Diverting Domestic Turmoil

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November 2021

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Abstract

When faced with intense domestic turmoil, governments may strategically engage in foreign interactions to divert the public's attention away from pressing domestic issues. I test this hypothesis for a globally representative sample of 190 countries, at the monthly level, over the years 1997-2014. Using high–frequency data on media–reported events, I find robust evidence that governments resort to diversionary strategies in times of domestic turmoil and that such diversion takes the form of verbally aggressive foreign interactions. Diversionary interactions are typically targeted at countries closely linked along cultural and geographic dimensions, and at countries with low levels of state capability. Interestingly, I do not find evidence of these strategies being effective in deterring domestic turmoil. Taken together, these findings provide new insights on governments' systematic use of verbally aggressive foreign interactions as a short-term, low-cost, low-risk, strategic tool, to divert domestic turmoil.

Keywords: Diversionary foreign policy, domestic turmoil, football, connectivity.
JEL classification: F51, H77

*SoDa Laboratories, Monash University; email: ashani.amarasinghe@monash.edu. I thank Paul Raschky for detailed conversations that greatly assisted in shaping this paper. I also thank Klaus Ackermann, Sascha Becker, Giovanni Caggiano, Gabriele Gratton, Roland Hodler, Sisira Jayasuriya, Miriam Kautz, Claudio Labanca, Federico Masera, Laura Panza, Laura Puzzello, Eik Swee, Haishan Yuan, Yves Zenou, as well as seminar participants at Monash University, Applied Young Economist Webinar (AYEW), Oz Virtual Econ Research Seminar (OVERS), Royal Economic Society (RES) Annual Conference and the European Public Choice Society (EPCS) Conference for helpful comments and suggestions. All errors are mine. I gratefully acknowledge support of the Australian Government through its Research Training Program Scholarship.

1 Introduction

During periods of domestic turmoil, it is in the interest of country leaders to divert the attention of the public away from pressing domestic issues. 'Diversionary foreign policy' is a manipulative tool used for this purpose, where governments engage in interactions with foreign entities in a manner that distracts the domestic population (Oakes, 2006; Bennet and Nordstrom, 2000; Fearon, 1998; Ostrom and Job, 1986). Such diversion is expected to lead towards increased support for the government, as citizens rally around their common national identity (Sobek, 2007).

The Falklands War of 1982 provides an ideal example in this regard. Argentina's military *junta* at the time was faced with severe domestic turmoil due to prolonged economic stagnation and accusations of human rights violations. To divert domestic attention, the regime exercised military power to 'reclaim' the disputed territories of the Falkland Islands and South Georgia. The subsequent war lasted 74 days, and allowed reprieve for the Argentinian military *junta* to stabilize the tumultuous situation at home (Femenia, 1996). In the United States (US), the 1998 airstrikes against suspected terrorist sites in Sudan and Afghanistan occurred at the height of the Monica Lewinsky scandal, with Bill Clinton at high risk of impeachment. The airstrikes led to a temporary rise in presidential approval ratings, although he was eventually impeached.[1] More recently, there have been signals that diversion can even take a more subtle, verbal form, which involves lower costs and risks compared to violent inter-state conflict. For example, in the years that Donald Trump was in office as president of the US, his use of social media was widely seen as serving the purpose of distraction in the face of unfavourable domestic conditions (Lewandowsky, Jetter & Ecker, 2020).[2]

[1] See, for example, *Washington Post*, "A dirty business," July 25, 1999.

[2] Famously, his somewhat surprising tweet mulling the purchase of the autonomous Danish territory Greenland came merely days after the US bond market yield curve inverted amid significant concerns of economic slowdown. The tweet led to major diplomatic tensions between the US and Denmark, including a cancellation of a scheduled presidential visit, thereby diverting the attention of the domestic population. See, for example, *The Independent*, "Trump lashes out after economic gloom deepens, as he jokes about trading Puerto Rico for Greenland", August 22, 2019. See also, *The Atlantic*, "Trump's attention-diversion tweet cycle goes international," November 30, 2017, *Financial Times*, "Donald Trump's tweets are weapons of mass distraction," September 26, 2017, and *The Guardian*, "Out of control? Or is Trump's tweeting designed to distract?," March 5, 2017.

Apart from such anecdotal evidence, the political economy literature documents multiple facets of diversionary foreign policy. This literature builds on the early work by Simmel (1955) and Coser (1956), who identify conflict as an essential element of group formation, where conflict with an out-group leads to the strengthening of in-group awareness and unity. The consequent boost in popularity incentivize leaders to embark on foreign conflict (Sobek, 2007; Pickering and Kisangani, 1998). In doing so, leaders may choose from substitutable policy alternatives ranging from extreme cooperation to extreme aggression, based on the costs and benefits involved (Bennet and Nordstrom, 2000).

My paper extends this literature on diversionary foreign policy by providing, to the best of my knowledge, the first causal estimates of the systematic use of diversionary foreign *interactions*, not necessarily limited to violent inter-state *conflict*, by governments across the world. Specifically, I combine high–frequency event data on domestic turmoil and governments' foreign interactions, with arguably 'exogenous' sentiment shocks in the form of football losses, for 190 countries, at the monthly level, over the years 1997-2014, to examine whether governments are more likely to engage in diversionary foreign interactions when domestic turmoil is high.

In the absence of a consistent measure capturing public sentiment towards governments, I first construct a novel quantitative *monthly* index of domestic turmoil, DT. For this purpose, I combine high–frequency data on actual physical events from media articles, retrieved from the Global Database of Event, Language and Tone (GDELT), with the conflict-cooperation scale introduced by Goldstein (1992). This index acts as the main explanatory variable of my study. Next, I derive the key outcome variables, which are quantitative measures of the cooperative/aggressive foreign interactions initiated by governments, at varying degrees of intensity. I consider four types of foreign interactions that governments engage in i.e., verbal cooperation, material cooperation, verbal conflict and material conflict. I incorporate country×year fixed effects to control for any unobservables that affect a particular country in a given year, as well as time-invariant country-specific features. Moreover, I include month-of-the-year fixed effects to capture any seasonal variations that simultaneously affect domestic turmoil and governments'

foreign interactions.

Despite the fine temporal granularity of the data and the comprehensive set of fixed effects however, this empirical estimation is threatened by potential endogeneity concerns due to joint determination and reverse causality. To causally infer the relationship, I use an instrumental variables (IV) strategy that leverages on public sentiment shocks resulting from unpredictable sports outcomes. Specifically, I focus on international football 'losses' experienced by a country, against closely ranked teams, as an arguably exogenous shock that affects public sentiments.

In the first part of the analysis I show that, at this fine temporal resolution, international football losses are a formidable shock that increases domestic turmoil. Exploiting this variation, I then provide causal evidence that domestic turmoil leads to an increase in governments' foreign interactions, particularly those classified as 'verbal' conflict. I argue that such increase in verbal conflict is caused by domestic turmoil, and that it provides evidence of governments diverting the public's attention by engaging in verbally aggressive foreign interactions. Preference for verbal aggression suggests that diversionary foreign policy is favoured by governments as a low-cost, low-risk strategy to manage domestic turmoil. Interestingly however, I do not observe evidence of diversionary interactions being successful in deterring domestic turmoil.

Next, using dyadic data on inter-state connectivity, as well as target–specific characteristics, I investigate whether leaders systematically choose their targets. I find that verbal aggression is typically directed at countries closely linked along religious, genetic, linguistic and geographic dimensions. I further observe that governments are more likely to direct their verbal aggression at 'weak' countries, as defined by low levels of national capability, military expenditure and population. Incidentally, I do not observe target countries responding to these verbal altercations, which prevents them from escalating to aggravated international conflicts. These findings further reiterate that diversionary strategies are utilized by governments in a manner that does not lead to significant economic costs or risks of retaliation.

Being, to the best of my knowledge, the first to provide systematic evidence on the

existence, nature and effectiveness of governments' diversionary strategies, this paper provides important policy implications on the optimal behaviors of the public and governments alike. From the public's perspective, being aware of, and proactively responding to, such strategic diversions become critically important if they are to effectively persist in the resistance towards the government's misbehavior. Indeed, the evidence on the (in)effectiveness of diversionary interactions suggest that the public do act competently, persisting in their endeavours and not being swayed by these short term diversions. From the government's perspective, this understanding of the domestic roots of international relations i.e., how domestic turmoil in one country can generate 'international' spillover effects on the network of countries, suggests that governments should monitor and respond to domestic turmoil, not only in their own country, but in other closely linked countries as well, for the overall welfare of the international system. The descriptive evidence on target countries' responses suggest that such monitoring prevents these domestically-driven, short-term verbal altercations from escalating in to persistent, large-scale conflicts.

This paper primarily contributes to the vast literature in political economy studying governments' strategic responses to citizen behavior, in particular, *diversionary* strategies in governments' *foreign policy agendas*. Existing work typically rely on traditional indicators of domestic turmoil, such as economic variables (rate of inflation or unemployment) or government approval ratings, combined with a dichotomous indicator of inter-state military force (Sobek, 2007; DeRouen, Jr., 2000; Morgan and Anderson, 1999; Miller, 1995; Ostrom and Job, 1986). Mitchell and Prins (2004) find that democracies have the most opportunities for diversion, while Pickering and Kisangani (2010) find that diversion occurs across autocracies as well. In the more recent literature, Lewandowsky, Jetter Ecker (2020) examine diversionary motives behind Donald Trump's tweeting. Eisensee and Strömberg (2007), Djourelova and Durante (2020) and Durante and Zhuravaskaya (2018) find that government behaviors are influenced by considerations of whether citizens are distracted by other important events. This literature is mainly US-centric,[3] and the evidence on diversionary interactions is inconclusive (Chiozza and Goemans, 2003;

[3] A few notable exceptions are Morgan and Anderson (1999) focusing on the United Kingdom; Nicholls, Huth and Appel (2010) focusing on Japan; and Sobek (2007) focusing on renaissance Italy.

Leeds and Davis, 1997; Meernik and Waterman, 1996).

My paper contributes to this niche literature in multiple ways. First, I introduce a novel measure of domestic turmoil that goes beyond traditionally used indicators such as the rates of inflation or unemployment. The imperfect suitability of these indicators, and their coarse level of aggregation, may have hindered existing studies from understanding the true causal relationship between domestic turmoil and diversionary interactions. Second, I use a broad set of outcome variables that captures the cooperative/aggressive nature of foreign interactions at varying degrees of intensity, instead of the traditional dichotomous outcome variable on inter-state war. This allows me to flexibly acknowledge the substitutable nature of the policy alternatives governments are faced with. Moreover, I add to the current knowledge of diversionary foreign policy on target selection (Spolaore and Wacziarg, 2016; Jung, 2014; Fordham 2005; Sprecher and DeRouen Jr., 2005) by examining whether governments systematically choose victims, based on a multitude of relationship networks between countries. To the best of my knowledge, this paper is the first to provide a globally-consistent, holistic picture of the causal evidence surrounding the systematic use of diversionary foreign policy.

My work also contributes to a burgeoning strand of the literature which focuses on using text-as-data to quantify societal aspects that were previously often overlooked due to data limitations (Gentzkow, Kelly and Taddy, 2019). The more recent work on this area focus on quantifying sentiment, at spatially disaggregated levels, for example using social media networks data (Baylis, 2020; Mitts, 2019; Barbera and Zeitzoff, 2017), as well as at a more aggregate level, for example using text data from newspaper articles (Benoit, Munger and Spirling, 2019; Shapiro, Sudhof and Wilson, 2020; Vegard and Thorsrud, 2019; Mueller and Rauh, 2018; Baker, Bloom and Davis, 2016). Closer to my work, Gentzkow and Shapiro (2010) use newspaper articles to develop an index of media slant, while Beattie (2020) uses a similar index to capture the portrayal of climate change in news articles. I contribute to this literature by developing, to my knowledge, the first quantitative monthly indicator of 'domestic turmoil' targeting governments, based on high–frequency, text–based, event data.

Finally, through the identification strategy, this paper relates to the literature linking outcomes of sporting events to people's sentiments. Ge (2018) and Card and Dahl (2011) link emotions following sporting events outcomes to taxi passengers' tipping behaviour and family violence, respectively, while Metcalfe, Burgess and Proud (2019) find a link between sporting events and student performance. At a more aggregate level, Edmans, García and Norli (2007) show that soccer losses lead to a significant reduction in stock returns. My paper is closely related to Depetris-Chauvin, Durante and Campante (2020) and Bertoli (2017), who explore the impact of football *wins* on nationalistic sentiments. My focus on sentiment shocks following football *losses* is complementary to theirs, and confirms the symmetric nature of the effects of sports outcomes on broad political outcomes.

The rest of this paper is organized as follows. I discuss the data and key variables in Section 2. Section 3 provides the empirical framework along with the baseline results and robustness checks. In Section 4, I explore whether countries systematically choose the targets of diversion. Section 5 examines the consequences of diversionary interactions, and Section 6 concludes.

2 Data

The unit of measurement is a country-month. The final data set consists of monthly observations for 190 countries, over the years 1997-2014.

2.1 Data on domestic turmoil and governments' foreign interactions

The dearth of data sources quantifying a society's behaviors at fine spatial and temporal resolutions has led to their under-representation in the policy discourse. However, with the advent of machine learning algorithms, many avenues enabling such quantification have opened up. In this study, I focus on quantifying two such societal aspects, i.e. domestic turmoil targeting governments and governments' interactions with foreign entities. For this purpose, I use data from GDELT, which is a real time open data global graph of

the human society, analyzed using news media (Leetaru and Schrodt, 2013). It monitors print, broadcast, and web news media in over 100 languages across every country, and is updated every 15 minutes. After being translated to English, natural language processing algorithms extract over 300 categories of activities based on CAMEO event codes (Gerner, Schrodt and Yilmaz, 2009), and approximately 60 attributes for each event.

These events belong to a wide spectrum of event types, from 'make a public statement' to 'appeal', 'demand', 'threaten', and 'engage in unconventional mass violence'. Locations of the actors – 'target' and 'source'– and the event itself, are reported. Events are classified under 'quad' classes based on their cooperative/aggressive nature i.e., verbal cooperation, material cooperation, verbal conflict and material conflict. Each event is also assigned a numeric score on the conflict-cooperation scale (Goldstein, 1992). This database is, therefore, a massive (containing approximately 120 million events over the sample period) and intricate data set of all media-reported events across the world.

2.1.1 Quantifying domestic turmoil

The public's perception of their governments is arguably a controversial societal aspect to quantify. In an ideal setting, one would record sentiments towards government performance from a random sample of citizens over a long period of time, at consistent temporal intervals, to arrive at such a quantification. While in surveys such as the World Values Survey (WVS) and the Afrobarometer survey respondents do express their views on governments, such survey data are not available consistently for each spatial and temporal unit, over a considerable period. Therefore, in the absence of such an ideal data set, I generate a quantification of public sentiments using revealed preferences observed via actual physical events (worthy of being) reported by the media.

For this purpose, I carefully sort through the entirety of events reported by GDELT. First, I identify all 'domestic' events, i.e., events where the locations of the source, the target and the incident itself, are within the same country. Next I extract all domestic events where the target is the government. Of these, I preserve events that were reported in at least three media reports.[4] Once aggregated at the country-year-month level, this

[4]Such filtering provides corroboration of the occurrence of an event, and rules out anomalies. It

data set consists of all domestic events targeted at the government, within a given country, for each month.

Next, I leverage on the Goldstein score (Goldstein, 1992) reported for each event type. This score captures the theoretical potential impact posed by each event type on the stability of a country, and takes in to consideration their inherent intensity of conflict and/or cooperation. On the Goldstein scale, each event type is assigned a score on a range of –10 (extreme conflict) to 10 (extreme cooperation). Since the objective is to quantify *domestic turmoil*, my focus is on events assigned a *negative* score on the Goldstein scale. Accordingly, based on a threshold Goldstein score of –5, I estimate the index of domestic turmoil (DT) using Equation (1) below.[5]

$$DT_{iymG\leq -5} = \frac{Dom_{iymG\leq -5}}{Dom_{iym-10\leq G\leq 10}} \tag{1}$$

Here, $Dom_{iymG\leq -5}$ refers to the number of domestic events targeting the government, recording a maximum Goldstein value of –5, and $Dom_{iym-10\leq G\leq 10}$ refers to the total number of domestic events targeting the government, on the full spectrum of the Goldstein scale (-10 $\leq$ G $\leq$ 10). $DT_{iymG\leq -5}$ is therefore a standardized indicator of domestic turmoil, which captures people's resentment towards their government, by expressing events attached with a negative sentiment score relative to all events targeted at the government. The standardized functional form of the DT index, as opposed to a simple count variable, renders it capable of capturing the change in negative sentiment towards the government *relative* to the change in positive sentiment, during each period. The standardization exercise also renders the index comparable across time and space.[6]

I conduct a number of exercises to confirm that DT is reasonably representative of existing (imperfect) measures of public sentiment. First, I focus on the US where a

also addresses potential media bias, and establishes confidence that the event was not artificially made prominent by a single media outlet pursuing a political agenda. Over the sample period, 55% of the events in GDELT were reported by at least 3 media sources. See Panel (a) in Figure A.1.

[5]Please see Table A.1 for scores relevant for each event category. I prefer a baseline threshold of –5 as it represents the mid point of the negative spectrum of the Goldstein scale, and encompasses a broad range of event categories associated with negative sentiments towards government. Results are robust to alternative thresholds (Table B.7).

[6]In Figures A.2 and A.3, I graphically illustrate the event composition of DT and the distribution of DT in a sample of countries, respectively.

relatively rich set of data is available as proxies for domestic turmoil. In Panels (a) and (b) of Figure A.4, I observe a close negative relationship between *DT* index against the US Presidential Approval Rate.[7] Panels (c) and (d) illustrate the positive and statistically significant relationship between *DT* and two indicators traditionally used as a proxies for domestic turmoil, i.e. the Consumer Price Index (CPI) and the unemployment rate.

Next, inspired by Sangnier and Zylberberg (2017), I explore the validity of *DT* using survey indicators. I generate an indicator of sentiments towards governments, using data from waves 3–6 of the WVS and waves 1–6 of the Afrobarometer survey, which overlay with the sample period.[8] In Figure A.5, I observe that at the country-year level, survey indicators are positively correlated with the *DT* index. In Figure A.6, using data on the exact date of the interview, I find that *DT* measured in the *period leading up to the interview* can indeed predict attitudes towards the government *at the interview*.

Next I consider protest events as a proxy for *DT*, using data from the Mass Mobilization Project (Clark and Regan, 2016), which records protests where 50 or more protesters publicly demonstrate *against the government*, for a globally representative sample of countries. I also obtain protest data from the Armed Conflict Location and Event Data (ACLED) project, which provides protest data for the African continent. I consider the number of protest events that occurred in a given country in a given month of the year, and use this as a proxy for *DT*. While *DT* is broader in scope, with protests being merely a single component of the *DT* index, in Table A.2 I observe a high correlation between *DT* and protest events.

Finally, I use data from the Integrated Crisis Early Warning System (ICEWS) database (Boschee, Lautenschlager, O'Brien, Shellman, Starz, 2015), which is an event data set similar to GDELT in structure, but smaller in size, recording approximately 15 million

[7] It is critical to note that, by definition, the Presidential Approval Rate and the *DT* index vary in their scopes and magnitudes. While the Presidential Approval Rate measures the *positive* public sentiment towards the *President*, *DT* measures *negative* public sentiments towards *any branch of the government*.

[8] In the WVS, I use the question, 'How much confidence do you have in the government?', which yields a set of hedonic answers, 'a great deal', 'quite a lot', 'not very much' or 'none at all'. In the Afrobarometer survey, I use the question, 'Do you approve or disapprove of the way the following people have performed their jobs over the past twelve months, or haven't you heard enough about them to say: President', where the answer can be 'strongly disapprove', 'disapprove', 'approve', or 'strongly approve'. Since my objective is to identify *negative* sentiments, I construct a variable equal to 1 if the respondent demonstrated negative attitudes towards the government, and zero otherwise.

events over the sample period. As with GDELT, ICEWS extracts event data from media articles in near real-time. It codes events to one of 300 events categories based on the CAMEO taxonomy, and also records an intensity score. Leveraging on this similarity, I generate an ICEWS-based indicator of *DT* using the same procedure described above. However, ICEWS does not provide the number of media articles that reported an event, which means that I cannot filter events reported in at least three media articles, as was done with GDELT. Nevertheless, in Table A.3, I observe that GDELT and ICEWS-based *DT* are positively and statistically significantly correlated.

These validation exercises highlight that the *DT* index is representative of existing, albeit imperfect, measures of public sentiments, and can be confidently applied for academic and policy making purposes in the absence of global data on domestic turmoil.

2.1.2 Quantifying governments' foreign interactions

Next, I generate outcome variables to capture the *nature* and the *frequency* of governments' international interactions. I again take a step-wise approach to extract events (a) initiated by a government, (b) targeted at foreign entities, and (c) appearing in at least three media reports. Next, I leverage on the 'quad class' classification provided by GDELT, where each event is assigned to one of four groups i.e., Verbal Cooperation (quad class 1), Material Cooperation (quad class 2), Verbal Conflict (quad class 3), and Material Conflict (quad class 4). I calculate quantitative measures on governments' foreign interactions using Equation (2),

$$FP_{iymQ} = \frac{Foreign_{iymQ}}{Foreign_{iym}} \tag{2}$$

where $Foreign_{iymQ}$ is the number of foreign interactions belonging to quad class Q initiated by the government in month m of year y, and $Foreign_{iym}$ is the *total* number of foreign interactions initiated by the government. Consistent with *DT*, the outcome variables are also standardized indicators that capture the relative change in governments' foreign interactions belonging to a particular quad class vis á vis other quad classes.[9]

[9]Information on the quad class categorization for each event type is available in Table A.1. In Figure

Next, I examine the validity of these FP indicators against alternative data sets. This is, however, a challenging exercise because almost all existing data sets on international interactions focus on either material aggression or material cooperation. Verbal aggression and verbal cooperation, to the best of my knowledge, have no quantitative representation in the empirical data domain. Indeed, one of the key contributions of this paper is to fill this void by introducing quantified indicators of such behaviors based on high–frequency event data.

