the treatment unlikely to be related to the error term. The identification assumption is parallel trends, which in this context means that the change in number of events in the case of a defeat or tie corresponds to what would have happened in the change of events if a country had not won the match it played.[1]

The estimation is for day windows in the proximity of each match for each country in sample whose team played. The election of its length presents a trade-off since including more days allows to study the persistence and the dynamic of the treatment, but also potentially includes confounding factors making the identification less clean. I use 5-day time windows for my main estimations, choosing a rather short window length in order to avoid confounding.[2] To identify the effect of victories on social unrest I estimate the following equation using OLS:

$$SU_{c,m,t} = \alpha + \beta Victory_{c,m,t} + \delta After_t + \Gamma_{c,m} + \varepsilon_{c,m,t} \tag{1}$$

where c, m and t denote country, match and if the period is before or after match. The dependent variable $SU_{c,m,t}$ is the logarithm of the sum of the number of daily active social unrest events in period t around match m of country c, plus 1. My treatment variable is $Victory_{c,m,t}$, which takes value 1 the period after a victory and 0 otherwise. $After_t$ takes value 1 if the period t is after match and the term $\Gamma_{c,m}$ are country-match fixed effects. The inclusion of fixed effect at the country-match level controls for any difference between countries and between each country in different periods of time, making the comparison within each country-match window. The error term $\varepsilon_{c,m,t}$ is corrected for heteroscedasticity and clustered at country-match level, having each cluster two observations (before and after each match for each African country whose team played). This assumption of standard errors allows arbitrary serial correlation of errors for periods around the same match for the same country.

[1] In following sections I show evidence suggesting this assumption holds.

[2] I also report results for 10 and 15 day-windows.

I expect $\beta < 0$ because victories are likely to reduce ethnic tensions and increase national unity (Depetris-Chauvin and Durante, 2017), and increase the sense of well-being of people (Healy et al., 2010), reducing the number of social unrest events. I also estimate the impact of defeats using the same specification, were I expect $\beta > 0$ because defeats affect negatively on the sense of well-being of people.

II.B Data and Sample Construction

I use data of social unrest events for the period 1990-2013 from the Social Conflict Analysis Database (SCAD) (version 3.1) (Salehyan et al., 2012). This database identifies reported social conflict events for African countries with population over one million, searching keyword in news wires from Associated Press (AP) and Agence France Presse (AFP). This makes the dataset to have English and French language coverage. It classifies each event in 10 types of actions, and includes the location of the event, the specific actor and target.[3] It also includes events of civil conflict obtained from the Uppsala University Armed Conflicts Database (Gleditsch et al., 2002) in a different category. In this paper I focus only on events in the following categories: organized demonstration, spontaneous demonstration, organized riot, spontaneous riot, general strike, limited strike; because the focus is on collective political action and not civil conflict dynamics like civil wars. I undertook a second procedure of data cleaning eliminating events related to crime, terrorism or civil conflict in general.[4] Considered events include workers' strike, students' marches and clashes between protesters but not rebels' movements or civil war battles.

Data of all official matches played by the senior male national teams for African countries over the period 1990-2013 comes from the FIFA statistical office. For each match, I have the final score, exact date, match location (at city level), teams, competition name and phase of competition.

I constructed the database of social unrest and football matches the following way. I defined 5-day windows around the date of football matches of African countries for the period 1990-2013, being my unit of observation one 5-days period before or after each match for each African country in sample whose team played.[5] Using SCAD data I identified the number of social unrest events on each day for each 5-day country-match period and added the number of events of each day within

[3] The type of actions are: organized demonstration, spontaneous demonstration, organized riot, spontaneous riot, general strike, limited strike, pro-government violence, anti-government violence, extra-government violence and intra-government violence.

[4] I eliminated events in the categories organized violent riot and spontaneous violent riots with the following authors: Al-Qaeda, Al-Shebab, armed bandits, armed gang, armed islamists, armed men, Bakata Katanga, Boko Haram, Boko Haram militants, cattle thieves, Democratic Forces for the Liberation of Rwanda, FNL-Ubugabo burihabwa, gang led by Orquilio Nhassengo, insurgents, Johnny Pual Koroma, Mbarara (Chadian herders), militia, Murundi People's Front, People's United Democratic Movement, Seleka rebels, The Black Tigers, unknown.

[5] Each match could have one or two teams of countries in sample as participants.

window.[6] I did not include each match's date because I don't know if each social unrest event on those days was before or after each match, being unable to identify if had happened before or after treatment. Matches' dates were not included also because after a big agglomeration of people (like in a stadium) in an event that produces strong emotions (like a football match), riots or violence could occur (i.e., clashes between football fans and police or riots outside the stadium) which are not related to collective political action. I focus mainly on high-stake games, reducing the sample to days within time windows around Africa Cup of Nations (CAN) and the FIFA World Cup (WC) finals leaving me with 814 matches for 33 African countries.[7] I focus on these matches because I expect that patriotic shocks and changes of mood will be stronger after finals of the main two competitions for African teams, as people would pay more attention to these results. In the placebo analysis, I consider only friendly matches of the countries in sample to show that low-stake matches do not affect social unrest.[8] Figure A.1, in Appendix A, shows the number of daily events on the period 1990-2013 per one million inhabitants of 1990 for the 48 countries in sample. It shows considerable heterogeneity in the number of events between countries, on the period of analysis.

To study the role of expectations and match outcomes on social unrest, I estimated the ex-ante probability of victory for each country on each match using the Elo Rating System (Elo, 1978).[9] For the construction of probabilities, I used data of ranking and match locations from FIFA. Due to data restrictions, this sample considers matches from August 8^{th} 1993 to October 9^{th} 2012, consisting in 659 high-stake matches, for the same group of countries.

Table 1 presents summary statistics for 5-day windows for all country-matches of the Africa Cup of Nations and World Cup finals, and for a reduced sample of country-matches with associated probability of winning (Panel B). Panel A presents mean, standard deviations, minimum values, maximum values and sample size of the sum of 5-day windows around 814 high-stake matches. Social unrest events have a wide variation, going from 0 to 16 events per period, with a mean of 0.599 events. Victories are 37.96% of matches' result in sample, consisting on 309 victories in total. Defeats are the result of 40.91% of sample's matches, consisting in 333 defeats. Panel B of

[6] I also constructed datasets for 10 and 15 days analogously.