Therefore, in the first validation exercise I focus only on material cooperation and material conflict. I use bilateral data on development assistance from the AidData database (Tierney et al., 2011) as a proxy for material cooperation. Data on bilateral sanctions, obtained from the Global Sanctions Database (Felbermayr, Kirilakha, Syropoulos, Yalcin and Yotov, 2020) act as a proxy for material conflict.[10] Country-year level correlations plotted in Figure A.8 demonstrate a strong positive correlation, both between the volume of aid disseminated by a country and its $Mat\ Coop$ index (Panel (a)), and between the imposition of sanctions and a country's $Mat\ Conf$ index (Panel (b)). In Table A.4 I examine these correlations at the dyad-year level, using the dyadic share of aid disseminated (Column (1)) and a binary indicator on intra-dyad imposition of sanctions (Column (2)). I observe that the strong positively correlations hold at the dyad level as well.

As a final test, I generate FP indicators using the ICEWS data set, using the same process described above, in relation to GDELT. In Table A.3, I observe that GDELT and ICEWS-based indicators on governments' foreign interactions are positively and statistically significantly correlated. Taken together, these examinations provide confidence that the quantified indicators of foreign interactions are representative of existing alternative data sets.

A.7 I present the event composition of the four FP categories, for each country.

[10] However, it should be borne in mind that the foreign interaction categories $Mat\ Coop$ and $Mat\ Conf$ are an aggregation of a variety of event types and aid and sanctions are merely a single component of these broad categories.

2.2 Football data

Data on football matches, both competitive and friendly, and their outcomes, are retrieved from the official website of the International Federation of Association Football (FIFA) as well as the six regional confederations associated with FIFA.[11] I collect data on approximately 15,000 football matches played over the period 1997–2014, including information on the date, location, opponent, scores and outcome (win/ loss/ draw) of each match.

Inspired by Edmans, García and Norli (2007), I identify 'unpredictable' matches based on the performance ratings of the opponents. Using annual rating scores extracted from World Football Elo Ratings system, the world's leading football ranking system, I calculate the rating differential between teams for each match. I identify 'unpredictable' matches as those played between teams with similar rating scores, i.e., where the rating differential between opponents is less than 150 points.[12] I then define variables to capture the occurrence and outcomes of football matches. Accordingly, $Football\ Match_{iym}$ is a count variable of the 'unpredictable' football matches played by country i in month m of year y. $Football\ Loss_{iym}$ and $Football\ Win_{iym}$ are count variables that capture outcomes of such 'unpredictable' matches.

2.3 Other data

Data from the Polity IV project (Marshall, Gurr and Jaggers, 2019) are used to generate time-invariant binary indicators that classify countries as democracies, autocracies and anocracies. Countries with an average polity score ≥ 6 (≤ -6) over the sample period are identified as democracies (autocracies). A country with a score between 5 and –5 is classified as an anocracy.

[11] That is, the Asian Football Confederation (AFC); Confederation of African Football (CAF); Union of European Football Associations (UEFA); Confederation of North, Central American and Caribbean Association Football (CONCACAF); Oceania Football Confederation (OFC); and South American Football Confederation (CONMEBOL).

[12] The rating differential between the top five teams over the sample period is approximately 110 points, while the it is 190 between the top ten teams. Based on these estimates, I use a rating difference of 150 points between opposing teams to define a match as a 'close' match. Edmans, García and Norli (2007) use a rating differential of 125 points, in line with the observation that at the time of the exercise, the rating difference between the top-ranked and $10th$ ranked country is 122 points. In Table B.5, I show robustness to multiple alternative rating differences.

I use World Bank data on country income classifications (Fantom and Serajuddin, 2016) to group countries based on income. Data on the Human Development Index (HDI), an annual country-level index based on life expectancy at birth, average years of schooling and per capita Gross National Income, is from the United Nations Development Programme (UNDP). I source global data on elections from the Constituency-Level Elections Archive (CLEA).

Data on historical conflict and trade between countries, as well as on population, national capability and military expenditure, are obtained from the Correlates of War Project (Barbieri and Keshk, 2016; Singer, 1987). I extract data from the the GeoDist database to identify the geodesic distance between two countries, and whether they belong to the same continent, or share a common language/common colonizer. I use data on genetic distance as estimated by Spolaore and Wacziarg (2016), as well as data on linguistic and religious distance provided by Spolaore and Wacziarg (2016), who in turn rely on estimations by Fearon (2003) and Mecham, Fearon and Laitin (2006), respectively.

3 Empirical framework

3.1 Baseline specification

I estimate the following relationship between domestic turmoil and governments' foreign interactions.

$$FP_{iym} = \alpha DT_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \tag{3}$$

Here, i, y and m refer to country, year and month, respectively. The dependent variable FP_{iym} is the standardized indicator of governments' foreign interactions, i.e. Verbal Cooperation, Material Cooperation, Verbal Conflict and Material Conflict, as developed in Equation (2). The independent variable DT_{iym} is the standardized indicator of domestic turmoil in Equation (1). $\mathbf{FE_{iy}}$ is a vector of country $\times$ year fixed effects, which accounts for time-variant unobservables in a given country in a given year, as well as

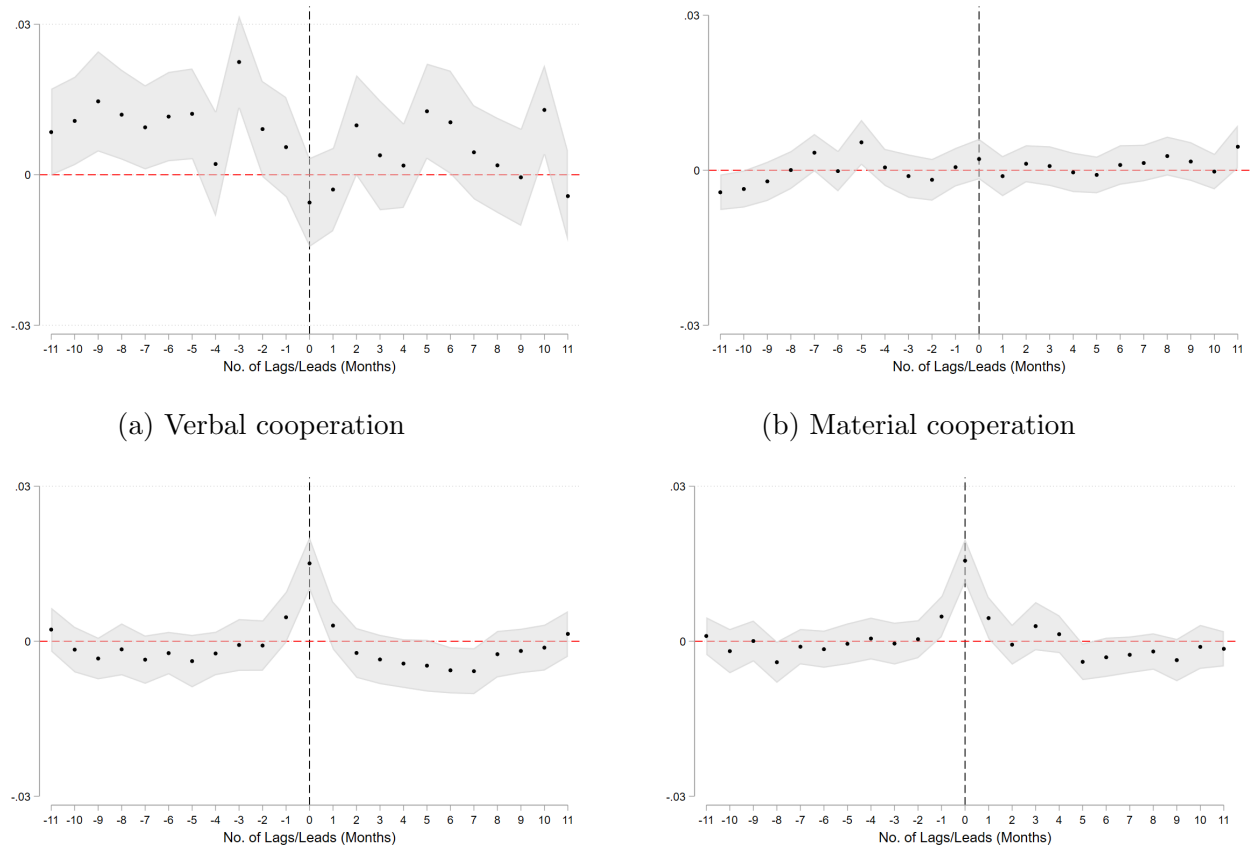
time-invariant country-specific features. $\mathbf{FE_m}$ is a vector of month–of–the–year fixed effects, and accounts for unobserved seasonal variation. The identification strategy therefore exploits the within-country-year variation in DT and FP, while conditioning for seasonalities.

The coefficient of interest, α, is the estimated effect of domestic turmoil on governments' foreign interactions. Since governments are faced with a spectrum of substitutable foreign interactions ranging from extreme cooperation to extreme aggression, α captures governments' propensity to choose a particular interaction over the alternatives. Accordingly, $\alpha > 0$ (< 0) for a given FP category indicates that, when domestic turmoil is high, governments are more (less) likely to choose foreign interactions belonging to this category.

Figure 1 plots the simple OLS relationship between the four FP categories and DT, including 11 monthly lags and leads. In Panels (a) and (b) of Figure 1, there appears no consistent pattern in the relationship between *cooperative* foreign interactions, both verbal and material, and DT. The statistically significant leads in Panel (a), which suggest that governments engage in more benevolent interactions in anticipation of domestic turmoil, become statistically insignificant closer to the month of interest, and no obvious pattern is discernible thereon. Interestingly, in Panels (c) and (d) there is a striking positive, short term relationship between domestic turmoil and aggressive foreign interactions, both verbal and material. This suggests that governments' are more likely to choose aggressive foreign interactions when domestic turmoil is high.

Despite the fine temporal granularity of the data and the large set of fixed effects however, these OLS estimates likely suffer from endogeneity concerns. For instance, governments' foreign interactions could affect the level of domestic turmoil, leading to reverse causality. There may also exist unobservable factors, unaccounted for by the extensive set of fixed effects, that simultaneously affect domestic turmoil and foreign interactions. Therefore, in the ensuing section I employ an alternative estimation strategy to causally infer this relationship between domestic turmoil and governments' foreign interactions.

Figure 1: Foreign interactions and *DT* over time - OLS estimates



(a) Verbal cooperation

(b) Material cooperation

(c) Verbal conflict

(d) Material conflict

Note: Figure shows the OLS correlations between governments' foreign interactions and *Domestic Turmoil* (*DT*) as per Equation 3, and additionally includes 11 monthly lags ($t > 0$) and leads ($t < 0$). All specifications include country×year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Shaded area indicates 90% confidence intervals.

3.2 Instrumental variable

To address concerns of endogeneity in the OLS estimates, I propose an IV strategy that leverages on outcomes of sporting events, particularly football matches, as public sentiment shocks that affect the level of domestic turmoil.

As a starting point, in Figure B.1 I examine the effects of a range of potential football outcomes, based on their expected/unexpected nature, on domestic turmoil. I identify unexpected football outcomes, i.e. where the outcome is reasonably unpredictable since both teams display similar levels of competence, as displaying a statistically significant effect on domestic turmoil. Specifically, unexpected losses have a strong positive impact

on domestic turmoil, while unexpected wins have a complementary negative impact. The absolute magnitude of the effect of unexpected wins is smaller than that of unexpected losses, signalling loss aversive behavior on the part of the public. I do not find an effect of expected losses/wins against weak opponents on domestic turmoil, potentially because these outcomes are, *ex-ante*, incorporated to the public's decision-making process by virtue of their predictability. Interestingly, I do not find statistically significant effects from unexpected losses against weak opponents or unexpected wins against strong opponents, despite their unpredictable nature, potentially due to the relative rarity of such outcomes in the data set, where less than 3% of the outcomes belong to this category.

With this understanding of the effects of football outcomes on public sentiments, and driven by the objective of quantifying *negative* public sentiments against the government, within my IV strategy, I use "unpredictable football losses" as an arguably exogenous shock that affects domestic turmoil. Accordingly, the first–stage is defined as follows.

$$DT_{iym} = \beta SL_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \tag{4}$$

The IV, SL_{iym}, is a count variable of the (men's) international football losses recorded by a country in a given month of a given year. The coefficient β captures the effect of football losses on domestic turmoil. I expect $\beta > 0$, indicating that football losses would lead to increased domestic turmoil.

3.2.1 Relevance of the IV

For the IV to be relevant, it is critical that football outcomes have a direct and significant impact on public sentiments. Football is the world's most popular sport (Nielsen, 2018), and the academic literature has established that football outcomes affect sentiments, both at the individual level and for the public at large (Edmans, García and Norli, 2007; Card and Dahl, 2011; Ge, 2018). Closely related to my work, Depetris-Chauvín, Durante and Campante (2020) find that football wins lead to the emergence of the national identity in Africa, while Bertoli (2017) suggests that the increased level of nationalism following football wins induces governments to behave aggressively on the international front.

This growing body of academic literature is supplemented by ample anecdotal evidence on this widespread interest in football influencing public sentiment, and shaping societies as well as government behavior. Perhaps the most important example comes from the 1954 FIFA World Cup Final, famously known as the 'miracle of Bern', where West Germany beat the heavily favoured Hungarian team. For Germans, this win led to the re-ignition of national pride and the creation of a collective identity (Foster, 2003), while for Hungarians, the loss led to widespread discontent in the run-up to the Hungarian Revolution.[13] Another example comes from the football war of 1969, where tensions between fans of El Salvador and Honduras following a FIFA World Cup qualifier led to the breakout of war between the two countries.[14]

Specifically related to the current context, many real-life examples portray that football losses have prompted domestic turmoil and aggressive diversionary tactics by national leaders. Famously, when faced with economic and political turmoil in the aftermath of the football loss to Algeria in 2009, Egyptian President Hosni Mubarak diverted the public's attention using aggressive foreign interactions that even involved recalling its ambassador from Algiers.[15] Another example is when the former Venezuelan president Hugo Chavez, amidst the country's inability to qualify for the FIFA World Cup in 2010, and domestic turmoil aggravated by hyperinflation, shortage of essential food items and crime, diverted the attention towards the US. Ironically, his diversionary tactic was to accuse the US military of diversionary military strikes while the global attention was focused on the progressing World Cup.[16] Infamously, anti-government protests erupted in Bolivia just days after the national football team's humiliating loss to Ecuador in the World Cup qualifiers in 2008. This was followed by diplomatic tensions targeted at the US, with Bolivian

[13] See, for example, www.thehardtackle.com, "The miracle of Bern: A game that changed Germany and Hungary forever," October 11, 2012.

[14] More recently, Iraq's win of the AFC Asian Cup in 2007 is widely believed to have unified the country despite many domestic political issues ranging from ethnic factionalism to invasion by the US military. (See *Reuters*, "Iraq's Asian Cup win transcends sports," July 30, 2007.) Related, but in a different sport, South Africa's win at the 1995 Rugby World Cup is cited as the 'game that made the nation' (Carlin, 2008), uniting a heavily fragmented nation just recovering from the end of apartheid.

[15] See, for example, *Voice of America News*, "Aftermath of Egyptian Football Loss to Algeria Raises Tensions," November 20, 2009. See also, *Time*, "The Political Fallout of Egypt's Soccer War," November 22, 2009.

[16] *Sydney Morning Herald*, "Chavez Accuses US of Military Moves during World Cup," June 26, 2010.

president Evo Morales ordering the US ambassador to leave the country.[17] These anecdotal examples portray football outcomes as important determinants of domestic turmoil, which in turn prompt diversionary strategies by governments, and thereby support the relevance of football losses as an IV within the current setting.

The relevance of the IV also relies heavily on the unpredictable nature of the football outcome. Where an extremely strong team plays against an extremely weak team, the public may have a fairly confident and accurate prediction of the outcome. It is, however, more difficult to predict the outcome in matches played against teams exhibiting similar levels of performance. Therefore, inspired by Edmans, García and Norli (2007), my empirical strategy focuses purely on 'unpredictable' football losses, i.e. losses in matches played between teams exhibiting a similar level of performance, where the rating differential between the teams is less than 150 points as per World Football Eloratings.[18] I also address the concern that football losses, as a sentiment shock, may only be relevant in countries with extraordinary levels of football popularity, by excluding such countries from the sample, as further discussed in Section 3.4.

3.2.2 Validity of the IV

The identification strategy rests on the assumption that sports outcomes affect governments' foreign interactions (FP_{iym}) only through domestic turmoil (DT_{iym}). I implement numerous measures to mitigate the risk that the exclusion restriction is violated. First, I include a comprehensive set of country $\times$ year fixed effects, which absorbs all time-invariant characteristics at the country level, as well as time-variant factors that might simultaneously affect football losses and domestic turmoil. Moreover, any seasonal unobservables are captured by the vector of month fixed effects.

Since the specific dates of football matches are predetermined, a threat to the exclusion restriction arises if governments manipulate such timings to engage in unpopular foreign interactions. To account for this concern, I revise the first and second–stage specifications

[17] *Reuters*, "Bolivia Tells U.S. Ambassador to Leave, Protests Mount," September 11, 2008.

[18] The cutoff of 150 points is inspired by the methodology employed by Edmans, García and Norli (2007). Please see Section 2.2 for more details. I also show robustness across alternative rating differentials in Table B.5.

as below.

$$DT_{iym} = \beta SL_{iym} + \gamma SM_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \tag{5}$$

$$FP_{iym} = \alpha DT_{iym} + \gamma SM_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \tag{6}$$

In the first–stage in Equation (5), the coefficient β now captures the direct effect of unpredictable occurrence of the *Football Loss* (SL_{iym}) on domestic turmoil, conditional on the predetermined *Football Match* (SM_{iym}) effect. The same control, SM_{iym}, is added to the second–stage in Equation (6), to maintain consistency.

Another concern on the exclusion restriction is whether domestic turmoil in the period leading up to a match can affect the performance of the national football team. To address this concern, I leverage on the high-frequency variation in *DT* and develop a country-week level panel, which allows me to examine whether *DT* in the pre-match weeks predict the probability of the *Football Loss*. As demonstrated in Figure B.4, I do not find any evidence of pre-match *DT*, up to 10 weeks prior, having such an effect.

Can football losses have a direct impact on the behavior of the government, for example by spurring nationalistic sentiments? In Table B.3 I do not find any evidence that *Government Unity* is affected by unpredictable football losses, thereby strengthening the exclusion restriction.[19] Finally, I acknowledge that a threat to the exclusion restriction arises if football losses directly influence governments to systematically interact with football opponents. To address this concern, in Table B.9 I exclude all government interactions directed at football opponents, and find that the results remain qualitatively and quantitatively similar.

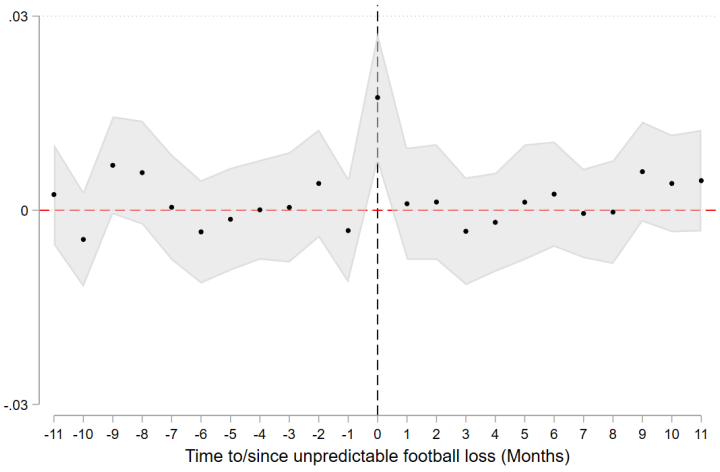
By virtue of the IV strategy implemented, these estimates represent the local average treatment effect (LATE), as per Imbens and Angrist (1994). Accordingly, compliers in this context are country-month observations that recorded an increase in *DT* following a

[19] *Government Unity* is calculated following the methodology used in 2.1.1, and restricting to 'within-government interactions' i.e., interactions where both the "target" and "source" are identified as domestic government actors.

football loss.[20] Football losses may have very particular effects on domestic turmoil and these effects may vary systematically from other potential sentiment shocks. This caveat should be borne in mind when drawing general conclusions using these estimates.

Before proceeding to the baseline estimates, Figure 2 provides a first look at the first–stage estimates, plotting the effect of SL_{iym} on DT_{iym} as per Equation 5, and leveraging on the temporal granularity of the data set by including 11 monthly lags and leads. I observe that unpredictable football losses have an immediate, positive and statistically significant effect on DT and that this effect is only visible in the contemporary period.[21]

Figure 2: Effect of unpredictable football losses on DT over time



Note: Figure shows the effect of unpredictable football losses on DT as per Equation 5, including 11 monthly leads ($t < 0$) and lags ($t > 0$). Additional controls include country× year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Grey area indicates 90% confidence intervals.

3.3 Baseline results

Table 1 presents the baseline results exploring the relationship between DT and governments' foreign interactions. Here, the dependent variables are the four categories of governments' foreign interactions – verbal cooperation (Columns 1 and 2), material cooperation (Columns 3 and 4), verbal conflict (Columns 5 and 6) and material conflict

[20]Figure B.5 provides the profiles of compliers and non-compliers in relation to key variables, i.e. *Domestic Turmoil*, income, population, polity score and military expenditure. This exercise is conducted as per Marbach and Hangartner (2020).

[21]In Figure B.2 I present the equivalent estimates for unpredictable football wins.

(Columns 7 and 8). For each dependent variable I report two specifications with different sets of fixed effects – odd-numbered columns present estimates with country and year fixed effects separately, while my preferred specifications, including country×year fixed effects, appear in even-numbered columns.[22]

Table 1: Baseline estimates: Effect of domestic turmoil on governments' foreign interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Verb\ Coop_{iym}$		$Mat\ Coop_{iym}$		$Verb\ Conf_{iym}$		$Mat\ Conf_{iym}$	
Panel A: OLS Estimates								
$Domestic\ Turmoil_{iym}$	-0.0151**	-0.0133***	0.0040*	0.0005	0.0249***	0.0168***	0.0214***	0.0154***
	(0.0063)	(0.0043)	(0.0021)	(0.0020)	(0.0028)	(0.0026)	(0.0022)	(0.0023)
Panel B: Reduced Form Estimates								
$Football\ Loss_{iym}$	-0.0021	-0.0008	-0.0002	-0.0003	0.0046**	0.0048**	0.0006	-0.0007
	(0.0043)	(0.0041)	(0.0016)	(0.0017)	(0.0020)	(0.0020)	(0.0015)	(0.0017)
Panel C: IV Estimates								
$Domestic\ Turmoil_{iym}$	-0.1296	-0.0424	-0.0095	-0.0158	0.2833*	0.2632**	0.0379	-0.0369
	(0.2691)	(0.2233)	(0.0971)	(0.0912)	(0.1449)	(0.1262)	(0.0937)	(0.0910)
				$Domestic\ Turmoil_{iym}$				
Panel D: First–Stage Estimates								
$Football\ Loss_{iym}$	0.0164***	0.0182***	0.0164***	0.0182***	0.0164***	0.0182***	0.0164***	0.0182***
	(0.0051)	(0.0050)	(0.0051)	(0.0050)	(0.0051)	(0.0050)	(0.0051)	(0.0050)
Kleibergen-Paap F-statistic	10.16	13.12	10.16	13.12	10.16	13.12	10.16	13.12
Controls:								
Country FE	YES	NO	YES	NO	YES	NO	YES	NO
Year FE	YES	NO	YES	NO	YES	NO	YES	NO
Country-Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Football Match	YES	YES	YES	YES	YES	YES	YES	YES
No. of observations	41,040	41,040	41,040	41,040	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190	190	190	190	190
Maximum Goldstein Score	-5	-5	-5	-5	-5	-5	-5	-5

Notes: The dependent variables in Panels A, B and C are foreign interactions initiated by a country's government, classified as $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$, expressed as a fraction of the total number of foreign interactions initiated. $Domestic\ Turmoil$ expresses all domestic events targeting the government that record a Goldstein score of -5 or less, as a fraction of all domestic events targeting the government. $Football\ Loss$ is the count of all football losses experienced by a country against an opponent with a rating differential of 150 points or less. Columns (1), (3), (5) and (7) include country and year fixed effects separately, while Columns (2), (4), (6) and (8) include country× year fixed effects. Both stages additionally control for month fixed effects, as well as $Football\ Match$, which is the number of close football matches played by the country over the period. The mean (standard deviation) of $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$ are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of $Domestic\ Turmoil$ is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

OLS estimates of equation (6) are presented in Panel A of Table 1. In Columns 1 and 2, I observe that domestic turmoil is negatively correlated with verbally cooperative foreign interactions initiated by governments. The positive correlation between domestic

[22]These results are robust to the inclusion of a range of alternative sets of fixed effects, as demonstrated in Figure B.6.

turmoil and materially cooperative foreign interactions in Column 3 disappears when country×year fixed effects are included (Column 4). Interestingly, and in line with the graphical illustration in Figure 1, in Columns 5–8 I observe a strong positive correlation between domestic turmoil and governments' aggressive foreign interactions, both verbal and material.

In Panel B I present the reduced form estimates. Observe that football losses have a positive and statistically significant effect on governments' verbally aggressive foreign interactions, and this relationship holds when controlling for country× year fixed effects as well. I do not observe an effect of football losses on the other three categories of foreign interactions initiated by governments.

First–stage estimates are presented in Panel D. I observe a strong positive relationship between unpredictable football losses and domestic turmoil, which reconfirms my proposition that football losses play an important role in shaping public sentiments towards their governments. In a context where the existing literature has thus far focused on the effects of football *wins* in shaping *positive* public sentiments, this result establishes the complementary relationship that football *losses* shape *negative* public sentiments.

Finally, in Panel C of Table 1, I present the second–stage estimates. Once instrumented via football losses, I observe a statistically significant effect of domestic turmoil on 'verbally' aggressive diversionary foreign interactions, with the coefficient in Column (6) indicating that a one standard deviation increase in domestic turmoil leads to a sizable 8 percentage point increase in verbal conflict.[23] Simultaneously, I do not observe a statistically significant effect of domestic turmoil on cooperative foreign interactions, verbal/ material (Columns 1-4 in Panel C), or on materially aggressive diversionary interactions, although the coefficients remain economically significant in line with the OLS estimates.

Taken together, these findings add interesting insights to our knowledge on diversion-

[23]I observe that OLS estimates are mostly biased towards zero, suggesting they underestimate the effect of DT on FP. Consider, for example, a situation where high DT leads governments to engage in aggressive foreign interactions, and they in turn face a backlash from the international community. Such backlash could, on one hand, induce the government to reduce its aggressive behaviour, leading to a reduction in FP. On the other hand, such foreign adversity could also induce the public to rally 'round the government, resulting in a reduction in DT. Where these back-and-forth effects materialize within a short time frame (within days or weeks), they would not be absorbed by the set of fixed effects. In both these situations therefore, OLS estimator will underestimate the true causal effect of DT on FP.

ary foreign policy. First, they provide causal evidence that diversionary interactions are systematically exercised, not just by a single country, but by governments across the globe, to strategically divert domestic turmoil. Second, these results redefine our understanding of diversionary foreign policy as purely involving war, arms, militants and death. Instead, I show that diversionary tactics are systematically practised using subtle, verbally aggressive foreign interactions as well. In the increasingly inter-connected international system, waging a fully-fledged international war involves non-trivial costs and risks. By contrast, verbally aggressive foreign interactions, such as a statement criticizing a foreign entity or a verbal demand made in a political speech, involve lower costs and risks, and are exercised with greater ease.[24] This fresh evidence on diversionary strategies, based on hitherto ignored subtle international interactions, therefore provides a new perspective on the use and nature of diversionary interactions in international relations.

3.3.1 Validating baseline results using alternative datasets

Now I validate the baseline results using two alternative data sets. First, I use the ICEWS event data set, which is similar in structure to GDELT, to generate indicators of DT and governments' foreign interactions, using the same process followed in Sections 2.1.1 and 2.1.2. However, no filtering is conducted based on the number of media articles reporting an event, due to the unavailability of this information in ICEWS. Second, I generate a count indicator of protests against the government using the Mass Mobilization project data. I then re-estimate the baseline specifications using these alternative indicators, and the results are presented in Figure 3.[25]

Panel (a) shows the baseline IV estimates using GDELT, as provided in Table 1. In Panel (b), I present estimates using ICEWS-based DT and FP indicators. I observe the same pattern as with the GDELT-based estimates, with strong evidence to suggest that governments engage in verbally aggressive foreign interactions when DT is high. The coefficient of interest is slightly higher than in the GDELT estimates, potentially attributable

[24] Interestingly, Panel (b) in Figure A.1 indicates that diversionary interactions increase with DT, suggesting they do not substitute other interactions, but are additional interactions on top the average levels of engagement.

[25] These estimates are presented in tabular format in Table B.2.

to the differences in the sizes of the two data sets (GDELT records approximately 120 million events, compared to 15 million events reported in ICEWS), as well as the unfiltered nature of the ICEWS data.[26] In Panels (c) and (d) I use protest data as a proxy for DT, combined with outcome variables generated via GDELT (Panel (c)) and ICEWS (Panel (d)), and reconfirm the baseline relationship in spite of protests being narrower in scope than DT. These findings therefore confirm that the baseline relationship holds across alternative data sets as well.

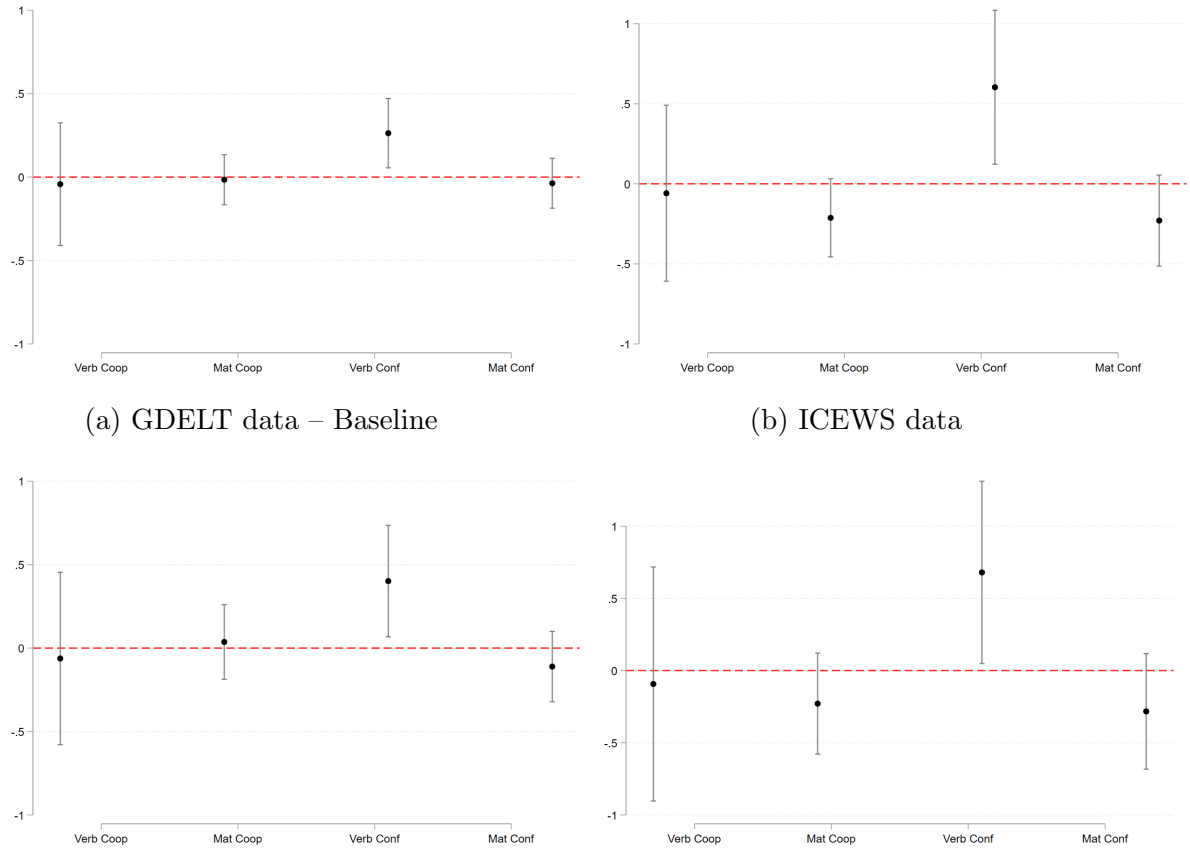
3.4 Robustness checks

I now present a number of robustness checks.

First, I focus on the robustness of the IV. In Table B.4, I consider alternative forms of the IV, i.e., inverse hyperbolic sine (IHS)–transformed count (Column (2)) and binary indicator (Column (3)) of football losses. Results are reflective of the baseline estimates (Column (1)), although in Column (3) the first–stage estimates are weaker, potentially because a binary indicator lacks the rich variation of a count variable. In Figures B.2 and B.1, I consider the effects of a range of other football outcomes, based on their expected and unexpected nature. I check the robustness of the baseline results to alternative definitions of an 'unpredictable' football loss in Table B.5. In Figure B.3 I examine the effects of competitive and friendly football matches within a single "horse race" specification, and observe a positive and statistically significant impact on DT only from competitive matches. Finally, I confirm the rationale underlying the first stage using survey data in Table B.6. I observe that individuals interviewed in the 30 days after a football loss are more likely to report negative sentiments towards their governments, compared to those interviewed 30 days prior.

[26] Specifically, the massive number of events in GDELT may potentially introduce measurement error due to the erroneous inclusion of irrelevant events, which can bias the estimates downwards. In ICEWS, the inability to filter by number of reports means that duplicate/uncorroborated events are included, which can bias the estimates upwards. Although my empirical strategy already accounts for these *within* each data set by (a) taking ratios of key variables, (b) applying a comprehensive set of fixed effects and (c) the use of an IV, these differences become pertinent when comparing the IV estimates between the two data sets.

Figure 3: Validation of baseline estimates using alternative data sets



(a) GDELT data – Baseline

(b) ICEWS data

(c) GDELT and protest data

(d) ICEWS and protest data

Note: Figure shows second stage estimates as per Equation 6. Panel (a) presents the GDELT-based baseline estimates. In Panel (b), the dependent and independent variables are based on ICEWS. In Panels (c) and (d), the independent variable is the IHS-transformed count of protests from the Mass Mobilization project, while the dependent variables are from GDELT and ICEWS, respectively. First stage KP F–statistics for Panels (a), (b), (c) and (d) are 13.12, 12.30, 10.04 and 10.04, respectively. No. of countries in Panels (a), (b), (c) and (d) are 190, 181, 130 and 130, respectively. Sample size is limited by data availability. All specifications include country× year fixed effects and month fixed effects. The unit of measurement is a country-month. Vertical lines indicate 90% confidence intervals, based on standard errors clustered at the country level.

In the more general robustness checks, Table B.7 presents estimates based on alternative Goldstein scale thresholds defining domestic turmoil (see Eq 1), based on Goldstein score cutoffs of –3, –4, –5, –6 and –7. In Figure B.6 I examine the robustness of baseline estimates to alternative sets of fixed effects. In Table B.8 I control for the total number of events reported in the period, to address any concerns that the changing nature of the universe of news can affect the estimates.

Figure B.7 provides a number of robustness checks on the sample of countries. In Panel (a), I exclude all 'small' countries i.e., those with a population below 500,000. In

Panel (b), I exclude all OECD countries. Results remain qualitatively and quantitatively similar. Next I address the potential concern that football losses may only be a sentiment shock in countries with high football popularity. This is a minute concern considering that, by virtue of the country×year set of fixed effects, the identification strategy exploits the *within*-country variation in football outcomes on DT, as opposed to the variation *between* countries. Nevertheless, in Panels (c) and (d) I exclude countries that ever played a world cup and top 20 countries in terms of football popularity (Nielsen, 2018), respectively, and confirm that the estimates are not driven by a selected set of countries.[27] I further confirm that the results are not driven by a single country or a country×year, by re-estimating the baseline specification excluding one country at a time (Figure B.8) and excluding one country×year at a time (Figure B.9). In Table B.9, I exclude foreign interactions with football opponents and find that the baseline results remain robust.

Next, in Table B.10, I re-estimate the baseline specification while including the lagged dependent variable (LDV) to capture potential trends in government behaviour. Interestingly, I observe that the magnitude of the baseline estimates slightly increase once the LDV is included (Column (6)) and that the coefficient on $Verb\ Conf_{iym-1}$ is negative. A simple comparison of the point estimates indicates that the negative effect of $Verb\ Conf_{iym-1}$ on $Verb\ Conf_{iym}$ is completely offset by the positive effect from DT_{iym}. This suggests that although governments are not consistently aggressive in international interactions, they do resort to aggression when faced with domestic turmoil.

An additional concern is whether these verbal aggressions were triggered by other countries' behavior towards the country of interest, instead of through domestic turmoil.

[27] Although these two robustness checks exclude many countries where football is extremely popular, there still remain a large number of countries for whom football can matter. For example, football is extremely popular in almost all African countries. According to The World Football Report (Nielsen, 2014), 76% of Africans reported as being interested in football, against a global average of 46%. However, no African country make it to the top 20 list, and only nine countries have ever qualified for a world cup. Moreover, the top twenty countries in football popularity only includes 3 South American countries, i.e., Chile, Mexico and Brazil. However, football is the most popular sport in almost every South American country, with 69% of the South American population reporting their interest in football (Nielsen, 2014). Three Asian countries that make it to the top twenty list in football popularity (i.e. Thailand, Malaysia and Singapore) and are therefore excluded from the sample in Panel (d), have never played a football world cup, and are therefore included in the sample in Panel (c). Football is very popular in Singapore, and is its national sport, despite the country never having played a world cup. Most team that never qualified for a world cup remain highly engaged in regional tournaments.

To address this concern, I generate an indicator of all interactions targeting country i that were initiated by country j. In Table B.11 I observe that the results remain robust when an aggregation of this indicator across all countries j is included as a control variable. Next, I go a step further and generate a dyadic data set that allows me to additionally control for dyad×year fixed effects, absorbing pre-existing time-invariant and time-variant dyadic relationships. Table B.12 shows that the results remain robust.

It may be possible that governments engage in diversionary interactions domestically, for example by strategically releasing policy announcements during periods of domestic turmoil. To explore this perspective, I follow the procedure developed in Section 2.1.1 to generate indicators of the government's *domestic* interactions (i.e. interactions initiated by the government, targeted at domestic actors, and occurring domestically). In Table B.13, I re-estimate the baseline specifications using these as the outcome variables. Although OLS estimates suggest that governments become more aggressive and less cooperative (Panel A) towards domestic actors during periods of domestic turmoil, I do not observe this relationship in the reduced form (Panel B) or IV estimates (Panel C).

Finally, in Table B.14, I employ an alternative identification strategy inspired by Manacorda and Tesei (2020), where public sentiments towards governments are identified as being influenced by mobile phone coverage, and its interaction with GDP cycles. I implement this identification strategy within a 3SLS setting.[28] I first predict mobile phone coverage and its interaction with GDP cycles using lightning strikes (Columns (3) and (4)), which are in turn used in the second stage to predict DT. In the third stage (Column (1)), I then examine effects of DT lead on foreign interactions. I observe that increased DT leads to a decline in verbally cooperative foreign interactions (Panel A), while verbally and materially aggressive foreign interactions increase (Panels C and D). Accordingly, under this estimation strategy too, I confirm the baseline finding that with increased DT, governments engage in aggressive diversionary foreign interactions. In fact, these estimates further suggest that such aggression may even take a more material form.

[28] This robustness check is only conducted for 47 African countries used in Manacorda and Tesei (2020). Due to the nature of available data, this test is conducted at the country-year level, over the years 1998–2012.

3.5 Heterogeneous effects

Now I examine whether the effects of domestic turmoil on diversionary foreign policy are heterogenous across different contexts. Arguably, causal identification of heterogenous effects within an IV setting is empirically challenging, due to the requirement of strong IVs for the multiple endogenous regressors (Sanderson and Windmeijer, 2016). Nevertheless, in the ensuing section I report such estimates, while cautioning of potential bias due to weak instruments. Accordingly, the second stage is redefined as;

$$FP_{iym} = \alpha_1 DT_{iym} + \alpha_2 (DT_{iym} \times C_i) + \gamma SM_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_m} + \epsilon_{iym} \tag{7}$$

where C_i is an indicator of time-invariant, country-specific characteristics. I then instrument for DT_{iym} and $DT_{iym} \times C_i$ using SL_{iym} and $SL_{iym} \times C_i$, with the first–stage being revised as follows.

$$DT_{iym} = \beta_1 SL_{iym} + \beta_2 (SL_{iym} \times C_i) + \gamma SM_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_m} + \epsilon_{iym} \tag{8}$$

The other first-stage equation, which is for the interaction term $DT_{iym} \times C_i$, is identical to equation 8 but with $DT_{iym} \times C_i$ as the dependent variable. Since C_i is time-invariant and country specific, it is already absorbed by the vector of country$\times$ year fixed effects, and therefore does not by itself enter the specification.

I first focus on the nature of political institutions, using the average polity score over the sample period to generate time-invariant binary indicators classifying countries as democracies (average polity score $\geq$ 6), autocracies (average polity score $\leq$ –6) and anocracies (average polity score 5 $\leq$ to $\geq$ -5). In Panel A of Table B.15, I observe that the effects are particularly manifested for anocracies. It seems plausible that anocratic regimes are more susceptible to the use of diversionary foreign policy where, in the absence of stable political institutions, governments attempt to keep the population diverted in the short run. It is also important to note that I do not observe any effects for autocracies where executive constraints are the lowest, suggesting that diversionary confrontations are

initiated as a strategic move instead of as an impulsive move.

In Panel B, I explore the heterogeneity of effects by country income levels. I generate a time-invariant binary variable $Income_i$, which is equal to 1 if a country was classified as a high/upper-middle income country in at least one year of the sample, and 0 otherwise. Effects are particularly prominent for low-income countries. In Panel C I observe that diversionary foreign interactions are prominently observed for countries with low levels of HDI. Overall, these results suggest that diversionary interactions are more prominently observed in developing countries with unstable political institutions.