[7] The countries are: Algeria, Angola, Benin, Botswana, Burkina Faso, Cameroon, Congo, Congo DR, Cote D'Ivoire, Egypt, Ethiopia, Gabon, Ghana, Guinea, Kenya, Liberia, Libya, Malawi, Mali, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Togo, Tunisia, Zambia, Zimbabwe.

[8] For placebo analysis I have matches for 48 countries, adding to the 33 countries with high-stake games the following 15 countries: Burundi, Central African Republic, Chad, Eritrea, Gambia, Guinea-Bissau, Lesotho, Madagascar, Mauritania, Mauritius, Somalia, South Sudan, Swaziland, Tanzania and Uganda.

[9] For the construction of probability of victory I followed the method used by Depetris-Chauvin and Durante (2017). First, because Elo rating is not available for the whole period of interest, I obtained the last available from elorating.net at February 17^{th} 2017. Second, I estimated through OLS the slope and intercept between FIFA ranking and Elo rating. Then using the obtained slope (1943.27) and intercept (-5.26) transformed monthly FIFA ranking to Elo rating. Finally, I used the formula of probability of victory elorating.net to obtain the probability of victory, which include difference in rating and if team played as local.

Table 1 shows summary statistics for a restricted sample of 659 matches with associated ex-ante probabilities. The range of social unrest events is similar and the mean increase to 0.636 events per period. In this sample 37.13% of matches were victories, 267 matches, and 40.75% were defeats, 293 matches.

Table 1: Summary Statistics (5-Day Window)

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: All High-Stake Matches				(N = 1628)
Social Unrest Events	0.599	1.89	0	16
Victories	0.38	0.485	0	1
Defeats	0.409	0.492	0	1
Panel B: High-Stake Matches With Associated Probabilities				(N=1318)
Social Unrest Events	0.668	2.014	0	16
Victories	0.378	0.485	0	1
Defeats	0.417	0.493	0	1
Panel C: High-Stake Matches and Country Characteristics				(N=1628)
Non-Violent Events	0.525	1.742	0	16
Violent Events	0.074	0.425	0	5
Non-Government-Targeted Events	0.204	0.846	0	5
Government-Targeted Events	0.395	1.508	0	15
Ethnic Fractionalization*	0.668	0.211	0.039	0.908
Autocracy Index*	2.799	2.454	0	9

Sample covers +/- 5 days around 814 country-matches in either CAN or World Cup Finals for panel A and C, and 719 country-matches for panel B. Restricted high-stake matches consider matches from August 8th 1993 to October 9th 2012, due to data restriction for constructing probabilities of winning. Social unrest data comes from the SCAD database. Football data comes from FIFA Statistical Office. Ethnic fractionalization data comes from Alesina et al. (2003). Autocracy index data comes from Marshall and Jaggers (2002).

*Ethnic Fractionalization takes one value per country (N = 33) and Autocracy Index takes one value per country-year (N = 174).

II.C Baseline Results

Table 2 presents estimates of equation (1) for victories and defeats. Column 1 shows the impact of victories on social unrest, having as baseline category ties and defeats. Column 2 shows the impact of defeats on social unrest, in relation to victories and ties. Column 3 shows the impact of victories on social unrest controlling for defeats, having as baseline category ties. Each column of this table reports three different levels of clustering for standard errors: by country, by country-year and by country-match level, reported in in parentheses, curly brackets and square brackets respectively. It also reports the estimated beta coefficient of victory and the mean number of events by period in sample.

Table 2: Impact of Victories and Defeats on Social Unrest Events (1990-2013)

	Dep. Var.: Ln(1 + Social Unrest Events)		
	(1)	(2)	(3)
Victory	-0.077		-0.086
	(0.029)**		(0.037)**
	{0.028}***		{0.041}**
	[0.030]**		[0.043]**
Defeat		0.041	-0.015
		(0.030)	(0.036)
		{0.026}	{0.039}
		[0.027]	[0.039]
Beta Coefficient	-0.054	-	-0.061
Observations	1,628	1,628	1,628
R-squared	0.869	0.868	0.869
Mean Number of Events	0.599	0.599	0.599

*** $p<0.01$ ** $p<0.05$ * $p<0.1$. Robust standard errors clustered at country level in parentheses, at country-year level in braces and at country-match level in square brackets. Each specification includes country-match fixed effects. Sample covers +/- 5 days around 814 matches in either Africa Cup of Nations (CAN) or World Cup (WC) Finals. Social unrest data comes from the SCAD dataset.

These results show that victories reduces significantly the number of social unrest event, implying a reduction by between 7.41% (in relation to ties and defeats) and 8.24% (controlling for defeats).[10] The effect of victories is statistically significant at least at 95% of confidence for all clustering levels. Having the number of events a mean of 0.599, the reduction is between 0.044 and 0.049 events by period on average. Another way of interpreting the magnitude of event reduction is to analyze the beta coefficients. Beta coefficients show how an increase in one standard deviation of the independent variable affects the independent variable in terms of its own standard deviation. In specifications 1 and 3, they suggest that an increase of victories in one standard deviation implies a reduction in between 0.054 and 0.061 standard deviations of the number of social unrest events. Both methods suggest a relevant reduction in the number of social unrest events.

Results also show that although the point estimate of the impact of defeats, in relation to victories and ties, is positive as expected it is not significant at usual levels of confidence in all

[10] Given the semi-log specification and that the treatment variable is a dummy I obtain the percentage change, in the dependent variable, according to the following formula: $100 \times (e^{\hat{\beta}} - 1)$ (Halvorsen et al., 1980).

considered clustering levels. Having as baseline category ties, the effect of defeats is even negative, although not significant. This suggests that victories are reducing social unrest, particularly compared to ties.

Table 3 reports the results of estimating equation (1) for 5, 10 and 15 days. This exercise is carried in order to test if the effect dissipates quickly, given the evidence of match results affecting for one hour for violent crime (Munyo and Rossi, 2013) and narrow time window in the same day for intra-household violence (Card and Dahl, 2011), although exists evidence of affecting for longer periods as in voting ten days after (Healy et al., 2010) and reducing conflict events for the following six months (Depetris-Chauvin and Durante, 2017). The standard errors are clustered at country, country-year and country-match level. It shows that the negative impact of victories on the number of social unrest is significant at least at 95% of confidence across all specifications and clustering levels, suggesting that the effect persists for at least 15 days after the match. The beta coefficients remain stable across specifications, but since the mean number of events is increasing in the length of the time window, the impact seems to be stronger in the short-term.