Are diversionary tactics motivated by election cycles? In Panel D of Table B.15 I define a binary variable $Election_{iym}$ which is equal to 1 if the country experienced an election in the given month of the given year, and 0 otherwise. I find no evidence of diversionary foreign interactions being driven by election-related political agendas. Although somewhat counter-intuitive, this result is supported by Panel A in Table B.15 where no evidence of diversionary foreign policy is observed in democracies, where elections arguably assume greater importance compared to anocracies and autocracies.

4 Which countries are targeted?

To identify whether governments systematically choose the targets of diversionary foreign interactions, I first build a dyadic data set of monthly foreign interactions between countries i and j (FP_{ijym}). Combining this data set with dyadic connectivity indicators, Z_{ij}, I estimate the following equation to examine if diversionary foreign interactions diffuse along dyadic connectivity networks.

$$FP_{ijym} = \delta_1 DT_{iym} + \delta_2 DT_{iym} \times Z_{ij} + \gamma SM_{iym} + \mathbf{FE_{ijy}} + \mathbf{FE_m} + \epsilon_{ijym} \tag{9}$$

The outcome variable is the ratio of foreign interactions between country i and j in month m of year y, classified in terms of their cooperative/aggressive nature. The coefficient of interest, δ_2, captures the effect of DT on foreign interactions between countries i and j connected via the time-invariant connectivity measure Z. I include a vector of

dyad×year fixed effects, FE_{ijy}, that absorbs both time-invariant and time-variant dyad-specific unobservables. Any pre-existing time-invariant geographic, cultural or economic relationships between two countries is accordingly absorbed by this vector. It also absorbs time-varying unobservables such as the changing levels of dyadic tensions/affiliations between dyads. Since Z_{ij} is dyad-specific and time-invariant, it is also absorbed by this vector of dyad-year fixed effects and does not enter the specification separately. As with the baseline specification, month fixed effects absorb all seasonal unobservables.

Supplementing this second stage equation, the first stage now includes two separate equations;

$$DT_{iym} = \tau_1 SL_{iym} + \tau_2 SL_{iym} \times Z_{ij} + \gamma SM_{iym} + \mathbf{FE_{ijy}} + \mathbf{FE_m} + \epsilon_{ijym} \tag{10}$$

The other first-stage equation is identical to equation 10 but with $DT_{iym} \times Z_{ij}$ as the dependent variable.

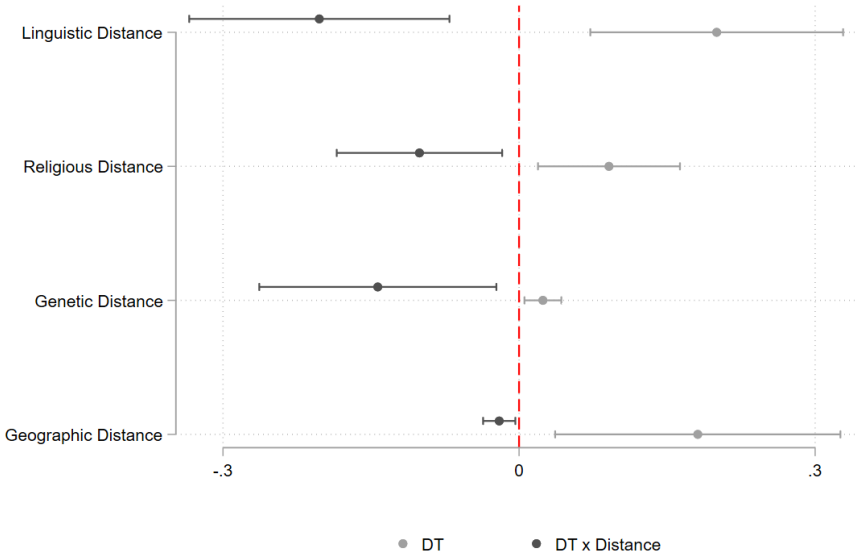
I first consider connectivity based on a range of distance measures between countries, i.e. geographic distance, as well as religious distance (Mecham, Fearon and Laitin, 2006), genetic distance (Spolaore and Wacziarg, 2016) and linguistic distance (Fearon, 2003). In Figure 4, I show the effect of these connectivity measures on verbally aggressive foreign interactions between country pairs, $Verb\ Conf_{ijym}$.[29] I observe that the effect of DT on verbally aggressive foreign interactions is decreasing in dyadic distance, across all four dimensions of distance. These effects are both statistically and economically significant.[30] Interestingly, these estimates suggest that governments' strategic diversionary tactics are particularly targeted at countries closer to their own, both geographically and culturally. This finding closely resonates with Spolaore and Wacziarg (2016) who document that closely related populations are more likely to enter in to disagreements due to their minimal heterogeneity in preferences over rival goods, government types or policies. Within the current context, targeting culturally similar and geographically closer countries might

[29] In Figure B.11, I present the estimation results for the three other types of foreign interactions, i.e. $Verb\ Coop_{ijym}$, $Mat\ Coop_{ijym}$ and $Mat\ Conf_{ijym}$.

[30] A one standard deviation increase in $DT_{ijym} \times Linguistic\ Distance_{ij}$ (0.3102), $DT_{ijym} \times Religious\ Distance_{ij}$ (0.2740), $DT_{ijym} \times Genetic\ Distance_{ij}$ (0.0434) and $DT_{ijym} \times Geographic\ Distance_{ij}$ (2.7373) is equivalent to a 6, 3, 1 and 5 percentage point decline in $Verb\ Conf_{ijym}$, respectively.

increase the effectiveness of diversionary tactics, as the public attention is more likely to be captivated when the aggression is targeted at a familiar, relatable country, as opposed to a country they are unfamiliar with. This finding also aligns with the estimates in Figure B.11 where I find that diversionary interactions are more likely to be targeted at countries sharing a common language or a common historical colonizer. Interestingly, I do not find evidence of target selection based on historical conflict. Alluding to the low-cost nature of these diversionary interactions, I also do not find evidence of important trade partners being targeted.

Figure 4: Target countries based on connectivity



Notes: Dots show the second–stage estimated coefficients of DT_{iym} and $DT_{iym} \times Z_{ij}$, with $Verb\,Conf_{ijym}$ as the dependent variable. Z_{ij} is an indicator of the distance between countries, along geographic, genetic, religious and linguistic dimensions. Each distance category represents a separate regression estimate. Geographic distance is log transformed. All specifications include dyad× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match$. The unit of measurement is a dyad-month. Horizontal lines show the 90% confidence interval based on standard errors clustered at the dyad level.

Finally, I examine whether specific characteristics of the target countries affect their selection in to the target group. I consider three key features of the target country, i.e., population, military expenditure, and the composite index of national capability (Singer, 1987) which expresses a country's relative level of material national capabilities in demographic, economic and military dimensions. As demonstrated in Columns (7)-(9)

of Table B.16, the effect of DT_{iym} on verbal aggression is declining in the target country's population, military power and national capability. This finding yet again illustrates the use of diversionary foreign policy as a low risk strategic tool, as weak countries are unlikely to respond with costly retaliations.

5 Domestic and international consequences

In this final step, I examine the consequences of diversionary foreign interactions. On the domestic front, policy makers would be interested in understanding whether these strategic actions serve the purpose of diverting the public's attention and, on the extreme, induce the public to rally around the flag. Complementarily on the international front, whether target countries retaliate is a key concern in determining the costs associated with diversionary interactions.

At the outset I acknowledge that causally identifying the consequences of diversionary interactions, within the current setting, is a challenging empirical exercise. In the simplest form, these consequences could potentially be examined via an OLS estimator, regressing the outcomes of interest in the next period, on governments' foreign interactions, as depicted in Equation 11 below.

$$Outcome_{iym+1} = \theta FP_{iym} + \gamma SM_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \tag{11}$$

However, such an estimation is likely plagued with endogeneity concerns – although reverse causality can be somewhat addressed by using a temporal lead of the outcome variable, there may still remain unobservables that simultaneously affect the predictors and outcomes. Indeed, the discussion in Section 3 is entirely focused on identifying and addressing such endogeneity concerns.

Within the latest literature, a similar exercise is conducted by Lewandowsky, Jetter and Ecker (2020), who examine the effectiveness of Donald Trump's diversionary tweets using a 3SLS estimator, which is considered a particularly suitable approach in situations where reciprocal causality is a possibility (Zellner and Theil, 1962). Inspired by this guid-

ance in the literature therefore, I employ a 3SLS estimator combining Equation (11) with the first and second stage equations in my IV strategy, i.e. Equations (5) and (6), respectively, as a system of simultaneous equations, to examine whether diversionary foreign interactions lead to domestic and international consequences. While fully acknowledging the need for further causal examinations, I nevertheless note that these estimates provide a first set of exploratory evidence in teasing out the policy implications of diversionary strategies.

I first examine the domestic consequences. One of the key objectives of diversionary strategies is to coerce citizens to rally around their common identity (Sobek, 2007). Therefore, I focus on whether public sentiments change following the exercise of diversionary strategies. For this purpose, I use indicators of DT and $Protests$ in the following month, $m + 1$, as outcome variables in Equation 11. I interpret a negative value on the coefficient of interest, θ, i.e. a reduction in $DT/Protests$, as a sign of the effectiveness of diversionary strategies. A positive or statistically insignificant coefficient would signal the ineffectiveness of these strategic interactions in serving the purpose of diversion.

Table B.17 demonstrates the results of this exercise. In Columns (1) and (2) I use the DT index developed in this paper as the outcome variable. Although OLS estimates show a positive and statistically significant increase in DT in the month following the use of verbally aggressive diversionary tactics, the effect is statistically insignificant in the 3SLS estimates presented in Column (2). In Columns (3) to (4) I use the index of DT developed using the ICEWS data set, while in Columns (5) and (6) I use data on protests from the Mass Mobilization project. Across all three data sets, I do not find statistically significant evidence that citizens respond to diversionary foreign interactions, suggesting that these strategic manipulations are ineffective in diverting domestic turmoil. This non-response also speak to the competence of citizens in assessing government behavior and persisting in their resistance, despite these strategic manipulations.

Next, I consider the international consequences, particularly examining if a response, peaceful or aggressive, can be observed from countries targeted by these diversionary interactions. For this purpose, I conduct the 3SLS exercise using the dyad-level data set

developed in Section 4. I first develop an indicator FP_{jiym+1} which captures the behaviour of target country j towards source country i, in the following month, and use this indicator as the outcome variable in the third stage of the 3SLS estimator.

In Table B.18, the OLS estimates indicate a positive and statistically significant relationship between verbal aggression by country i and all four categories of responses in the next period. However, as discussed, these estimates are likely to suffer from endogeneity concerns. Interestingly, in the 3SLS estimates, I do not observe a statistically significant response from targeted countries, across all four categories of foreign interactions, suggesting that target countries do not respond to these verbally aggressive diversionary interactions.[31] While mindful of the exploratory nature of this exercise, I note that these findings are in alignment with the other findings of this paper that verbally aggressive diversionary interactions, which involve low probability of retaliation, are exercised by governments as a low-cost, low-risk strategic tool. The absence of an international response also suggests that these domestically-driven, short-term verbal altercations are less likely to escalate in to persistent, large-scale conflicts.

6 Conclusion

This paper provides new and systematic evidence on how governments divert domestic turmoil. I first propose a novel indicator that quantifies domestic turmoil at a fine degree of temporal granularity, based on high–frequency data on approximately 120 million events recorded in global news media articles. I combine this index with quantitative indicators of governments' foreign interactions, based on their cooperative/aggressive nature and the degree of intensity. Using a monthly level panel data set for 190 countries from 1997–2014, and exploiting 'close' football losses as a negative public sentiment shock, I find that governments resort to diversionary tactics in times of domestic turmoil and that such diversion takes the form of verbal aggression.

[31] Despite their imprecise nature, I further observe that the coefficients on verbally and materially cooperative interactions (Columns (2) and (4)) are positive, while the coefficients on verbally and materially aggressive interactions (Columns (6) and (8)) are negative, hinting that, if at all, target countries behave in a pacifying and non-retaliatory manner.

Next, I find that diversionary interactions are typically targeted at culturally and geographically closer countries. Target countries are also, typically, those with low levels of population, military expenditure and state capability, suggesting that such diversionary strategies are exercised in a manner that aims to avoid large–scale costs or risks of retaliation. In terms of the broader consequences, domestically, I do not observe these strategic manipulations being effective in diverting domestic turmoil. Internationally, I observe that target countries do not respond to such aggressive behavior, again highlighting their low–cost, low-risk nature.

Taken as a whole, the exercise undertaken in this paper provides important implications for academics, policy makers and the public alike. It expands the boundaries of academic research on the relationship between governments and the public, by taking, to my knowledge, the first step in quantifying domestic turmoil, on a global scale and at a fine level of temporal resolution. Importantly, it sheds light on the 'subtle' behaviours of governments and the public, which typically get overlooked amidst the more obvious and 'visible' interactions. From the public's perspective, I document the importance of the public being aware of, and proactively responding to, manipulative strategies employed by the government. I also highlight the importance of governments monitoring the domestic roots of international relationships as a critical success factor in maintaining solidarity within the international system. Importantly, this paper lays the foundation for future work on causally identifying the effects and mechanisms driving governments' diversionary behavior, when faced with domestic and international adversity.

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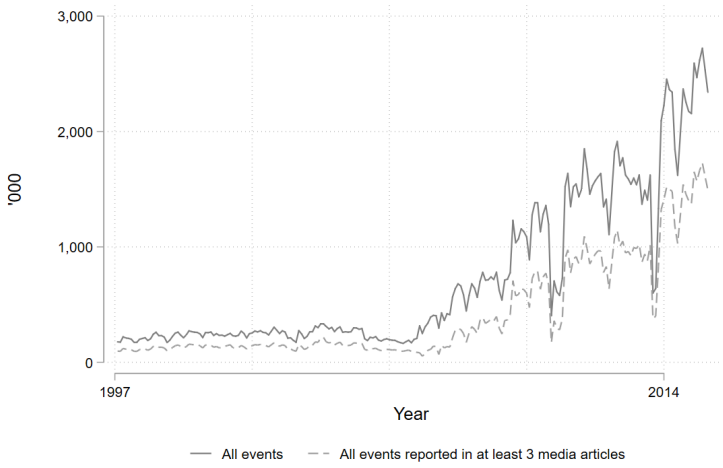
Online Appendix

Diverting Domestic Turmoil

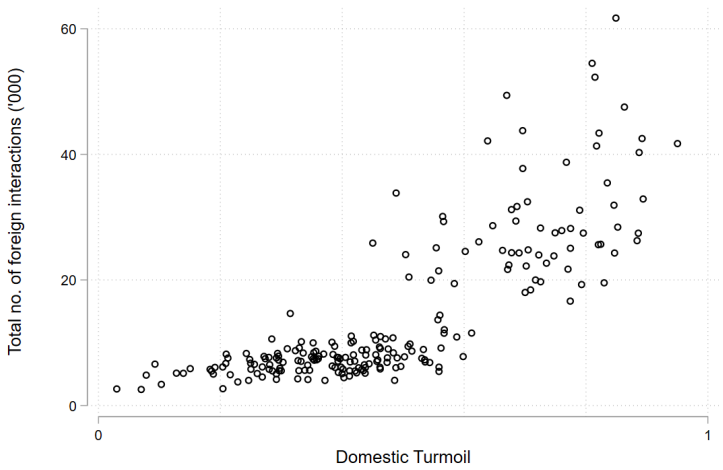
Ashani Amarasinghe[1]

A Additional data description

Figure A.1: Descriptives of GDELT event types



(a) GDELT - All reported events vs all events reported in at least 3 sources



(b) Total number of governments' foreign interactions and *DT*

Notes: Panel (a) plots the total number of events reported by GDELT and the number of events reported in at least 3 sources, over time. For the sample period, this share is 55% on average. Panel (b) shows the relationship between the total *number* of foreign interactions initiated by governments and the index of *DT*.

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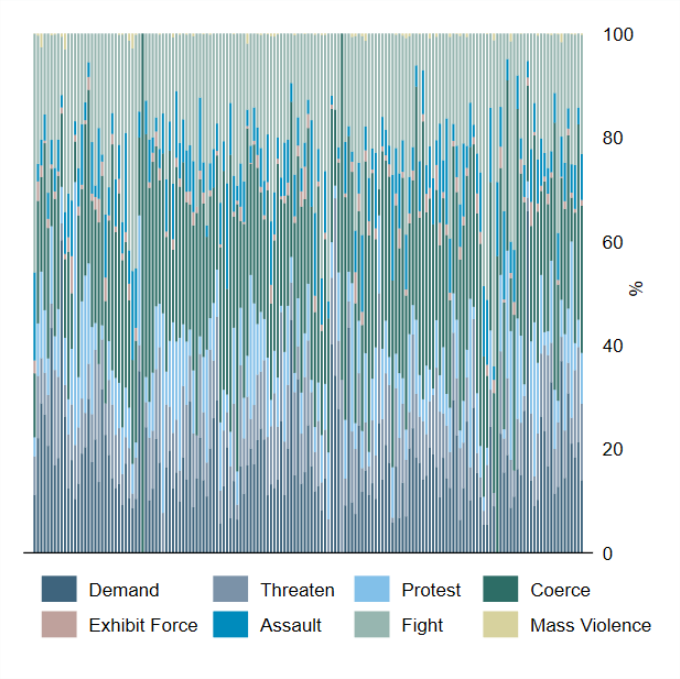
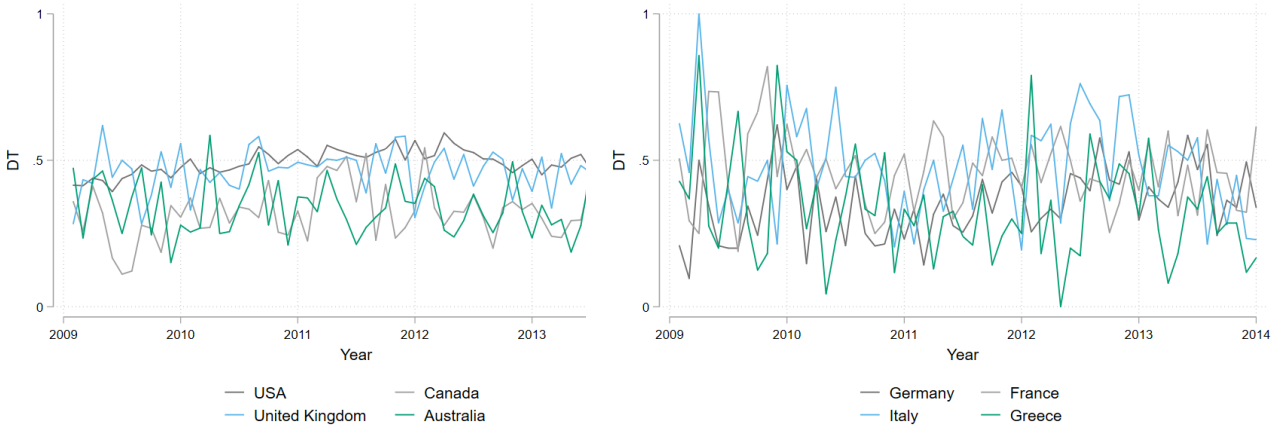
Figure A.2: Components of *DT*



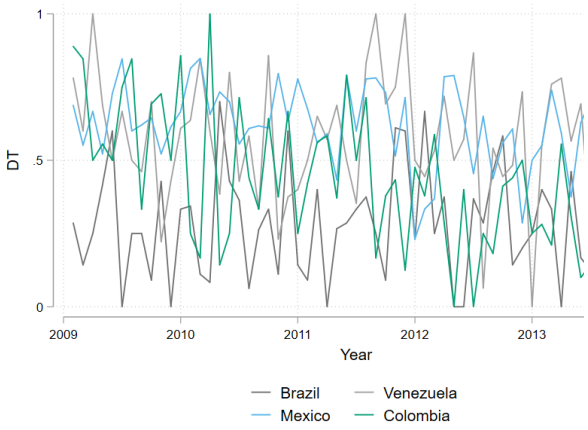
Note: Figure shows the components of *DT* for each country in the sample. Each bar represents a country. The coloured components show the percentage share of the different event categories within the *DT* index for the relevant country. *DT* is calculated as per Equation (1), based on domestic events targeted at the government.