Table 3: Impact of Victories on Social Unrest Events by Day Window (1990-2013)

	Dep. Var.: Ln(1 + Social Unrest Events)		
	(1)	(2)	(3)
Victory	-0.077	-0.098	-0.104
	(0.029)**	(0.033)***	(0.044)**
	{0.028}***	{0.038}**	{0.050}**
	[0.030]**	[0.044]**	[0.053]**
Beta Coefficient	-0.054	-0.053	-0.048
Observations	1,628	1,628	1,628
R-squared	0.869	0.832	0.818
Mean Number Events	0.599	1.202	1.822
Day Window	5	10	15

*** p<0.01 ** p<0.05 * p<0.1. Robust standard errors clustered at country level in parentheses, at country-year level in braces and at country-match level in square brackets. Each specification includes match fixed effects. Sample covers +/- 5, 10 and 15 days around 814 important official matches defined as matches in either CAN or World Cup Finals, respectively. Social unrest data comes from the SCAD dataset.

II.D Threats To Identification

The key identifying assumption for difference-in-differences estimation is that trends would be similar in treatment and control groups without treatment (Angrist and Pischke, 2008). This assumption makes the change in the number of social unrest events for the control group a valid counterfactual for the treated and the estimation of the treatment effect feasible.

To investigate the validity of this assumption, first, I analyze if my specification only captures an endogenous reaction to future games (i.e., people could anticipate the match result an change their behavior). In particular, to test whether my results are driven by pre-trends I do a falsification, estimating equation (1) for a false victory 5 days before each victory on high-stake matches. Thus, I compare the number of social unrest events 6 to 10 days before a victory to the number of these events 1 to 5 days before. It should report no effect of victories if the results are not driven by pre-trends. The first column of Table 4 presents the result of this test, with standard errors corrected for heteroscedasticity and clustered at country-match level.[11] It shows that there is no statistically significant difference between the number of social unrest events before the match takes place, suggesting that treatment and control group present parallel trends.

Another possible concern with my identification strategy is that my specification could be capturing only strategic behavior of protesters. If they know that people are less willing to protest after victories of their national teams, then they could make protests the days before expected win matches. To test this interpretation, I estimate the baseline specification only for expected close matches, matches were the ex-ante probability of winning is between the fourth and seventh decile of the constructed probability of victory.[12] Column 2 of Table 4 presents the result of this test for matches that were expected ex-ante to be close. It shows that even with the sample reduced to around one third, the effect is significant showing that my main estimates are not explained by strategic behavior of protesters and supports that my treatment is plausibly exogeneous.

Finally, only the fact of winning matches could reduce social unrest, independent of its relative importance. To test this possibility, I estimate the baseline equation only for friendly matches, where we should see no significant effect to support my hypothesis that people react only for most significant matches. Column 3 of Table 4 presents the result of estimating equation (1) only for friendly matches over the period 1990-2013. It shows that victories in friendly matches have no significant effect on reducing social unrest, showing that the only thing that matters is high stake matches. The effect is even positive, albeit noisy.

[11] This assumption of standard errors applies to all estimations in Table 4.

[12] Figure A.2, in Appendix C, shows the mean share of victories for each decile of the distribution of probabilities of victory.

Table 4: Threats to Identification

	Dep. Var.: Ln(1 + Social Unrest Events)		
	Falsification	Expected Close Matches	Friendly Matches
	(1)	(2)	(3)
Victory	0.035	-0.119*	0.007
	(0.031)	(0.061)	(0.011)
Beta Coefficient	-	-0.080	-
Observations	1,628	530	9,098
R-squared	0.883	0.858	0.884
Mean Number of Events	0.643	0.651	0.511

*** $p<0.01$ ** $p<0.05$ * $p<0.1$. Robust standard errors clustered at country-match level in parentheses. Each specification includes country-match fixed effects. Column 1 estimates the effect of false victories 5 days before, with a sample that cover -10/-1 days before 814 matches in either Africa Cup of Nations (CAN) or World Cup finals. Sample of Column 2 includes 530 matches in either CAN or World Cup finals, were the expected ex-ante probability of winning was between the fourth and seventh decile of distribution. Sample of Column 3 cover +/- 5 days around 4549 friendly matches for African countries between 1990-2013. Social unrest data comes from the SCAD dataset.

II.E Event Study

Another way of testing parallel trends assumption, and whether results are driven by strategic behavior of protesters, is to carry an event study. Considering 9 days before and after each high-stake match I divided my day sample in 3 days bands, in order to reduce noise. I estimated the interaction of winning with each band on the average number of social unrest events, using the 3 days before the match as baseline category. To support my hypothesis of parallel trends it should show no significant effect of the interaction between victory and days bands before treatment, and a significant effect after treatment begins.

Figure 1 presents the result of the event study for victories. Confidence intervals were constructed with 95% of confidence and robust standard errors, clustered at country-match level. This figure shows that the interaction between victories and days bands before treatment is never significantly different from zero at 95% of confidence in all cases. After treatment, we see negative point estimates and significant effect for the 1/3 and 7/9 time windows at 95%, and significant at 90% for 4/6 band. These results suggest a significant and negative impact of victories on the number of social unrest events the days after, persistent at least 9 days, and that treatment and control groups have similar trends before victory, satisfying the identification assumption.

Figure 1: Number of Social Unrest Events in the Proximity of a Victory (3-Day Bandwiths)

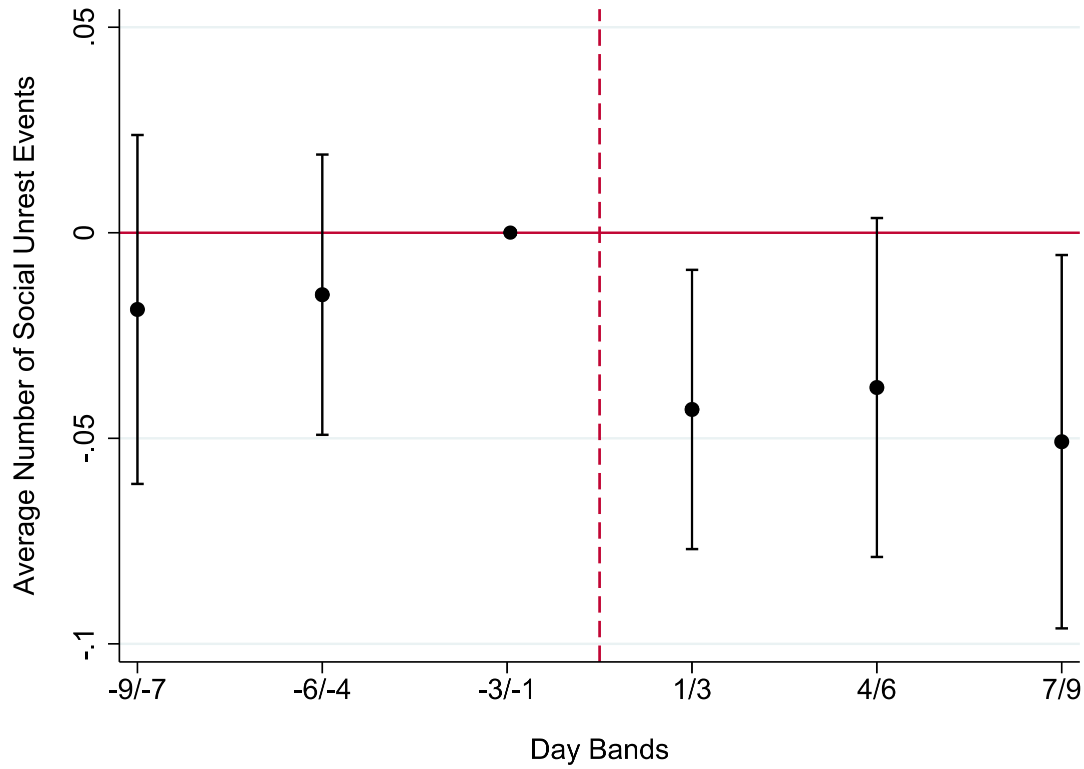

Figure plots point estimates and confidence intervals at 95% for 6 dummies indicating 3 days bands for the number of social unrest events within a 9-day time window around a National Male Football Team's victory in a match of the African Cup of Nations or the World Cup finals. The block -3/-1 was normalized to zero. The specification includes country-match fixed effects. Confidence intervals were constructed with robust standard errors clustered at country-match level.

II.F Additional Robustness Checks

In appendix B I carry two extra robustness checks. Table A.1 presents estimates of equation (1) for the total number of social unrest events, the number of social unrest events transformed using inverse hyperbolic sine transformation (IHS), and for the logarithm of the number of events plus one using Poisson regression with fixed and random effects, respectively. It shows that the impact of victories on social unrest remains significant for all specifications, except for Poisson regression with random effects. Table A.2 presents the estimation of victories on social unrest at the extensive margin, making the dependent variable a dummy indicating if at least one event was reported in the period and 0 otherwise, using a linear probability model with standard errors clustered at country-match level. The first column of this table shows that victories reduce the probability of realization of at least one social unrest event in 7.3% for the 5 following days in relation to ties and defeats, at 99% of confidence.

Additionally, in Appendix D, Figure A.3 presents a sensitivity analysis, showing the estimated betas and t-statistics obtained from estimating equation (1) for high-stake games considering 5-day windows, eliminating one country on each estimation. It shows that the main results are robust to the elimination of any of the countries in sample (t-statistic of at least -1.99).

III. Exploring Channels

In order to test implications of the main two channels (national unity and mood changes), in this section I explore heterogeneous effects of victories depending on the type of event (if is violent or non-violent and government-targeted or non-government-targeted), the ethnic fractionalization of each country, the autocracy level of each country's regime and the ex-ante expectations associated to each match's result.[1]

III.A Impact of Victories by Type of Event

To exploit the heterogeneous impact of victories depending on the type of events, I classified events in line with Hendrix and Salehyan (2012). I categorized events depending on the intention to harm people and destroy property, considering demonstrations and strikes to be non-violent events, and riots to be violent events. Also, I classified events depending on if the main target is the local or central government, dividing events in government-target or non-government-targeted accordingly. The method of estimation is analogous with the baseline results, considering 5 days, but restricting the dependent variable to the number of events of each category separately (i.e., for estimating the impact of victories on non-violent events I only consider non-violent ones).

If the main channel is mood changes, I would expect victories to affect more violent events than non-violent ones, as there is evidence of mood change affecting violent behavior (Munyo and Rossi, 2013). In addition, if mood is the main driver, I may expect that victories affect more government-targeted events since victories of local sport teams increase voting of incumbent (Healy et al., 2010). If the main channel is national unity, I should expect a reduction in violent events as well, but no difference between government-targeted and non-government targeted events change, as Depetris-Chauvin and Durante (2017) find victories does not translate in an increase in approval

[1] While one of my key hypothesized underlying mechanisms would suggest that victories should reduce the prevalence ethnic-motivated unrest events thus echoing Depetris-Chauvin and Durante (2017)'s finding of successful collective experiences priming national pride and reducing ethnic tensions, SCAD data does not provide meaningful variation needed to directly test this hypothesis. Indeed, reported ethnic-motivated events are rather rare in my dataset: the prevalence of these type of events is below 1 percent.

or trust in incumbent. The implications of both channels do not compete in this context, but only increase the expected impact of victories on violent events.

Panel C of Table 1 presents the mean, standard deviation, minimum and maximum values of events categorized by violence or if the government is the main target. There is a higher fraction of non-violent than violent events, with mean 0.525 and 0.074 each. Non-government-targeted events have a mean of 0.204 events on each considered period, having a maximum of 5 events. Government-targeted events have a mean of 0.395, having between 0 and 15 events each period of 5 days.

Table 5 presents the results of estimating equation (1) separately for each category. It reports that victories have a negative impact in all specifications as expected. Regarding the violence of events, it shows that victories only reduces significantly (at 99% of confidence) the violent ones by 4.78%, having no impact on the non-violent ones. In relation to if the government is the main target, Table 5 reports that victories only affect significantly government-targeted events (at 90% of confidence), reducing them by 4.3%.