Figure A.3: *DT* in selected countries

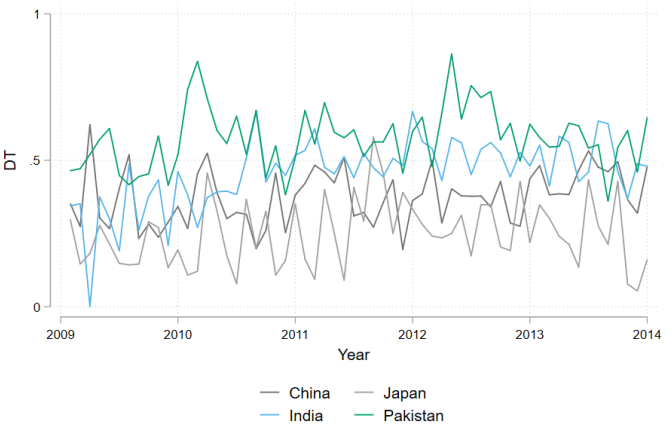


(a) "Western" countries

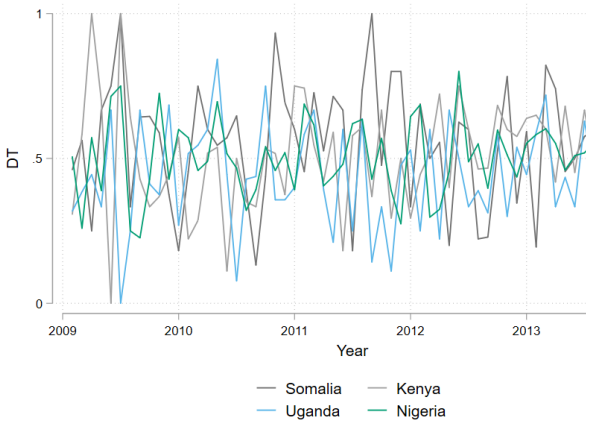
(b) European countries



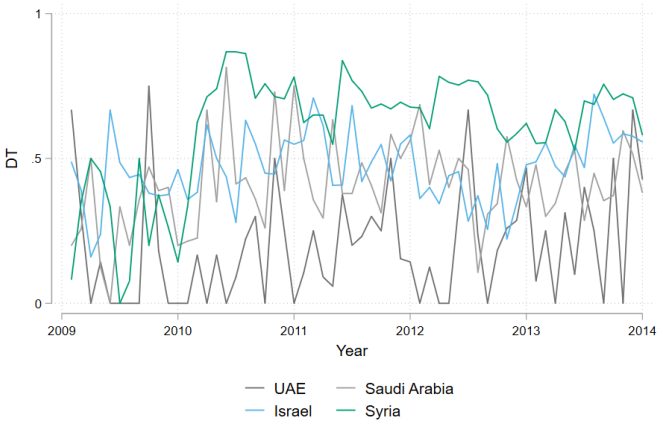
(c) Latin American countries



(d) Asian countries



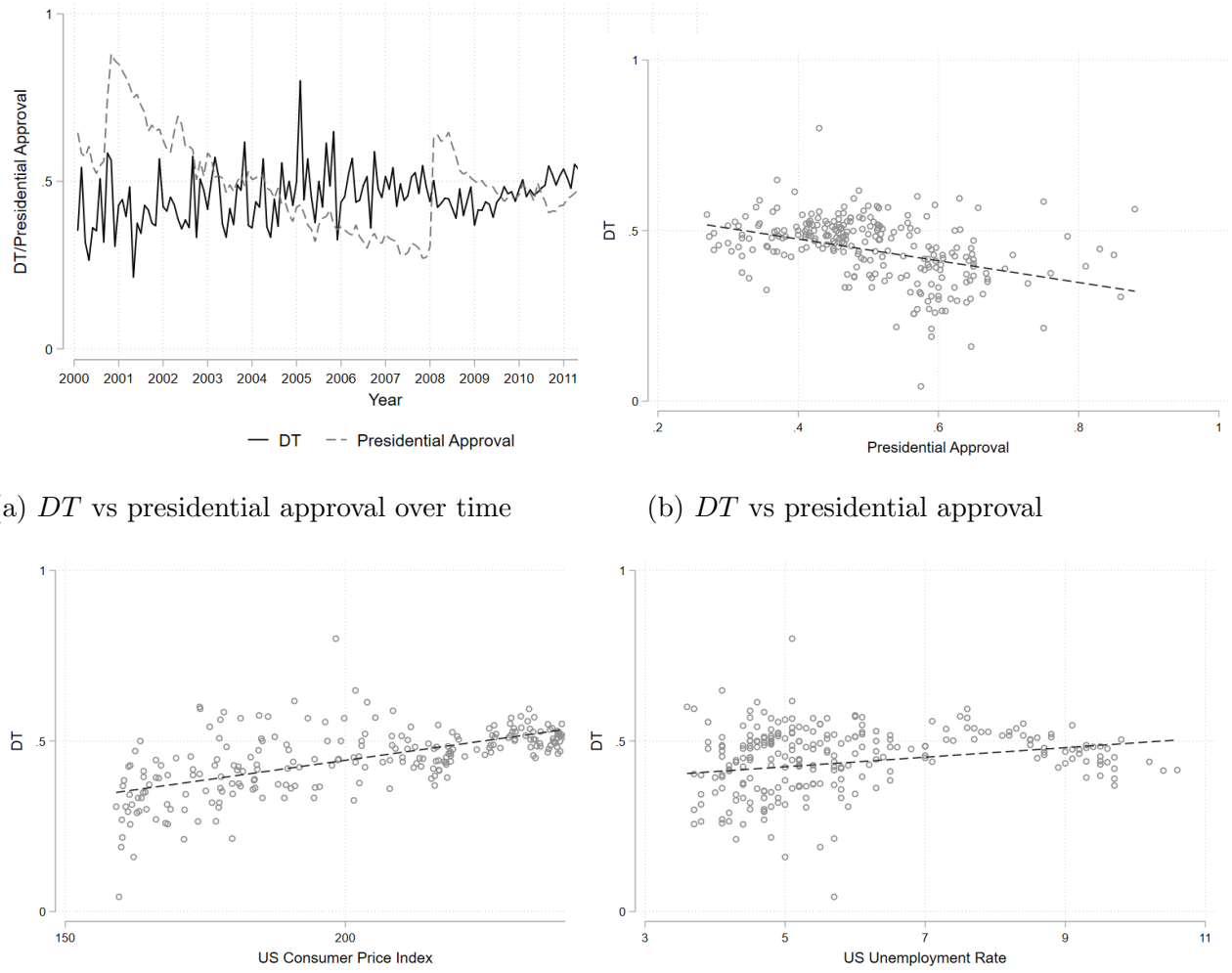
(e) African countries



(f) Middle-Eastern countries

Note: Figure shows the distribution of D) for a set of selected countries representing the key global regions. DT is calculated as per Equation (1). $0 \leq DT \leq 1$.

Figure A.4: *DT* in the US



(a) *DT* vs presidential approval over time

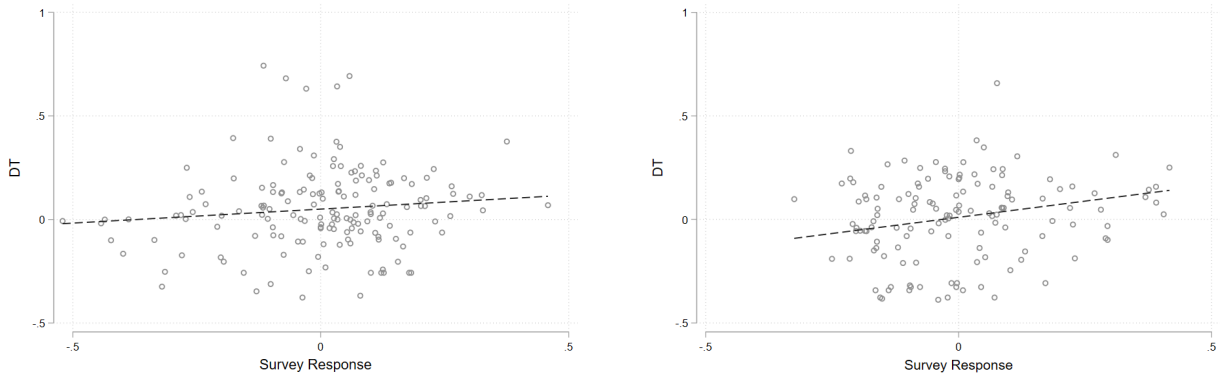
(b) *DT* vs presidential approval

(c) *DT* vs CPI

(d) *DT* vs unemployment rate

Notes: Figure shows the relationship between *DT* and key sentiment/economic indicators in the US. Panel (a) shows the relationship between the *DT* index and the US presidential approval rate over time. Panels (b), (c) and (d) demonstrate the scatter plots and lines of best-fit between *DT* and US presidential approval rate, CPI and unemployment rate, respectively. Data on presidential approval ratings are from the American Presidency Project. Data on CPI and unemployment rate are sourced from the Federal reserve Bank of St. Louis. Data is at the monthly level. The standardized β coefficients for Panels (b), (c) and (d) are *-0.3960 (p=0.0000), 0.5845 (p=0.0000)* and *0.2616 (p=0.0000)*, respectively.

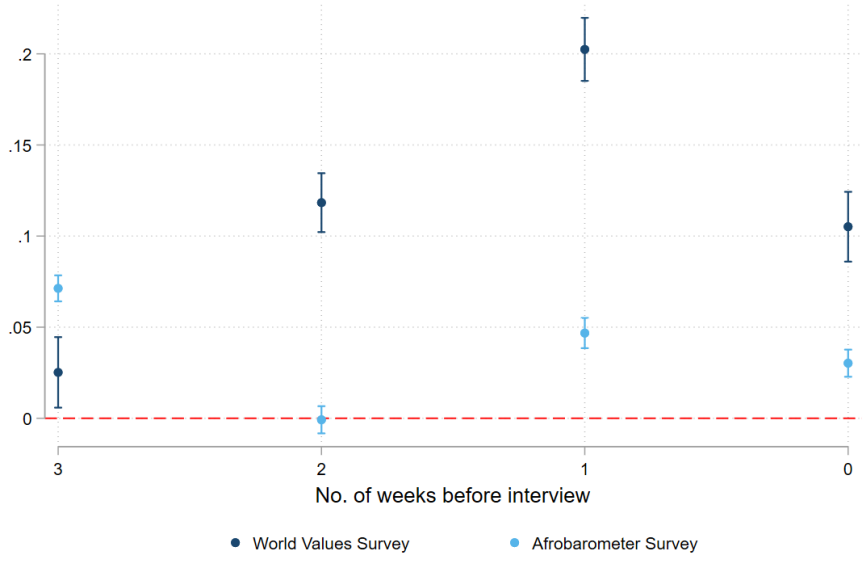
Figure A.5: *DT* and survey indicators



(a) World Values Survey (b) Afrobarometer Survey

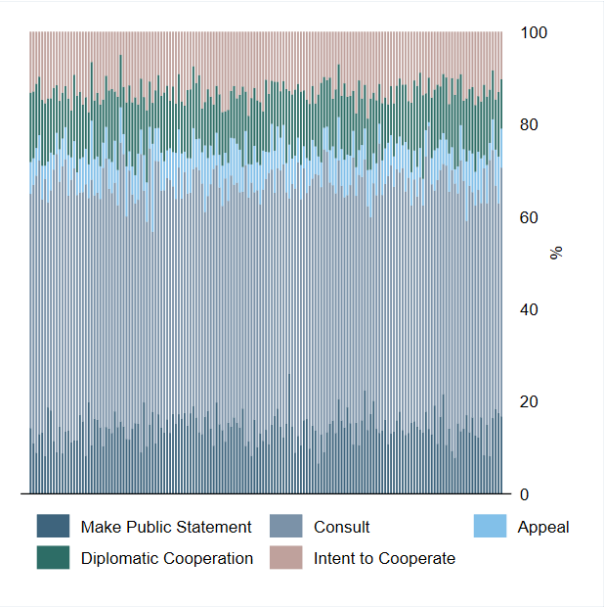
Notes: Figure shows the relationship between *DT* and survey responses. Panels (a) and (b) plot *DT* against a standardized measure of expressed dissatisfaction with government/president as per the World Values Survey and the Afrobarometer survey, respectively. The unit of measurement is a country-year. The β coefficients for Panels (a) and (b) are *0.135 (p=0.058)* and *0.313 (p=0.000)*, respectively. Number of observations is 157 (Panel (a)) and 101 (Panel (b)).

Figure A.6: Effect of pre-interview *DT* on survey interview outcomes

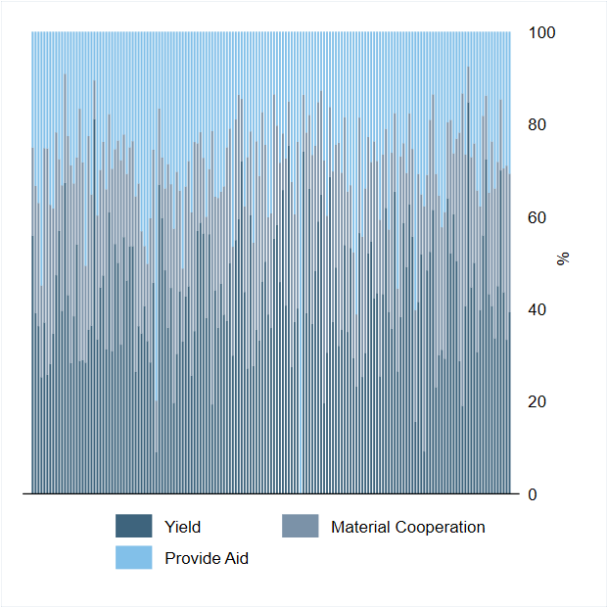


Note: Figure shows the effect of *DT* in the weeks before an interview on expressed dissatisfaction with government/president at the interview. The unit of analysis is a respondent. Country×round, year, and week fixed effects are included. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

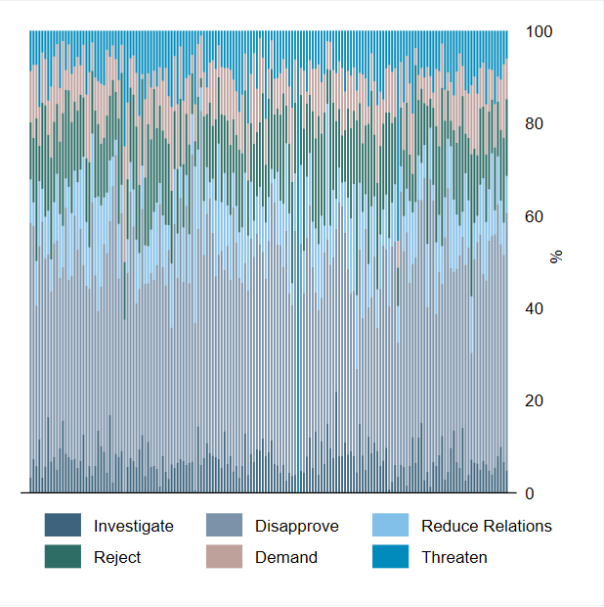
Figure A.7: Components of FP categories



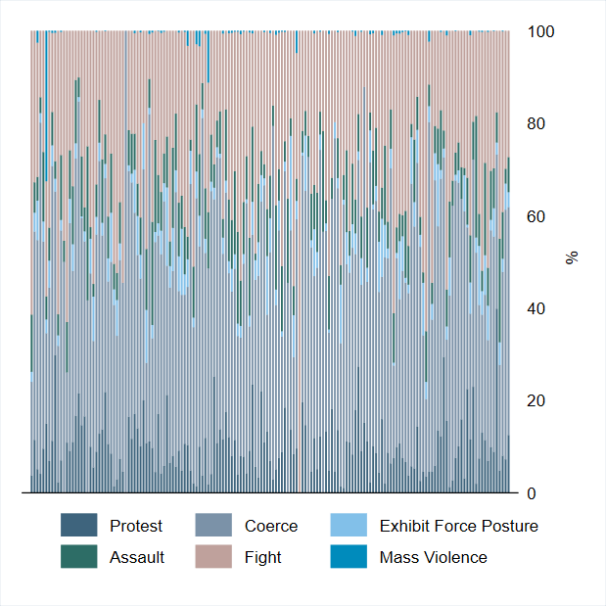
(a) FP – Verbal cooperation



(b) FP – Material cooperation



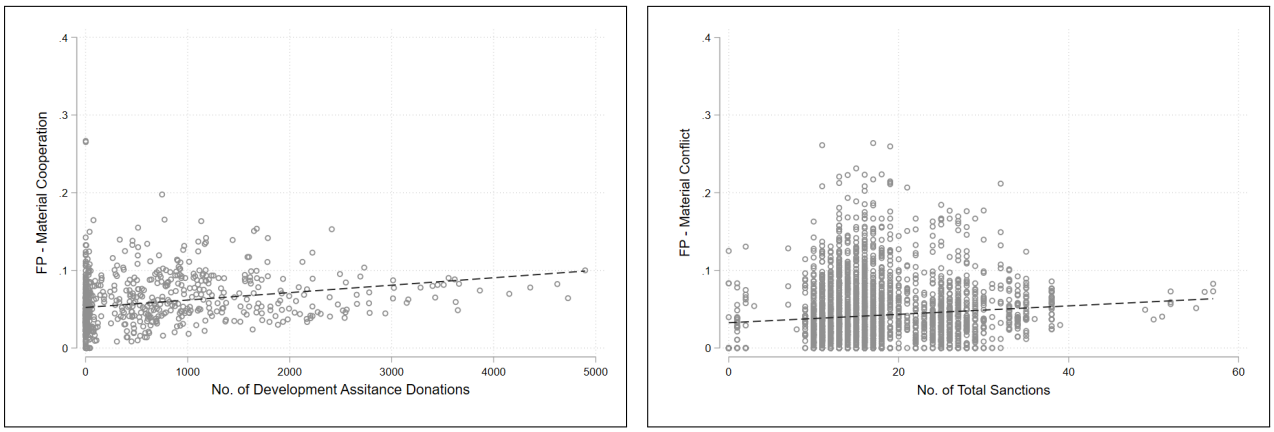
(c) FP – Verbal conflict



(d) FP – Material conflict

Note: Figure shows the components of each FP category for each country in the sample. The coloured components show the percentage share of the event categories within each FP category. FP is calculated as per Equation 2 based on events initiated by the government and targeted at a foreign entity.

Figure A.8: External validity of FP categories



(a) Material cooperation vs donations of development assistance

(b) Material aggression vs imposition of sanctions

Notes: Figure shows the relationship between FP and related alternative data sets. Panel (a) plots the quantified indicator of 'Material Cooperation' against the number of times a country engaged in donations of development assistance. Panel (b) plots the quantified indicator of 'Material Conflict' against the number of sanctions imposed by the country. The unit of measurement is a country-year. The standardized β coefficients for Panels (a) and (b) are *0.2592 (p=0.0000)* and *0.0086 (p=0.0000)*, respectively. Number of observations is 774 (Panel (a))and 3,340 (Panel (b)).

Table A.1: CAMEO events, Goldstein scores, and quad class classification

Goldstein Scale	CAMEO Event Description	Quad Class
7.0	Provide Aid	Material Cooperation
6.0	Engage in Material Cooperation	Material Cooperation
5.0	Yield	Material Cooperation
4.0	Express Intent to Cooperate	Verbal Cooperation
3.5	Engage in Diplomatic Cooperation	Verbal Cooperation
3.0	Appeal	Verbal Cooperation
1.0	Consult	Verbal Cooperation
0.0	Make Public Statement	Verbal Cooperation
-2.0	Investigate	Verbal Conflict
-2.0	Disapprove	Verbal Conflict
-4.0	Reduce Relations	Verbal Conflict
-4.0	Reject	Verbal Conflict
-5.0	Demand	Verbal Conflict
-6.0	Threaten	Verbal Conflict
-6.5	Protest	Material Conflict
-7.0	Coerce	Material Conflict
-7.2	Exhibit Force Posture	Material Conflict
-9.0	Assault	Material Conflict
-10.0	Fight	Material Conflict
-10.0	Engage in Unconventional Mass Violence	Material Conflict

Source: The Computational Event Data System

Table A.2: Correlation between DT and protests

	(1) $Mass\ Mobilization\ Protest_{iym}$	(2) $ACLED\ Protest_{iym}$	(3) $Mass\ Mobilization\ Protest_{iym}$	(4) $ACLED\ Protest_{iym}$
DT_{iym} $(GDELT)$	0.0662***	0.3048***		
	(0.0087)	(0.0485)		
DT_{iym} $(ICEWS)$			0.0800***	0.3754***
			(0.0103)	(0.0688)
Observations	28,080	10,368	28,080	10,368
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
No. of countries	130	48	130	48

Notes: This table depicts the correlations between *Domestic Turmoil* indicators (derived via GDELT and ICEWS data sets) and number of protests targeted at governments. Columns (1) and (3) use data on protests from the Mass Mobilization Project, while Columns (2) and (4) use data from ACLED (which only covers the African continent). The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table A.3: Correlation between $GDELT$ and $ICEWS$ indicators

		(1)	(2)	(3)	(4)	(5)
				ICEWS		
		DT_{iym}	$Verb\ Coop_{iym}$	$Mat\ Coop_{iym}$	$Verb\ Conf_{iym}$	$Mat\ Conf_{iym}$
GDELT	DT_{iym}	0.3326***				
		(0.0264)				
	$Verb\ Coop_{iym}$		0.3222***			
			(0.0258)			
	$Mat\ Coop_{iym}$			0.0494***		
				(0.0073)		
	$Verb\ Conf_{iym}$				0.1770***	
					(0.0156)	
	$Mat\ Conf_{iym}$					0.1261***
						(0.0160)
Controls:						
Country FE		YES	YES	YES	YES	YES
Year FE		YES	YES	YES	YES	YES
Month FE		YES	YES	YES	YES	YES
Observations		39,096	39,096	39,096	39,096	39,096
No. of countries		181	181	181	181	181

Notes: This table depicts the correlations between the key explanatory and outcome variables derived using $GDELT$ and $ICEWS$ datasets, while accounting for country, year and month fixed effects. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

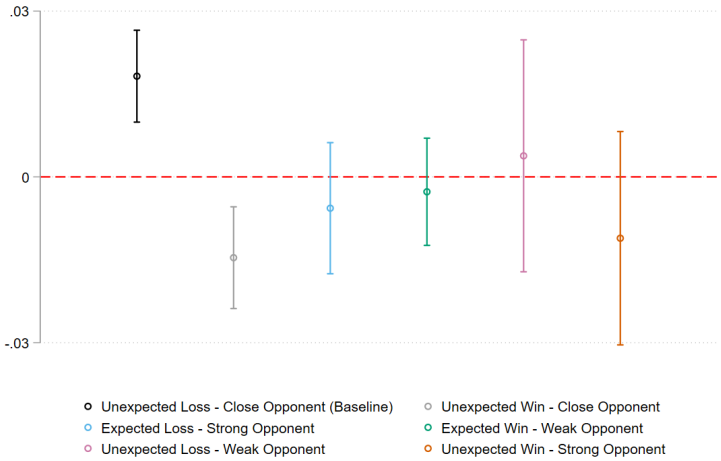
Table A.4: Dyadic correlation between FP alternative indicators