Table 5: Impact of Victories on Social Unrest Events by Type of Event (1990-2013)

	Dep. Var.: Ln(1 + Social Unrest Events)			
	Non-Violent	Violent	Government Targeted	Non-Government Targeted
	(1)	(2)	(3)	(4)
Victory	-0.035	-0.049***	-0.044*	-0.037
	(0.028)	(0.019)	(0.025)	(0.024)
Beta Coefficient	-0.026	-0.096	-0.037	-0.043
Observations	1,628	1,628	1,628	1,628
R-squared	0.872	0.671	0.869	0.807
Mean Number of Events	0.525	0.074	0.395	0.204

*** $p<0.01$ ** $p<0.05$ * $p<0.1$. Robust standard errors clustered at the country-match level in parentheses. Each specification includes match fixed effects. Sample covers +/- 5 days around 814 important official matches defined as matches in either CAN or World Cup Finals. Social unrest data comes from the SCAD dataset.

The results of estimating the extensive margin by category are shown in Table A.2, in Appendix B. The estimates of victory are in the same direction in all specifications, but are only statistically significant for violent (at 99% of confidence) and for non-government-targeted (at 90%) events.

Considering the results of the previous two tables I have strong evidence of violent event reduction, and mixed evidence of a heterogeneous impact depending on if the government is the main target. These finding support national unity channel, as violent events are strongly reduced, and partly mood shift channel, as violent events are strongly reduced as well, but I do not have clear evidence of a stronger change on government-targeted events.

III.B Impact of Victory by Level of Ethnic Fractionalization and Government Autocracy

If the channel at play is boost in national unity, I expect the impact of victories to be more visible in countries where there is weaker national identity. Also, this channel could have a different impact depending on the level of autocracy of countries' government, in the case that the increase of identification with the country as a whole depends on the regime type. Conversely, it is less clear how would a mood shock differ depending on these characteristics. As only one channel (national unity) is active in this case, I expect that they do not compete or cooperate in this context.

In autocratic regimes, the costs and benefits of protesting are different in relation to more democratic ones, as autocratic regimes are less willing to answer demands of citizens and more likely to repress (Carey, 2006). Consequently, I expect that protesters in autocracies are more involved, as they are willing to carry higher costs, making their behavior less affected by football matches' results. In this case, I would expect a stronger impact of victories in less autocratic regimes.

I grouped my sample in countries with high ethnic fractionalization if country's ethnic fractionalization is over the mean of the countries in sample, and with low ethnic fractionalization if it is below the mean.[2] I use data of ethnic fractionalization from Alesina et al. (2003), having one value per country of ethnic fractionalization.[3] For the second exercise, I classified countries as with high autocracy if the autocracy level is six or more, and with low autocracy if it is five or less. I obtained data of autocracy from Polity4 (Marshall and Jaggers, 2002). Its autocracy index measure level of "institutionalized autocracy" on each country, having integer values from 0 to 10.[4] Panel C of Table 1 shows that the sample mean for the 33 countries with high-stake matches of ethnic fractionalization is 0.668, having a minimum value of 0.039 and maximum value of 0.908, and autocracy index mean

[2] I computed the mean for 47 of the 48 African countries in sample, because I do not have data ethnic fractionalization for South Sudan. The mean of ethnic fractionalization for the considered 47 countries is 0.66. Only considering the 33 countries with high-stake matches the degree of ethnic fractionalization is roughly similar: 0.668.

[3] The formula for computing the degree of ethnic fractionalization is:

$$Fract_j = 1 - \sum_{i=1}^{N} s_{ij}^2$$

where s_{ij} represents the share of group i on country j.

[4] Its construction considers measures of the competitiveness of participation in politics, regulations of participants of elections, the competitiveness of executive election and constrains to chief executive.

of 2.799, with a standard deviation 2.454, and values between 0 and 9.

The estimation method is analogous with the previous section. I estimate equation (1) using OLS with standard errors clustered at country-match level, but restricting sample depending on the levels of autocracy and ethnic fractionalization of each country. Given the evidence of patriotic shocks reducing ethnic identification and tensions (Depetris-Chauvin and Durante, 2017), I expect a stronger impact of victories in highly ethnically diverse countries. Exploiting the differences in autocracy levels of regimes, if the national unity channel is stronger for countries with more representative regimes or the protesters in autocracies are more involved and less affected by match results, I would expect that the effect of victories is stronger in less autocratic regimes.

Table 6 explores the relation between victories and number of social unrest events depending on the ethnic fractionalization and autocracy level of each country. The first two columns report the results depending on if the countries' ethnic fractionalization is over the mean (high ethnic fractionalization) or below (low ethnic fractionalization). Third and fourth columns show the estimates depending on if countries' autocracy index is six or more (high autocracy) or if it is five or less (low ethnic autocracy). The first two columns report that irrespective of the ethnic fractionalization of countries the point estimates of victories are negative on social unrest, but the effect is only statistically significant for countries with high ethnic fractionalization. This suggests that the effect is only relevant in ethnically diverse countries, where the number of events are reduced in 7.69%. Note that sample size is smaller for countries with low fractionalization, being around one third of the sample of countries with high ethnic fractionalization. This could partly explain the higher standard errors and insignificance of its estimate, so is possible that also exists an effect on countries with low ethnic fractionalization that it is not captured. These results support the channel of national unity and reduction of ethnic tensions, having a stronger impact in countries more ethnically diverse and more likely to, precisely, have ethnic tensions. The next two columns show the impact of victories depending on the autocracy level of regimes. It reports no statistically significant impact of victories in countries with high autocracy, and surprisingly a positive point estimate. It also shows a statistically strong reduction of 9.88% in the number of events on the following 5 days for countries with low autocratic regimes. Previous results suggest that football matches may increase national unity more when the government is less autocratic or that difference in "willingness" to protest, irrespective of higher protesting costs for participants on autocratic regimes, makes protesters in autocracies less affected by victories.

Table 6: Impact of Victories on Social Unrest Events by Ethnic Fractionalization and Autocracy Levels (1990-2013)

	Dep. Var.: Ln(1 + Social Unrest Events)			
	Ethnic Fractionalization		Autocracy	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Victory	-0.080**	-0.067	0.073	-0.103***
	(0.034)	(0.066)	(0.093)	(0.031)
Beta Coefficient	-0.065	-0.036	0.048	-0.074
Observations	1,226	402	234	1,394
R-squared	0.824	0.928	0.871	0.869
Mean Number of Events	0.445	1.067	0.718	0.579

*** $p<0.01$ ** $p<0.05$ * $p<0.1$. Robust standard errors clustered at the country-match level in parentheses. Each specification includes match fixed effects. Sample covers +/- 5 days around 814 important official matches defined as matches in either CAN or World Cup Finals. Social unrest data comes from the SCAD dataset.

III.C Impact of Expectation Shocks

If national unity is at play, I may not anticipate expectations to matter. However, one may think that the mood channel would be strongly dependent on whether the win was anticipated or not. To study the impact of expectations shocks I assume that fans generate expectations on games similar than the predicted by the Elo rating system (Elo, 1978).[5] This could be a strong assumption. To relax this assumption and for ease of interpretation I define that a team is expected to win if the probability of winning is in the highest 10% of the distribution. Analogously, a team is expected to lose if it's probability of winning is in the lowest 10% of distribution. Here I only assume that fans consider matches in the lowest decile of probabilities expected defeats and matches in the highest decile expected victories. Figure A.2 of Appendix C presents the mean of the share of victories by decile of expected probability of victory. It shows that the mean share of victories for the highest decile is close to 0.7 and the mean share of victories for the lowest decile is around 0.15 for high-stake matches, supporting that in these deciles Elo rating is a good predictor of match results.

I estimate equation (1) for expected win and expected loss matches separately, using OLS with robust standard errors clustered at country-match level. Due to the evidence of shocks affecting

[5]In particular, I constructed the ex-ante probability of winning using the formula of elorating.net.

mood I expect that the impact of victories in expected loss matches, which produce euphoria, is stronger than victories in expected win ones (Munyo and Rossi, 2013). In the same fashion, I expect that defeats in expected win matches would produce frustration, having a stronger effect than defeats in expected loss matches (Card and Dahl, 2011; Munyo and Rossi, 2013; Carvalho and Zilberman, 2017). Only mood channel should be active in this case as is not clear the role of expectations on national unity.

Table 7 presents the impact of victories and defeats depending on ex-ante expectations. The first two columns reports the impact of victories and defeats after 130 matches which were expected to be win, and columns 3 and 4 presents their impact after 132 matches which were expected to be loss. Point estimates suggest that the unexpected results have a stronger impact on social unrest as expected. In the case of victories, it shows that unexpected ones reduce the number of social unrest events in 17.47%, being significant although the small sample (132 observations) and large standard errors. For victories that were expected, the point estimate is close to 0 and not significant. Regarding defeats, the point estimate for unexpected ones is higher than in previous estimations whereas the point estimate of expected ones closer to zero. Their impact is not significant in both categories. These results present a strong argument in favor of euphoria and mood switch as being at least partially responsible for reducing the number of social unrest events.

Table 7: Impact of Expectation Shocks on Social Unrest Events (1990-2013)

	Dep. Var.: Ln(1 + Social Unrest Events)			
	Expected Win		Expected Loss	
	(1)	(2)	(3)	(4)
Victory	0.009		-0.192*	
	(0.119)		(0.103)	
Defeat		0.135		0.029
		(0.173)		(0.091)
Beta Coefficient	0.006	0.047	-0.137	0.037
Observations	130	130	132	132
R-squared	0.916	0.917	0.753	0.744
Mean Number of Events	1.308	1.308	0.265	0.265

*** $p<0.01$ ** $p<0.05$ * $p<0.1$. Robust standard errors clustered at the country-match level in parentheses. Each specification includes match fixed effects. Sample covers +/- 5 days around 65 expected win important matches defined as matches with winning expectation in the top 10% of distribution for columns 1 and 2, and 66 expected loss important matches defined as matches with winning expectation in the bottom 10% of distribution for columns 3 and 4. Important official matches are defined as matches in either CAN or World Cup Finals. Social unrest data comes from the SCAD dataset.

IV. Conclusion

Given the impact of social unrest in societies this paper investigates if it is affected by sudden patriotic shocks and mood changes using football match outcomes as exogenous change. I document a negative impact of victories on the number of social unrest in the short-term, reducing them in more than 7% the following days, and no impact of defeats. This reduction in social unrest appears to be driven mostly by the national unity produced by football victories since I find a strong statistical evidence supporting its main predictions: larger impact of victories for violent events, countries with high ethnic fractionalization, and countries with less autocratic regimes. The last effect could be partly due to the kind of participants which are willing to protests facing higher costs of protesting in autocracies, being them less affected by victories. However, I cannot reject that part of the effect also occurs through improved mood in the population after victories since, even if defeats have no impact in the number of events and that I have mixed evidence of the impact of victories depending on if the government is the main target, I find an especially strong effect for unanticipated victories, which produce euphoria, and a strong reduction of violent events, as well.

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Appendix A Events by Country

Figure A.1: Social Unrest Events by Country (1990-2013) Per Million Inhabitants of 1990