	(1) Aid_{ijy}	(2) $Sanctions_{ijy}$
$Mat\ Coop_{ijy}$	0.0464***	
	(0.0119)	
$Mat\ Conf_{ijy}$		0.3043***
		(0.0358)
Controls:		
Dyad FE	YES	YES
Year FE	YES	YES
Observations	126,252	505,008
Mean DV	0.0029	0.0915
Std. deviation DV	0.0210	0.2883

Notes: This table depicts the dyadic correlations between governments' foreign interactions in GDELT and other existing data sets. Aid_{ijy} is the share of aid given to country j from the total amount of aid disseminated by country i in year y. $Sanctions_{ijy}$ is a binary indicator equalling to one if country i imposed sanctions against country j in year y. The mean (standard deviation) of $Mat\ Coop$ and $Mat\ Conf$ are 0.0036 (0.0190) and 0.0023 (0.0174), respectively. The unit of analysis is a dyad-year. Sample size is determined by data availability. Standard errors, clustered at the dyad level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

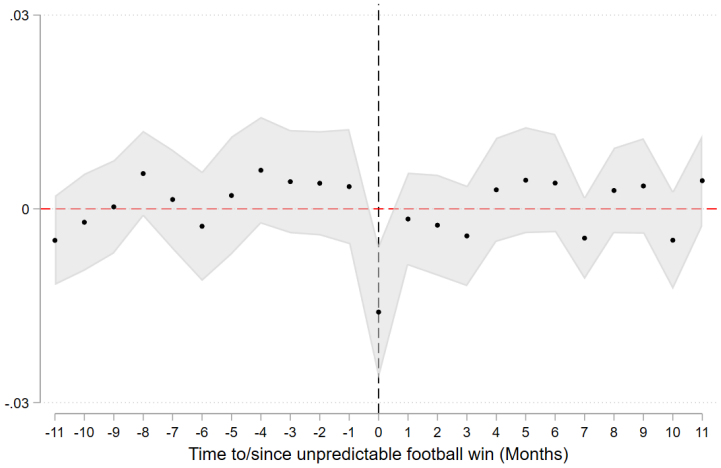
B Robustness checks and heterogeneity

Figure B.1: *DT* and types of football outcomes



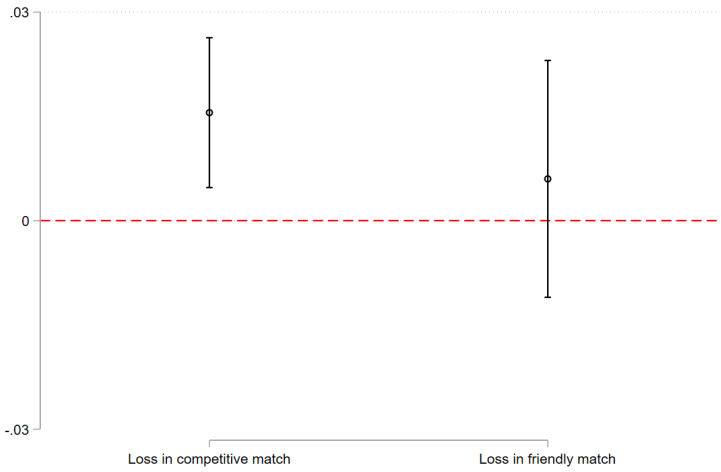
Note: Figure shows the effect of other football outcomes on *Domestic Turmoil* (*DT*) as per Equation 5. The opponent is identified "close" if the rating difference is within ±150 points. The opponent is identified as strong (weak) if the rating differential is greater than 150 points upwards (downwards). Additional controls include country× year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure B.2: Effect of unpredictable football wins on *DT* over time



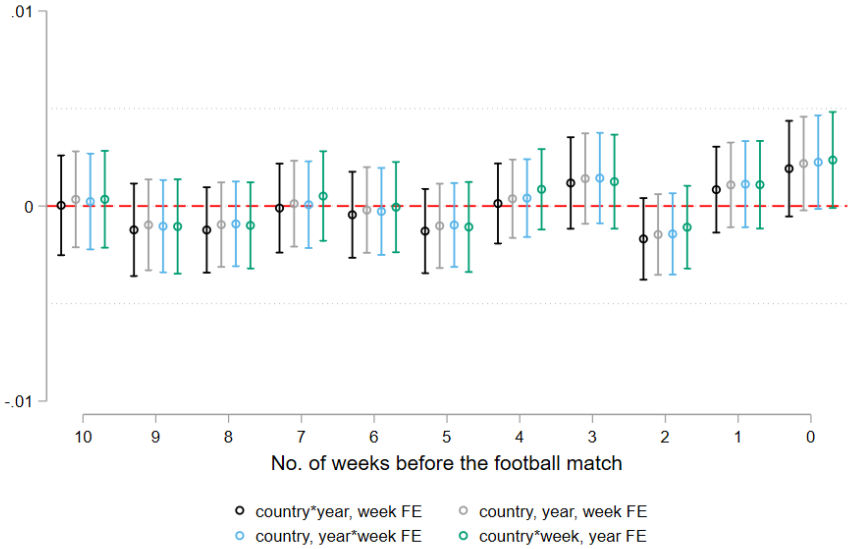
Note: Figure shows the effect of unpredictable football wins on *DT* as per Equation (5), including 11 monthly leads ($t < 0$) and lags ($t > 0$). Additional controls include country× year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure B.3: Effect of competitive vs friendly football matches on *DT*



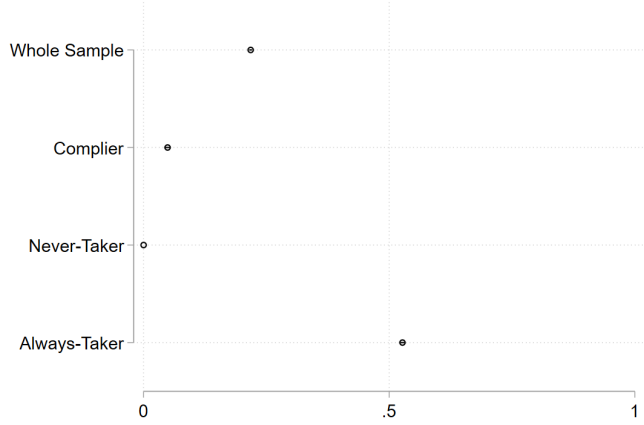
Note: Figure shows the effect of competitive and friendly matches on *DT*. Country× year fixed effects and month fixed effects are included. Additional controls include the number of football matches played by the country over the period. The unit of measurement is a country-month. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure B.4: Effect of pre-match *DT* on football losses

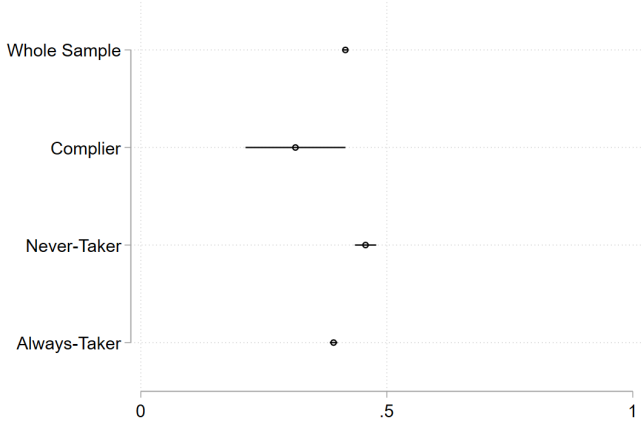


Note: Figure shows the effects of *Domestic Turmoil* (*DT*) in the 10 weeks before a match on the probability of losing the match, estimated with different sets of fixed effects as indicated. The unit of analysis is a country-week. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

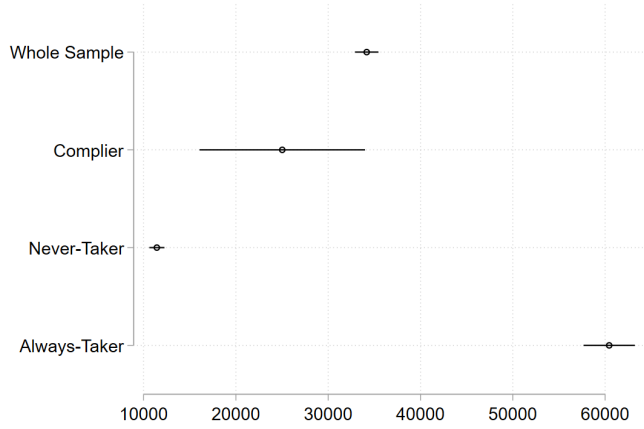
Figure B.5: Profiling compliers, always-takers and never-takers



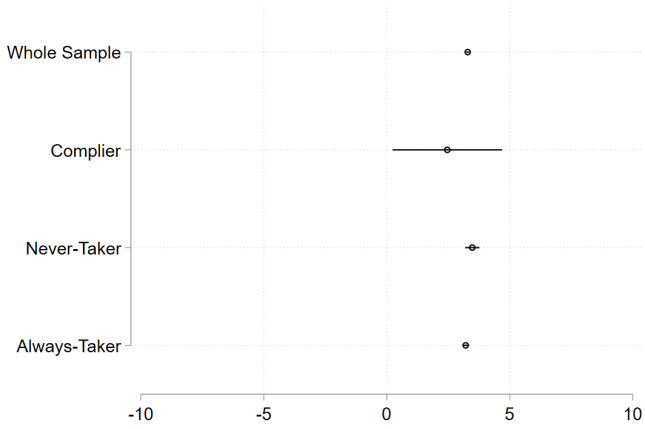
(a) *Domestic Turmoil*



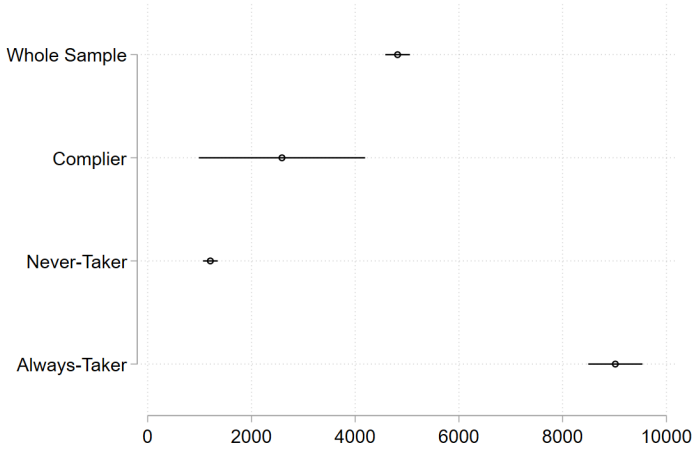
(b) High income



(c) Population ('000)



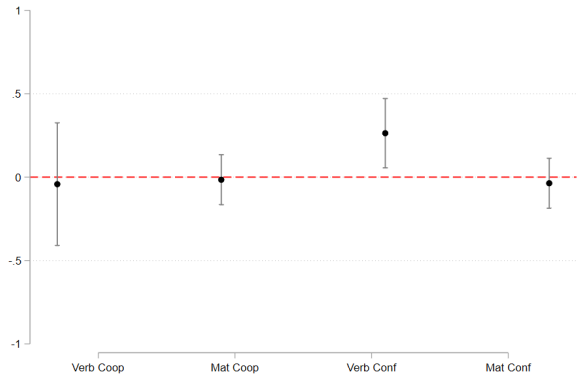
(d) Average polity score



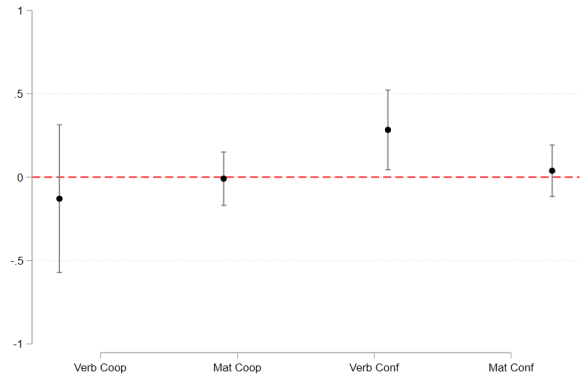
(e) Military expenditure (US $ '000)

Note: Figure shows descriptive statistics (i.e. mean and 95% confidence interval) of key variables, for the sample as well as the sub-populations of compliers, never-takers and always takers, with respect to the IV. Panel (a) considers the *DT* index, while Panel (b) distinguishes between these groups based on an binary variable classifying countries with GDP above the median values as high income countries. Panels (c), (d) and (e) consider the differences in the average values of population, polity score and military expenditure. Circles depict the average values for each sub-population, while the horizontal lines depict the 95% confidence intervals. This exercise is conducted as per Marbach and Hangartner (2020).

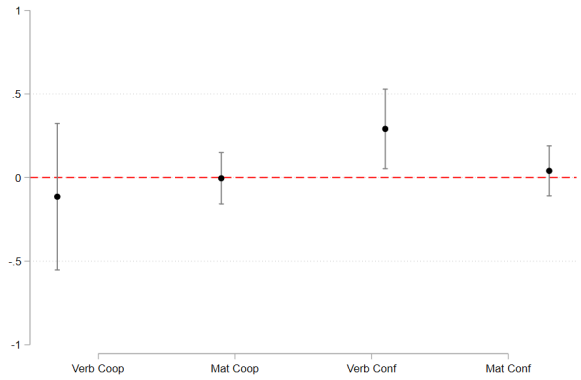
Figure B.6: Alternative fixed effects



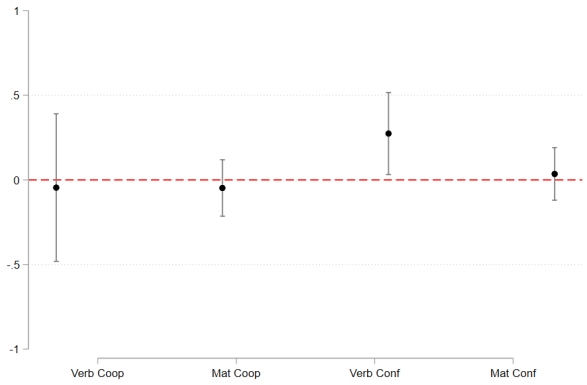
(a) Baseline



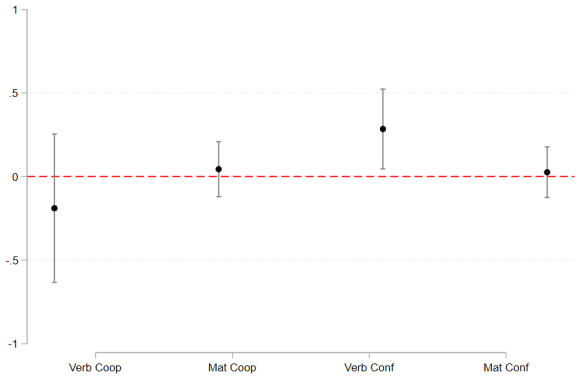
(b) Country, year, month FE



(c) Country, year×month FE



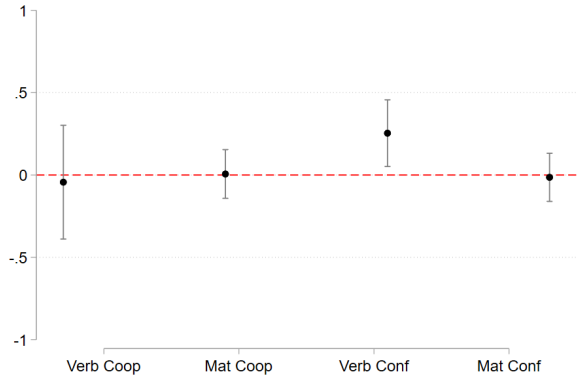
(d) Country×month, year FE



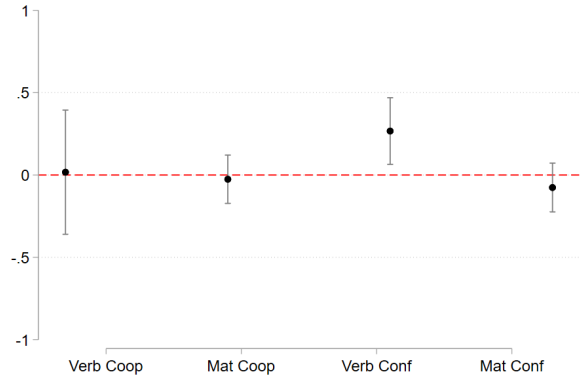
(e) Continent×year×month FE

Note: Figure shows 2SLS estimates as per Equation 6, with each panel incorporating a different set of fixed effects. First stage KP F–statistics for Panels (a), (b), (c) (d) and (e) are 13.12, 10.16, 10.89, 9.79 and 9.94, respectively. The unit of measurement is a country-month. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

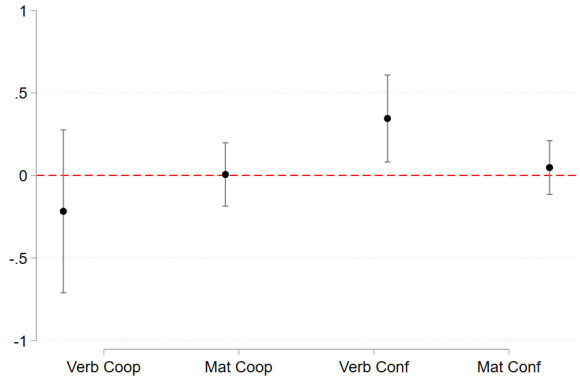
Figure B.7: Robustness checks on sample selection



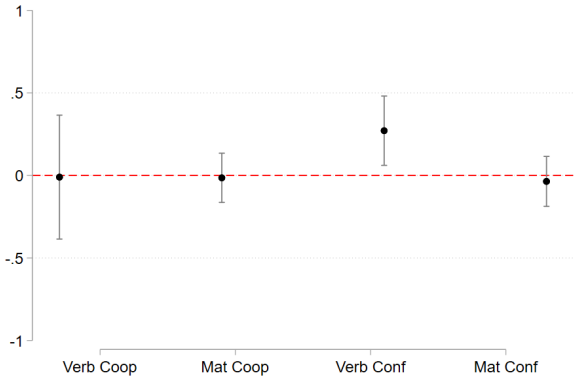
(a) Excluding small countries



(b) Excluding OECD



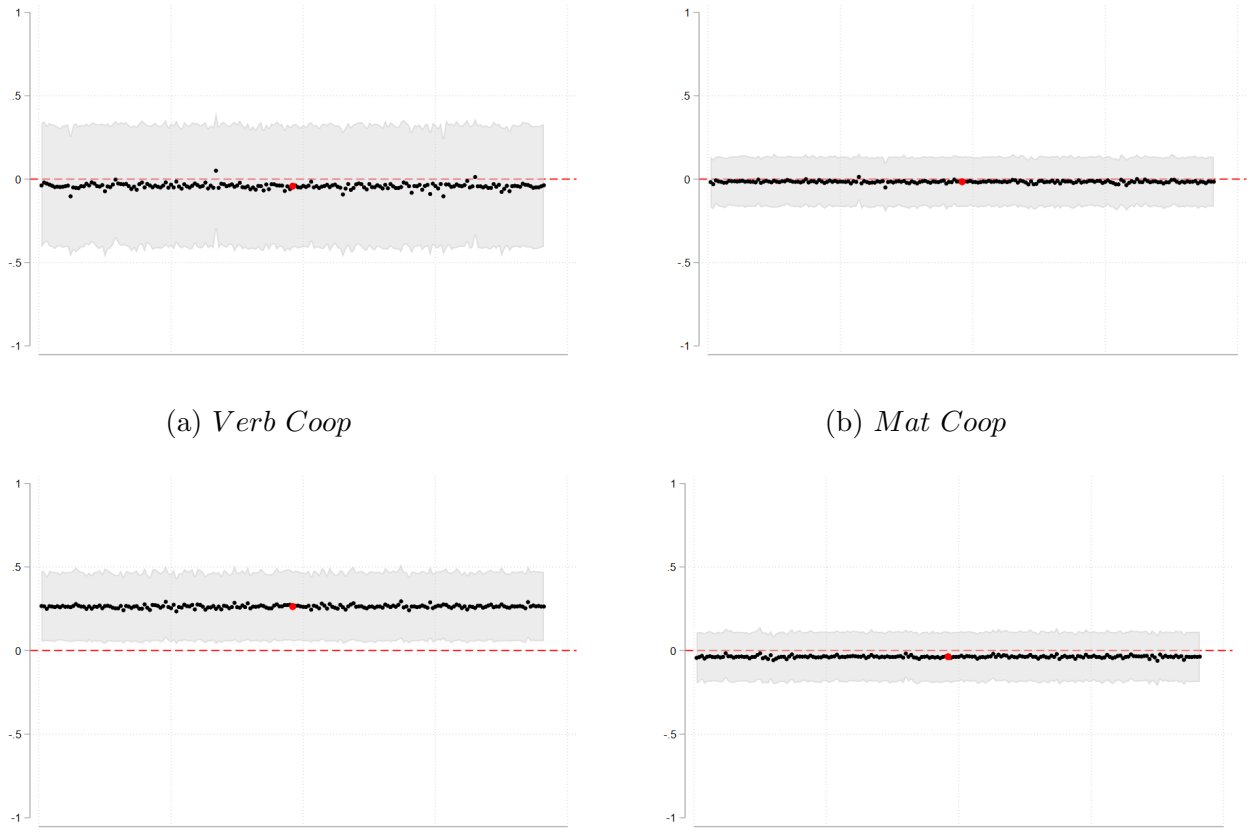
(c) Excluding countries that played a world cup



(d) Excluding countries with high football popularity

Note: Figure shows second stage estimates as per Equation 6, but each panel excludes a set of countries from the sample, as indicated in the panel captions. First stage KP F–statistics for Panels (a), (b), (c) and (d) are 13.03, 14.70, 9.26 and 14.21, respectively. All specifications include country$\times$ year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure B.8: Dropping one country at a time

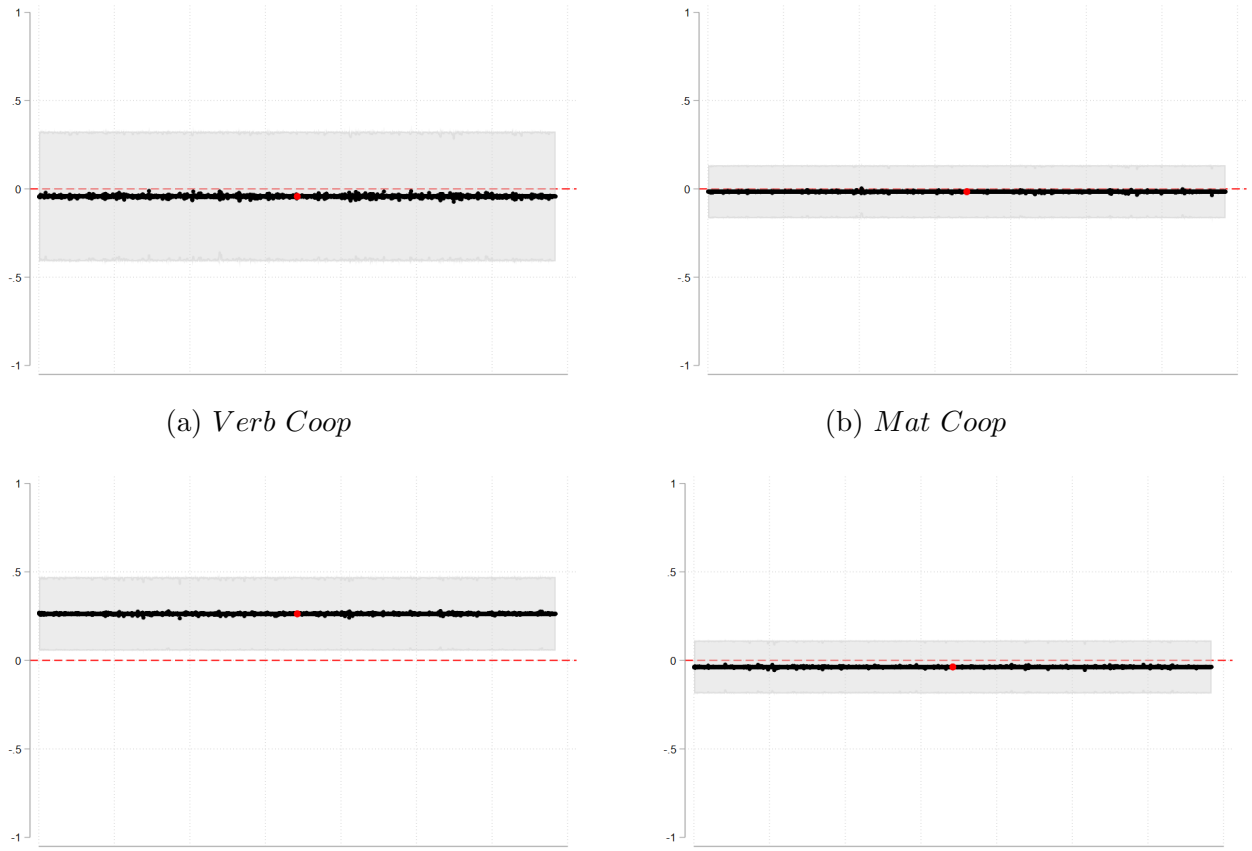


(a) *Verb Coop* (b) *Mat Coop*

(c) *Verb Conf* (d) *Mat Conf*

Note: Figure shows second stage estimates as per Equation 6, when excluding one country at a time from the sample. Each dot represents a separate regression estimate. The dependent variable for Panels (a), (b), (c) and (d) are *Verb Coop*, *Mat Coop*, *Verbal Conf* and *Mat Conf*, respectively. The red circle in each panel indicates the baseline estimate for the full sample. All specifications include country×year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Shaded area indicates the 90% confidence interval.

Figure B.9: Dropping one country×year at a time

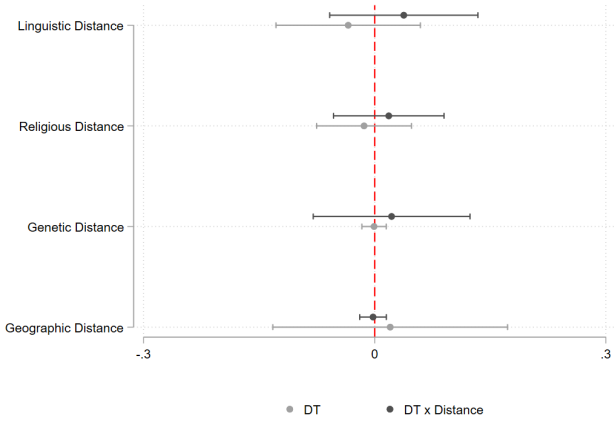


(a) *Verb Coop* (b) *Mat Coop*

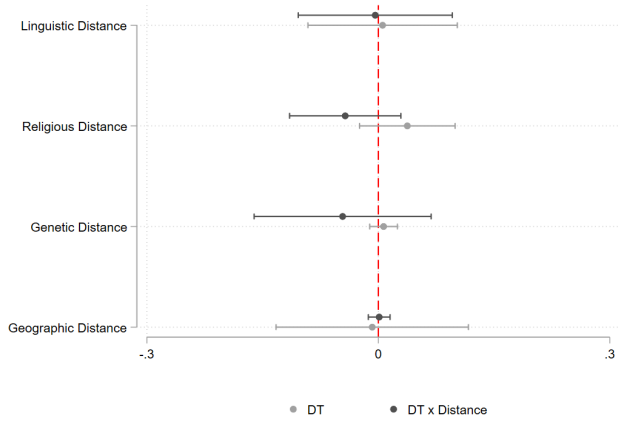
(c) *Verb Conf* (d) *Mat Conf*

Note: Figure shows second stage estimates as per Equation 6, when excluding one country×year at a time from the sample. Each dot represents a separate regression estimate. The dependent variable for Panels (a), (b), (c) and (d) are *Verb Coop*, *Mat Coop*, *Verbal Conf* and *Mat Conf*, respectively. The red circle in each panel indicates the baseline estimate for the full sample. All specifications include country×year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Shaded area indicates the 90% confidence interval.

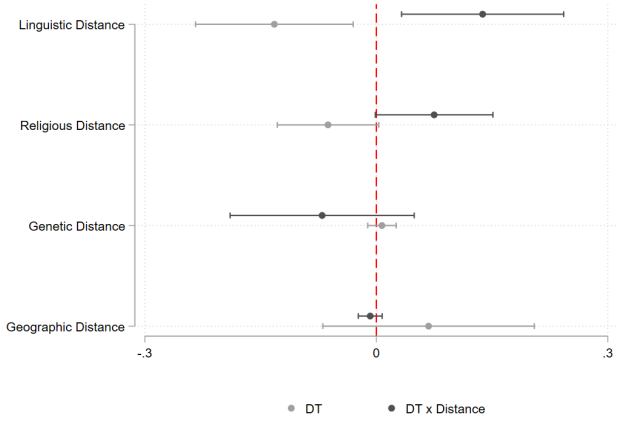
Figure B.10: Target countries based on connectivity



(a) *Verb Coop*



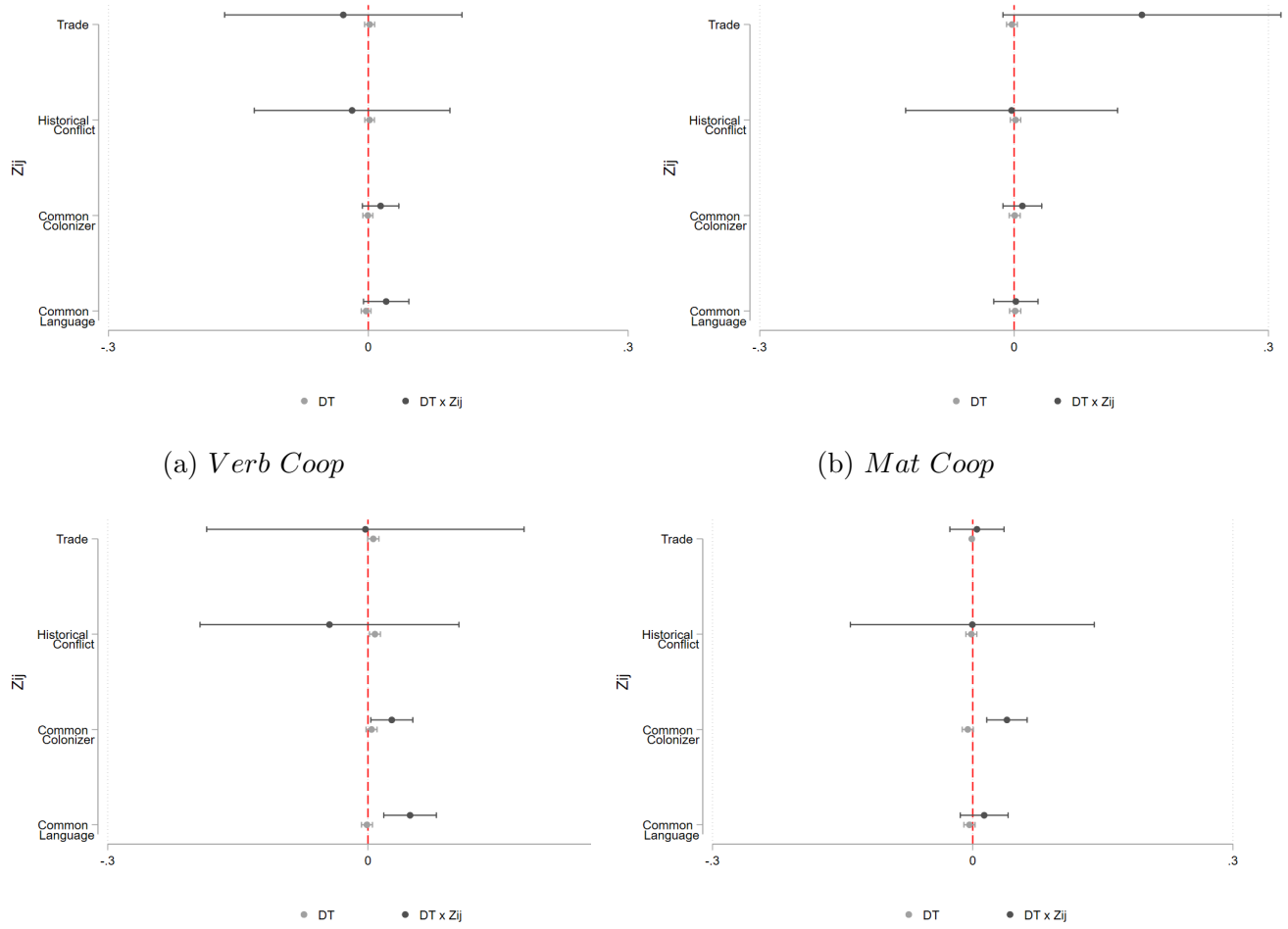
(b) *Mat Coop*



(c) *Mat Conf*

Notes: Dots show the second–stage estimated coefficients of DT_{iym} and $DT_{iym} \times Z_{ij}$. Z_{ij} is an indicator of the distance between countries, along geographic, genetic, religious and linguistic dimensions. Geographic distance has been log transformed. The dependent variable in Panels (a), (b) and (c) are $Verb\ Coop_{ijym}$, $Mat\ Coop_{ijym}$ and $Mat\ Conf_{ijym}$, respectively. Each distance category represents a separate regression estimate. All specifications include dyad× year fixed effects and month fixed effects. Both stages additionally control for *Football Match*. The unit of measurement is a dyad-month. Horizontal lines show the 90% confidence interval based on standard errors clustered at the dyad level.

Figure B.11: Target countries based on other connectivity measures



(a) *Verb Coop*

(b) *Mat Coop*

(c) *Verb Conf*

(d) *Mat Conf*

Notes: Dots show the second–stage estimated coefficients of DT_{ijym} and $DT_{ijym} \times Z_{ij}$. For relationships based on common language, common colonizer and past conflict, Z_{ij} assumes a value of 1 if the countries share a common colonizer, a common language, or a history of conflict. Where the relationship is based on Trade, Z_{ij} is $Exports_{ij}/GDP_i$, for the first year of the sample. The dependent variable in Panels (a), (b), (c) and (d) are $Verb\ Coop_{ijym}$, $Mat\ Coop_{ijym}$, $Verb\ Conf_{ijym}$ and $Mat\ Conf_{ijym}$, respectively. Each connection category represents a separate regression estimate. All specifications include dyad× year fixed effects and month fixed effects. Both stages additionally control for *Football Match*. The unit of measurement is a dyad-month. Horizontal lines show the 90% confidence interval based on standard errors clustered at the dyad level.

Table B.1: Descriptive statistics for key variables

	No. of Observations	Mean	Standard Deviation	Minimum	Maximum
			GDELT		
Domestic Turmoil	41,040	0.2179	0.3113	0	1
Foreign Verbal Cooperation	41,040	0.6835	0.3483	0	1
Foreign Material Cooperation	41,040	0.0478	0.1036	0	1
Foreign Verbal Conflict	41,040	0.0692	0.1249	0	1
Foreign Material Conflict	41,040	0.0420	0.1018	0	1
			ICEWS		
Domestic Turmoil	39,096	0.2386	0.3974	0	1
Foreign Verbal Cooperation	39,096	0.4212	0.4449	0	1
Foreign Material Cooperation	39,096	0.0252	0.1116	0	1
Foreign Verbal Conflict	39,096	0.0648	0.1797	0	1
Foreign Material Conflict	39,096	0.0394	0.1455	0	1
Football Loss	41,040	0.1149	0.3639	0	4
Football Match	41,040	0.3165	0.6918	0	8

Notes: Domestic Turmoil is a standardized indicator recording all domestic events targeting the government, recording a Goldstein score of -5 or less, expressed as a fraction of all domestic events targeting the government. Foreign interactions initiated by a country's government, classified as *Verb Coop*, *Mat Coop*, *Verb Conf* and *Mat Conf*, are also standardized indicators, expressed as a fraction of the total number of foreign interactions initiated by the government. *Football Loss* and *Football Match* are the counts of all football losses and matches experienced by a country, respectively, against an opponent with a rating differential of 150 points or less.

Table B.2: Validity of baseline results against alternative datasets

	(1) *GDELT* (*Baseline*)	(2) *ICEWS*	(3) *GDELT and Protests*	(4) *ICEWS and Protests*
Panel A: IV Estimates	Dependent Variable: $Verb\ Coop_{iym}$			
$Domestic\ Turmoil_{iym}$	-0.0424	-0.0589		
	(0.2233)	(0.3341)		
$Protests_{iym}$			-0.0623	-0.0933
			(0.3143)	(0.4928)
Mean DV	0.6835	0.4212	0.6835	0.4212
Std. Deviation DV	0.3483	0.4449	0.3483	0.4449
Panel B: IV Estimates	Dependent Variable: $Mat\ Coop_{iym}$			
$Domestic\ Turmoil_{iym}$	-0.0158	-0.2124		
	(0.0912)	(0.1483)		
$Protests_{iym}$			0.0367	-0.2291
			(0.1361)	(0.2128)
Mean DV	0.0478	0.0252	0.0478	0.0252
Std. Deviation DV	0.1036	0.1116	0.1036	0.1116
Panel C: IV Estimates	Dependent Variable: $Verb\ Conf_{iym}$			
$Domestic\ Turmoil_{iym}$	0.2632**	0.6034**		
	(0.1262)	(0.2923)		
$Protests_{iym}$			0.4017**	0.6796*
			(0.2032)	(0.3838)
Mean DV	0.0692	0.0648	0.0692	0.0648
Std. Deviation DV	0.1249	0.1797	0.1249	0.1797
Panel D: IV Estimates	Dependent Variable: $Mat\ Conf_{iym}$			
$Domestic\ Turmoil_{iym}$	-0.0369	-0.2297		
	(0.0910)	(0.1730)		
$Protests_{iym}$			-0.1107	-0.2831
			(0.1283)	(0.2434)
Mean DV	0.0420	0.0394	0.0420	0.0394
Std. Deviation DV	0.1018	0.1455	0.1018	0.1455
Panel E: First–Stage Estimates	Dependent Variable:			
	$Domestic\ Turmoil_{iym}$		$Protests_{iym}$	
$Football\ Loss_{iym}$	0.0182***	0.0190***	0.0175***	0.0175***
	(0.0050)	(0.0054)	(0.0052)	(0.0052)
Kleibergen-Paap F-statistic	13.12	12.30	10.04	10.04
Mean DV	0.2179	0.2386	0.0551	0.0551
Std. Deviation DV	0.3113	0.3974	0.2419	0.2419
Controls:				
Country-Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Football Match	YES	YES	YES	YES
No. of Observations	41,040	39,096	28,080	28,080
No. of Countries	190	181	130	130

Notes: This table provides the baseline estimates, when using alternative data sets. Column (1) presents the baseline estimates based on GDELT data. Column (2) uses ICEWS data for both the dependent and independent variables. In Columns (3) and (4), the dependent variable is the IHS-transformed number of protests, as extracted from the Mass Mobilization Project data set, while the dependent variables are from GDELT and ICEWS, respectively. Panel E provides first–stage estimates. Sample size is determined by data availability. All specifications include country×year fixed effects and month fixed effects. Both stages additionally control for *Football Match*. The mean (standard deviation) of *Domestic Turmoil - GDELT*, *Domestic Turmoil - ICEWS* and *Protests* is 0.2179 (0.3113), 0.2386 (0.3974) and 0.0551 (0.2419), respectively. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.3: Football losses and government unity

	(1)	(2)	(3)
	$Government\ Unity_{iym}$		
$Football\ Loss_{iym}$	0.0024	0.0022	0.0021
	(0.0038)	(0.0038)	(0.0039)
Controls:			
Country FE	YES	YES	NO
Year FE	YES	NO	NO
Month FE	YES	NO	YES
Year-month FE	NO	YES	NO
Country-year FE	NO	NO	YES
Football Match	YES	YES	YES
Observations	41,040	41,040	41,040
No. of countries	190	190	190
Min. Goldstein Score	5	5	5

Notes: This table examines the impact of football losses on positive sentiment within government. $Government\ Unity_{iym}$ expresses the number of within-government interactions with a Goldtein score of more than 5, as a proportion of the total number of within-government interactions over the period. $Football\ Loss_{iym}$ is the number of football losses experienced by a country against an opponent with a rating differential of 150 points or less. Both stages additionally control for $Football\ Match_{iym}$. The mean (standard deviation) of *Government Unity* and *Football Loss* is 0.0822 (0.1933) and 0.1149 (0.3639), respectively. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.4: Alternative forms of the IV

	(1)	(2)	(3)
Panel A: IV Second–Stage Estimates	Dependent Variable: $Verb\ Coop_{iym}$		
$Domestic\ Turmoil_{iym}$	-0.0424	-0.0694	-0.0443
	(0.2233)	(0.2547)	(0.4095)
Panel B: IV Second–Stage Estimates	Dependent Variable: $Mat\ Coop_{iym}$		
$Domestic\ Turmoil_{iym}$	-0.0158	0.0263	0.1418
	(0.0912)	(0.1015)	(0.1666)
Panel C: IV Second–Stage Estimates	Dependent Variable: $Verb\ Conf_{iym}$		
$Domestic\ Turmoil_{iym}$	0.2632**	0.3068**	0.4339*
	(0.1262)	(0.1469)	(0.2613)
Panel D: IV Second–Stage Estimates	Dependent Variable: $Mat\ Conf_{iym}$		
$Domestic\ Turmoil_{iym}$	-0.0369	-0.0188	0.0288
	(0.0910)	(0.1028)	(0.1573)
Panel E: IV First–Stage Estimates	Dependent Variable: $Domestic\ Turmoil_{iym}$		
$Football\ Loss_{iym}$ $(Count)$	0.0182***		
	(0.0050)		
$Football\ Loss_{iym}$ $(IHS-transformed\ Count)$		0.0198***	
		(0.0064)	
$Football\ Loss_{iym}$ $(Dummy)$			0.0101**
			(0.0048)
Kleibergen-Paap F-statistic	13.12	9.657	3.874
Controls:			
Country-Year FE	YES	YES	YES
Month FE	YES	YES	YES
Football Match	YES	YES	YES
No. of Observations	41,040	41,040	41,040
No. of countries	190	190	190
Maximum Goldstein Score	-5	-5	-5

Notes: This table provides the 2SLS estimates when using alternative forms of the football loss variable (i.e. Football Loss, IHS-transformed Football Loss and Football Dummy) as the IV. The dependent variables in Panels A, B, C and D are $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$, respectively. Panel E provides first–stage estimates. All specifications include country× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match_{iym}$. The mean (standard deviation) of the dependent variable in Panels A, B, C and D are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of $Domestic\ Turmoil$ is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.5: Alternative definition of 'unpredictable' football losses