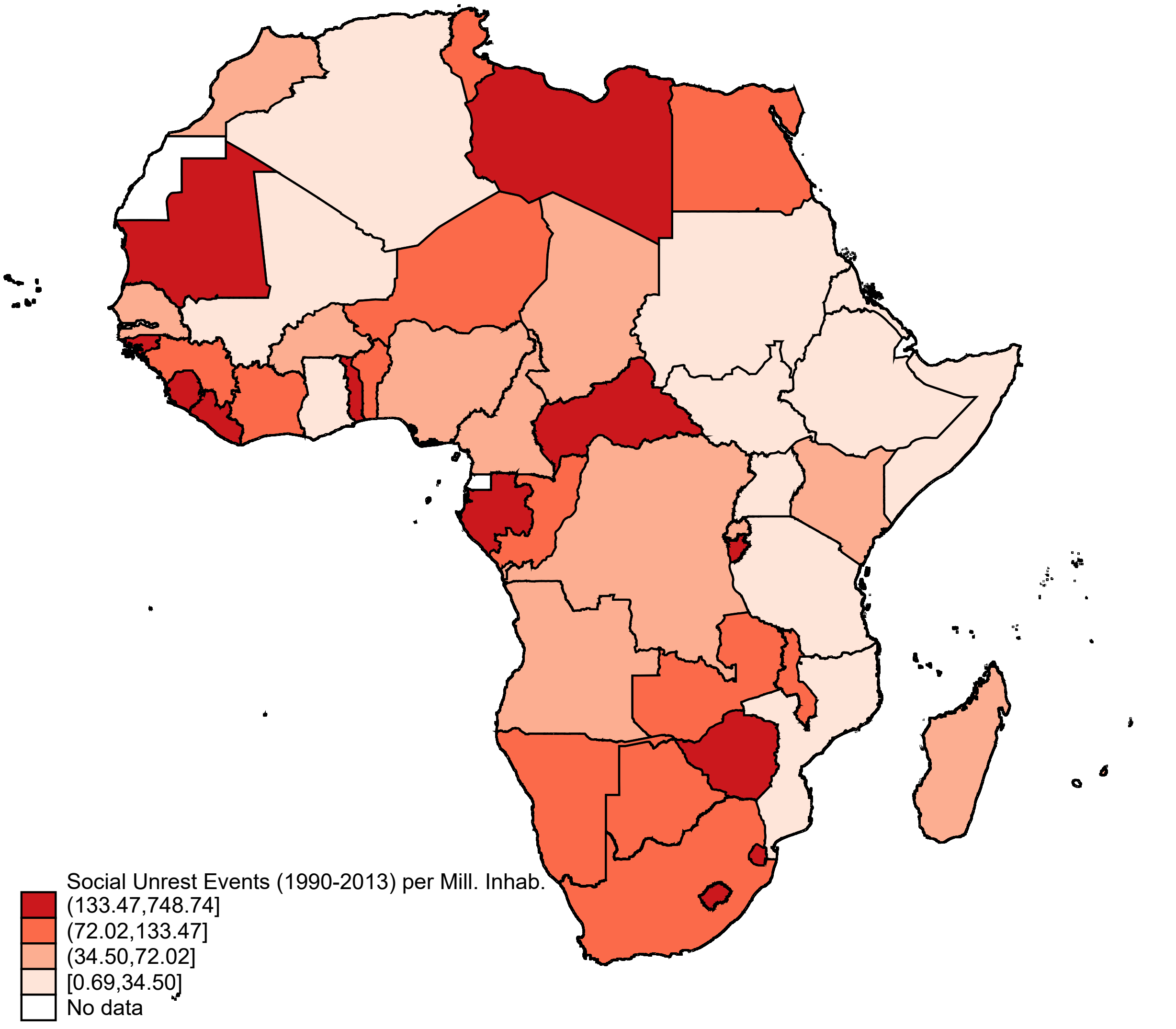

Figure presents the total number of social unrest events in the period 1990-2013, every one million inhabitants of 1990 for each country in sample. Social unrest data comes from the SCAD dataset. Data of inhabitants in 1990 comes from the World Bank (World Development Indicators). Administrative area data comes from Hijmans et al. (2012).

Appendix B Robustness Check and Extensive Margin

Table A.1: Robustness Check: Impact of Victories on Social Unrest Events (1990-2013)

	Dep. Var.: Ln(1 + Social Unrest Events)			
	(1)	(2)	(3)	(4)
	Total Number of Events	IHS	Poisson FE	Poisson RE
Victory	-0.211**	-0.097**	-0.279**	-0.186
	(0.089)	(0.039)	(0.136)	(0.132)
Observations	1,628	1,628	370	1,628
R-squared	0.906	0.866		
Mean Number of Events	0.599	0.599	2.635	0.599

*** $p<0.01$ ** $p<0.05$ * $p<0.1$. Robust standard errors clustered at country-match level in parentheses. Each specification includes match fixed effects. Sample covers +/- 5 days around 814 important official matches defined as matches in either CAN or World Cup Finals for columns 1, 2 and 4, and 185 important official matches for column 3. Social unrest data comes from the SCAD dataset.

Table A.2: Impact of Victories on the Extensive Margin of Social Unrest (1990-2013)

	Dep. Var.: Extensive Margin Social Unrest				
	(1)	(2)	(3)	(4)	(5)
	All Events	Non-Violent	Violent	Gov-Target	Non Gov-Target
Victory	-0.073***	-0.027	-0.056***	-0.026	-0.040*
	(0.027)	(0.024)	(0.020)	(0.023)	(0.022)
Observations	1,628	1,628	1,628	1,628	1,628
R-squared	0.769	0.776	0.625	0.761	0.718
Mean Number of Events	0.599	0.525	0.074	0.395	0.204

*** $p<0.01$ ** $p<0.05$ * $p<0.1$. Robust standard errors clustered at country-match level in parentheses. Dependent variable takes value one if at least one social unrest event happened in the period, 0 otherwise. Each specification includes match match fixed effects. Sample covers +/- 5 days around 814 important official matches defined as matches in either CAN or World Cup Finals. Social unrest data comes from the SCAD dataset.

Appendix C Share of Victories by Decile of Probability of Victory

Figure A.2: Mean Share of Won Matches by Decile of Expected Victory (Elo Rating)

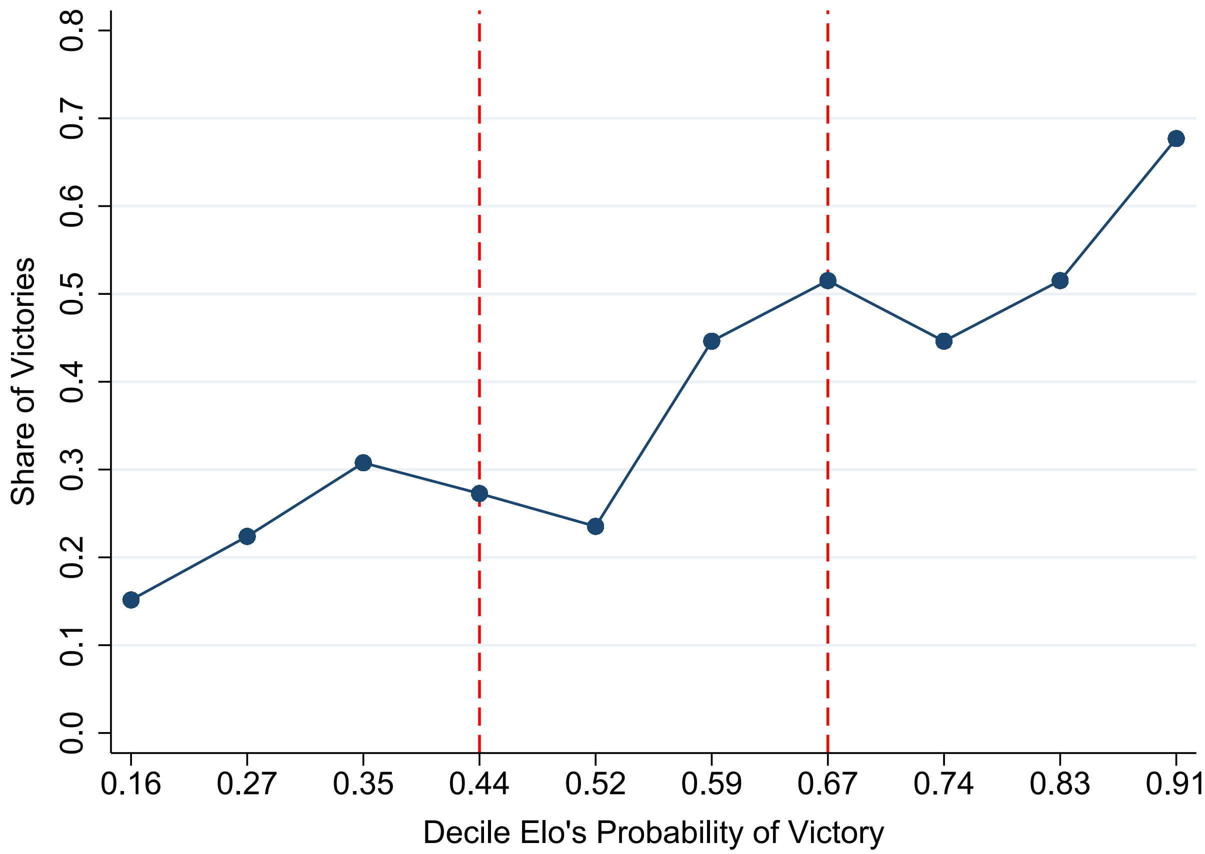

Figure presents the mean share of won matches by decile of expectation of victory, using Elo rating method for construction of probabilities of victories. Between the red dashed lines are the matches considered expected to be close, used in Column 3 of Table 4. First and tenth decile are considered expected loss and expected win matches, respectively. Data of football matches comes from FIFA Statistical Office.

Appendix D Sensitivity Analysis

Figure A.3: Sensitivity of Betas and t-statistics to the Exclusion of Each Country

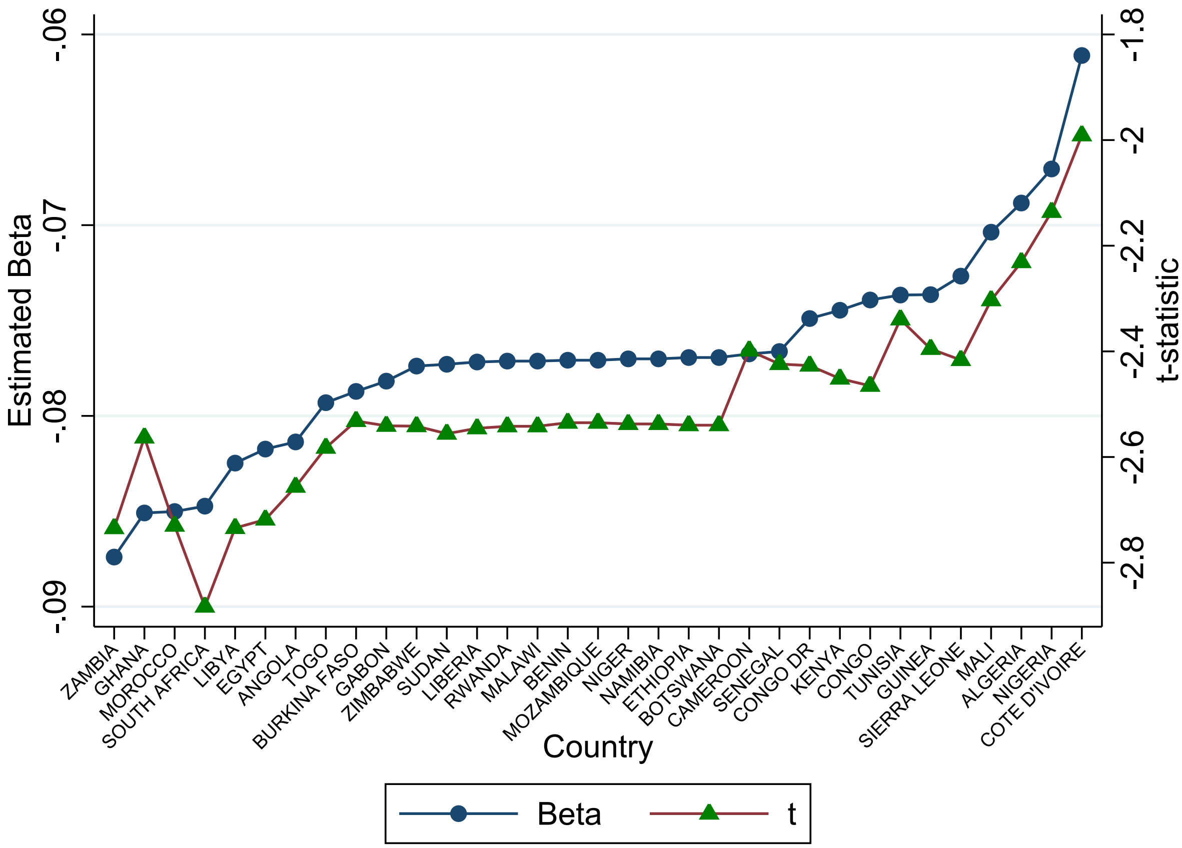

Figure presents the estimated betas and t-statistics of the baseline estimation (equation (1) for 5-day windows) for all the 33 countries with high-stake games in sample, eliminating one on each estimation. Data of social unrest comes from the SCAD dataset.