Rating Difference	(1) ≤ 120	(2) ≤ 130	(3) ≤ 140	(4) ≤ 150	(5) ≤ 160	(6) ≤ 170	(7) ≤ 180	(8) ≤ 190	(9) ≤ 200
Panel A: IV Second–Stage Estimates				Dependent Variable: $Verb\ Coop_{iym}$					
$Domestic\ Turmoil_{iym}$	-0.0601	-0.0372	-0.0526	-0.0424	-0.0001	-0.0585	0.0372	0.0301	0.0340
	(0.3083)	(0.2524)	(0.2271)	(0.2233)	(0.2477)	(0.2558)	(0.2524)	(0.3260)	(0.3875)
Panel B: IV Second–Stage Estimates				Dependent Variable:$Mat\ Coop_{iym}$					
$Domestic\ Turmoil_{iym}$	0.0185	0.0300	0.0089	-0.0158	-0.0562	-0.0161	-0.0313	-0.0495	-0.0333
	(0.1268)	(0.1062)	(0.0900)	(0.0912)	(0.0995)	(0.0977)	(0.0956)	(0.1170)	(0.1397)
Panel C: IV Second–Stage Estimates				Dependent Variable: $Verb\ Conf_{iym}$					
$Domestic\ Turmoil_{iym}$	0.3134	0.2695*	0.2674**	0.2632**	0.2727*	0.2453*	0.2803**	0.3576*	0.4092
	(0.1930)	(0.1510)	(0.1353)	(0.1262)	(0.1464)	(0.1401)	(0.1361)	(0.1841)	(0.2490)
Panel D: IV Second–Stage Estimates				Dependent Variable$Mat\ Conf_{iym}$					
$Domestic\ Turmoil_{iym}$	-0.0687	-0.0809	-0.0367	-0.0369	-0.0563	-0.0581	-0.0735	-0.0755	-0.0952
	(0.1210)	(0.1065)	(0.0907)	(0.0910)	(0.0982)	(0.0979)	(0.0952)	(0.1240)	(0.1517)
Panel E: IV First–Stage Estimates				Dependent Variable:$Domestic\ Turmoil_{iym}$					
$Football\ Loss_{iym}$	0.0149***	0.0166***	0.0185***	0.0182***	0.0168***	0.0165***	0.0172***	0.0136***	0.0109**
	(0.0056)	(0.0052)	(0.0052)	(0.0050)	(0.0051)	(0.0049)	(0.0048)	(0.0047)	(0.0046)
Kleibergen-Paap F-statistic	7.143	10.06	12.49	13.12	11	11.49	13.03	8.433	5.531
Controls:									
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Football Match	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of Observations	41,040	41,040	41,040	41,040	41,040	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190	190	190	190	190	190
Maximum Goldstein Score	-5	-5	-5	-5	-5	-5	-5	-5	-5
Rating Difference	120	130	140	150	160	170	180	190	200

Notes: This Table provides the 2SLS estimates of the baseline specification under alternative specifications of 'close' football matches, ranging from rating differences of 120–200 between opposing teams. The dependent variables in Panels A, B, C and D are $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$, respectively. Panel E provides first–stage estimates. All specifications include country× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match$. The mean (standard deviation) of the dependent variable in Panels A, B, C and D are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of *Domestic Turmoil* is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.6: Negative sentiments following football losses - Survey responses

	(1)	(2)	(3)	(4)
	Dependent Variable: *Negative Sentiments towards Governments*			
	Afrobarometer Survey		WVS	
$Football\ Loss_{iym} \times Post$	0.0317	0.0258*	0.0991*	0.0650***
	(0.0808)	(0.0107)	(0.0389)	(0.0201)
Controls:				
Football Loss	YES	YES	YES	YES
Country-Survey Round FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES
Week FE	NO	YES	NO	YES
No. of observations	27,474	27,474	5,747	5,747
Mean DV	0.3550	0.3550	0.6061	0.6061
Std. deviation of DV	0.2077	0.2077	0.1640	0.1640

Notes: This Table shows the effect of football losses on negative sentiments expressed at surveys. Columns (1) and (2) use response from the Afrobarometer survey while Columns (3) and (4) are based on the WVS. The dependent variable is a binary indicator capturing the negative sentiments towards the government. Please see Section 2.1.2 of the manuscript for more information on how these variables were constructed. *Post* is a binary variable equal to one if the respondent was interviewed in the 30 days following a football loss, and zero for those interviewed 30 days prior to the loss. The mean (standard deviation) of the independent variable in Columns (1)-(2) and (3)-(4) are 0.3856 (0.4868) and 0.7743 (0.4181), respectively. The unit of measurement is an individual respondent. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.7: Alternative definition of DT

Goldstein Score	(1) ≤ -3	(2) ≤ -4	(3) ≤ -5	(4) ≤ -6	(5) ≤ -7
Panel A: IV Estimates	Dependent Variable: $Verb\ Coop_{iym}$				
$Domestic\ Turmoil_{iym}$	-0.0907	-0.0640	-0.0424	-0.0469	-0.0538
	(0.4786)	(0.3376)	(0.2233)	(0.2460)	(0.2829)
Panel B: IV Estimates	Dependent Variable: $Mat\ Coop_{iym}$				
$Domestic\ Turmoil_{iym}$	-0.0338	-0.0239	-0.0158	-0.0175	-0.0200
	(0.1966)	(0.1380)	(0.0912)	(0.1009)	(0.1155)
Panel C : IV Estimates	Dependent Variable: $Verb\ Conf_{iym}$				
$Domestic\ Turmoil_{iym}$	0.5627	0.3966*	0.2632**	0.2907**	0.3333**
	(0.3470)	(0.2128)	(0.1262)	(0.1419)	(0.1619)
Panel D: IV Estimates	Dependent Variable: $Mat\ Conf_{iym}$				
$Domestic\ Turmoil_{iym}$	-0.0789	-0.0556	-0.0369	-0.0408	-0.0467
	(0.1957)	(0.1374)	(0.0910)	(0.1015)	(0.1171)
Panel E: First–Stage Estimates	Dependent Variable: $Domestic\ Turmoil_{iym}$				
$Football\ Loss_{iym}$	0.0085**	0.0121***	0.0182***	0.0165***	0.0144***
	(0.0040)	(0.0046)	(0.0050)	(0.0044)	(0.0040)
Kleibergen-Paap F-statistic	4.562	7.047	13.12	14.09	13.03
Controls:					
Country-Year FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Football Match	YES	YES	YES	YES	YES
No. of Observations	41,040	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190	190
Maximum Goldstein Score	-3	-4	-5	-6	-7

Notes: This table provides the 2SLS estimates of the baseline specification under alternative definitions of *Domestic Turmoil*, ranging from Goldstein scores of ≤-3 to ≤-7. The dependent variables in Panels A, B, C and D are $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$, respectively. Panel E provides first–stage estimates. All specifications include country× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match$. The mean (standard deviation) of the dependent variable in Panels A, B, C and D are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of *Domestic Turmoil* is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.8: Controlling for all reported events

	(1) $Verb\ Coop_{iym}$	(2) $Mat\ Coop_{iym}$	(3) $Verb\ Conf_{iym}$	(4) $Mat\ Conf_{iym}$
Panel A: OLS Estimates				
$Domestic\ Turmoil_{iym}$	-0.0133***	0.0005	0.0168***	0.0154***
	(0.0043)	(0.0020)	(0.0026)	(0.0023)
Panel B: Reduced Form Estimates				
$Football\ Loss_{iym}$	-0.0008	-0.0003	0.0048**	-0.0007
	(0.0041)	(0.0017)	(0.0020)	(0.0017)
Panel C: IV Estimates				
$Domestic\ Turmoil_{iym}$	-0.0438	-0.0157	0.2649**	-0.0357
	(0.2230)	(0.0910)	(0.1262)	(0.0909)
Panel D: First–Stage Estimates	Dependent Variable: $Domestic\ Turmoil_{iym}$			
$Football\ Loss_{iym}$	0.0183***	0.0183***	0.0183***	0.0183***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Kleibergen-Paap F-statistic	13.16	13.16	13.16	13.16
Controls:				
Country-Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Football Match	YES	YES	YES	YES
All Events	YES	YES	YES	YES
No. of Observations	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190
Maximum Goldstein Score	-5	-5	-5	-5

Notes: This table replicates Table 1 but additionally controls for all reported events in the given country over the given month. All specifications include country× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match_{iym}$. The mean (standard deviation) of the dependent variable in Panels A, B, C and D are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of *Domestic Turmoil* is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.9: Excluding foreign interactions with football opponents

	(1) $Verb\ Coop_{iym}$	(2) $Mat\ Coop_{iym}$	(3) $Verb\ Conf_{iym}$	(4) $Mat\ Conf_{iym}$
Panel A: OLS Estimates				
$Domestic\ Turmoil_{iym}$	-0.0132***	0.0002	0.0165***	0.0152***
	(0.0043)	(0.0020)	(0.0026)	(0.0023)
Panel B: Reduced Form Estimates				
$Football\ Loss_{iym}$	-0.0005	-0.0004	0.0048**	0.0002
	(0.0042)	(0.0017)	(0.0020)	(0.0017)
Panel C: IV Estimates				
$Domestic\ Turmoil_{iym}$	-0.0248	-0.0207	0.2660**	0.0095
	(0.2288)	(0.0934)	(0.1257)	(0.0935)
Panel D: First–Stage Estimates	Dependent Variable: $Domestic\ Turmoil_{iym}$			
$Football\ Loss_{iym}$	0.0182***	0.0182***	0.0182***	0.0182***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Kleibergen-Paap F-statistic	13.12	13.12	13.12	13.12
Controls:				
Country-Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Football Match	YES	YES	YES	YES
No. of Observations	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190
Maximum Goldstein Score	-5	-5	-5	-5

Notes: This table replicates Table 1 but excludes foreign interactions with countries who were football opponents in the given time period. All specifications include country× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match_{iym}$. The mean (standard deviation) of the dependent variables in Columns (1), (2), (3) and (4) are 0.6832 (0.3487), 0.0479 (0.1039), 0.0691 (0.1249) and 0.0419 (0.1021), respectively. The average value of *Domestic Turmoil* is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.10: Including the lagged dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Verb\ Coop_{iym}$		$Mat\ Coop_{iym}$		$Verb\ Conf_{iym}$		$Mat\ Conf_{iym}$	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$Domestic\ Turmoil_{iym}$	-0.0135***	-0.1054	0.0005	-0.0147	0.0170***	0.2810**	0.0155***	-0.0318
	(0.0043)	(0.2228)	(0.0020)	(0.0909)	0.0026)	(0.1309)	(0.0023)	(0.0910)
$Verb\ Coop_{iym-1}$	-0.0537***	-0.0540***						
	(0.0075)	(0.0075)						
$Mat\ Coop_{iym-1}$			-0.0695***	-0.0695***				
			(0.0069)	(0.0070)				
$Verb\ Conf_{iym-1}$					-0.0557***	-0.0646***		
					(0.0077)	(0.0094)		
$Mat\ Conf_{iym-1}$							-0.0543***	-0.0527***
							(0.0076)	(0.0079)
First Stage Estimates				Dependent Variable: $Domestic\ Turmoil_{iy}$				
$Football\ Loss_{iym}$		0.0184***		0.0184***		0.0183***		0.0184***
		(0.0050)		(0.0051)		(0.0051)		(0.0051)
Kleibergen-Paap F-statistic		13.00		13.03		12.81		12.95
Controls:								
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Football Match	YES	YES	YES	YES	YES	YES	YES	YES
Lagged Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
No. of Observations	40,850	40,850	40,850	40,850	40,850	40,850	40,850	40,850
No. of countries	190	190	190	190	190	190	190	190
Maximum Goldstein Score	-5	-5	-5	-5	-5	-5	-5	-5

Notes: This table replicates the baseline estimates but additionally controls for the lagged dependent variable in both stages. All specifications include country× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match_{iym}$. The mean (standard deviation) of the dependent variable in Panels A, B, C and D are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of $Domestic\ Turmoil$ is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.11: Controlling for other countries' behavior

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Verb\ Coop_{iym}$		$Mat\ Coop_{iym}$		$Verb\ Conf_{iym}$		$Mat\ Conf_{iym}$	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
DT_{iym}	-0.0164***	-0.0357	-0.0001	-0.0123	0.0152***	0.2656**	0.0145***	-0.0330
	(0.0042)	(0.2114)	(0.0020)	(0.0904)	(0.0026)	(0.1259)	(0.0022)	(0.0905)
First Stage Estimates		Dependent Variable: $Domestic\ Turmoil_{iym}$						
$Football\ Loss_{iym}$		0.0184***		0.0184***		0.0184***		0.0184***
		(0.0050)		(0.0050)		(0.0050)		(0.0050)
Kleibergen-Paap F-statistic		13.35		13.35		13.35		13.35
Controls:								
Country × Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
$\sum_{j=1}^{j=J} Verb\ Coop_{jiym}$	YES	YES	YES	YES	YES	YES	YES	YES
$\sum_{j=1}^{j=J} Mat\ Coop_{jiym}$	YES	YES	YES	YES	YES	YES	YES	YES
$\sum_{j=1}^{j=J} Verb\ Conf_{jiym}$	YES	YES	YES	YES	YES	YES	YES	YES
$\sum_{j=1}^{j=J} Mat\ Conf_{jiym}$	YES	YES	YES	YES	YES	YES	YES	YES
$Football\ Match_{iym}$	YES	YES	YES	YES	YES	YES	YES	YES
Observations	41,040	41,040	41,040	41,040	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190	190	190	190	190

Notes: The Table depicts the baseline OLS and IV estimates, but additionally control for foreign interactions by other countries j, targeted at country i, i.e. $\sum_{j=1}^{j=J} Verb\ Coop_{jiym}$, $\sum_{j=1}^{j=J} Mat\ Coop_{jiym}$, $\sum_{j=1}^{j=J} Verb\ Conf_{jiym}$ and $\sum_{j=1}^{j=J} Mat\ Conf_{jiym}$. All specifications include country× year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match$. The mean (standard deviation) of the dependent variable in Panels A, B, C and D are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of $Domestic\ Turmoil$ is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the dyad level, are in parenthesis.

Table B.12: Dyadic diversion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Verb\ Coop_{ijym}$		$Mat\ Coop_{ijym}$		$Verb\ Conf_{ijym}$		$Mat\ Conf_{ijym}$	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$Domestic\ Turmoil_{iym}$	0.0001***	0.0012	0.0004***	0.0012	0.0003***	0.0046**	0.0005***	-0.0001
	(0.0001)	(0.0012)	(0.0001)	(0.0020)	(0.0001)	(0.0023)	(0.0001)	(0.0022)
First Stage Estimates				Dependent Variable: $Domestic\ Turmoil_{iym}$				
$Football\ Loss_{iym}$		0.0183***		0.0183***		0.0183***		0.0183***
		(0.0051)		(0.0051)		(0.0051)		(0.0050)
Kleibergen-Paap F-statistic		13.03		13.03		13.03		13.03
Controls:								
Dyad × Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
$Football\ Match_{jym}$	YES	YES	YES	YES	YES	YES	YES	YES
$Verb\ Coop_{jiym-1}$	YES	YES	YES	YES	YES	YES	YES	YES
$Mat\ Coop_{jiym-1}$	YES	YES	YES	YES	YES	YES	YES	YES
$Verb\ Conf_{jiym-1}$	YES	YES	YES	YES	YES	YES	YES	YES
$Mat\ Conf_{jiym-1}$	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650
No. of countries	190	190	190	190	190	190	190	190

Notes: The Table depicts the OLS and 2SLS estimates using a dyad-month level data set. All specifications include dyad× year fixed effects and month fixed effects. Both stages control for $Football\ Match$, as well as for foreign interactions by other countries j, targeted at country i, i.e. $Verb\ Coop_{jiym-1}$, $Mat\ Coop_{jiym-1}$, $Verb\ Conf_{jiym-1}$ and $Mat\ Conf_{jiym-1}$. The mean (standard deviation) of the dependent variable in Columns (1)-(2), (3)-(4), (5)-(6) and (7)-(8) are 0.0040 (0.03801), 0.0021 (0.0366), 0.0023 (0.0378) and 0.0020 (0.0361), respectively. The average value of $Domestic\ Turmoil$ is 0.2180, with a standard deviation of 0.3113. The unit of measurement is a dyad-month. Standard errors, clustered at the country j level, are in parenthesis.

Table B.13: The effect of DT on governments' domestic interactions

	(1) $Verb\ Coop_{iym}$	(2) $Mat\ Coop_{iym}$	(3) $Verb\ Conf_{iym}$	(4) $Mat\ Conf_{iym}$
Panel A: OLS Estimates				
$Domestic\ Turmoil_{iym}$	-0.0342***	0.0015	0.0350***	0.0616***
	(0.0068)	(0.0025)	(0.0032)	(0.0040)
Panel B: Reduced Form Estimates				
$Football\ Loss_{iym}$	0.0047	-0.0023	-0.0001	0.0038
	(0.0048)	(0.0020)	(0.0029)	(0.0023)
Panel C: IV Estimates				
$Domestic\ Turmoil_{iym}$	0.2552	-0.1281	-0.0045	0.2087
	(0.2680)	(0.1144)	(0.1570)	(0.1423)
Panel D: First–Stage Estimates	Dependent Variable: $Domestic\ Turmoil_{iym}$			
$Football\ Loss_{iym}$	0.0182***	0.0182***	0.0182***	0.0182***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Kleibergen-Paap F-statistic	13.12	13.12	13.12	13.12
Controls:				
Country-Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Football Match	YES	YES	YES	YES
No. of observations	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190
Maximum Goldstein Score	-5	-5	-5	-5

Notes: The dependent variables in Panels A, B and C are domestic interactions initiated by a country's government, classified as $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$, expressed as a fraction of the total number of foreign interactions initiated. $Domestic\ Turmoil$ expresses all domestic events targeting the government that record a Goldstein score of -5 or less, as a fraction of all domestic events targeting the government. $Football\ Loss$ is the count of all football losses experienced by a country against an opponent with a rating differential of 150 points or less. Both stages additionally control for $Football\ Match$, which is the number of close football matches played by the country over the period. The mean (standard deviation) of the dependent variables in Columns 91), (2), (3) and (4) are 0.5755 (0.3850), 0.0539 (0.1224), 0.0768 (0.1420) and 0.0493 (0.1186), respectively. The average value of $Domestic\ Turmoil$ is 0.2179, with a standard deviation of 0.3113. The unit of measurement is a country-month. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.14: Alternative specification based on Manacorda and Tesei (2020)

	(1)	(2)	(3)	(4)
Panel A	$Verb\ Coop_{iy}$	$Domestic\ Turmoil_{iym}$	$Coverage_{iy}$	$\Delta\ GDP_i \times Coverage_{iy}$
$Domestic\ Turmoil_{iy}$	-0.6251**			
	(0.2930)			
$Coverage_{iy}$		7.8482***		
		(2.9750)		
$\Delta\ GDP_i \times Coverage_{iy}$		-1.2370		
		(0.8460)		
$Lightning_{iy}$			-0.0015***	-0.0016***
			(0.0006)	(0.0002)
$\Delta\ GDP_i \times Lightning_{iy}$			0.0008	0.0313***
			(0.0033)	(0.0018)
Panel B	$Mat\ Coop_{iy}$	$Domestic\ Turmoil_{iym}$	$Coverage_{iy}$	$\Delta\ GDP_i \times Coverage_{iy}$
$Domestic\ Turmoil_{iy}$	0.0021			
	(0.0691)			
$Coverage_{iy}$		6.9836**		
		(3.0203)		
$\Delta\ GDP_i \times Coverage_{iy}$		-1.5581*		
		(0.8679)		
$Lightning_{iy}$			-0.0015***	-0.0016***
			(0.0006)	(0.0002)
$\Delta\ GDP_i \times Lightning_{iy}$			0.0007	0.0313***
			(0.0033)	(0.0018)
Panel C	$Verb\ Conf_{iy}$	$Domestic\ Turmoil_{iym}$	$Coverage_{iy}$	$\Delta\ GDP_i \times Coverage_{iy}$
$Domestic\ Turmoil_{iy}$	0.4996***			
	(0.1333)			
$Coverage_{iy}$		7.0141**		
		(2.9373)		
$\Delta\ GDP_i \times Coverage_{iy}$		-1.5467*		
		(0.8276)		
$Lightning_{iy}$			-0.0015***	-0.0016***
			(0.0006)	(0.0002)
$\Delta\ GDP_i \times Lightning_{iy}$			0.0007	0.0313***
			(0.0033)	(0.0018)
Panel D	$Mat\ Conf_{iy}$	$Domestic\ Turmoil_{iym}$	$Coverage_{iy}$	$\Delta\ GDP_i \times Coverage_{iy}$
$Domestic\ Turmoil_{iy}$	0.1737**			
	(0.0791)			
$Coverage_{iy}$		7.1908**		
		(2.9985)		
$\Delta\ GDP_i \times Coverage_{iy}$		-1.4811*		
		(0.8574)		
$Lightning_{iy}$			-0.0015***	-0.0016***
			(0.0006)	(0.0002)
$\Delta\ GDP_i \times Lightning_{iy}$			0.0007	0.0313***
			(0.0033)	(0.0018)
Controls:				
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
No. of Observations	695	695	695	695
No. of countries	47	47	47	47

Notes: Table shows the 3SLS estimates examining relationship between FP and DT when using (a) lightning strikes as a predictor of mobile phone coverage (Columns (3) and (4)) and (b) using mobile phone coverage as a predictor of $Domestic\ TurmoilT$ (Column (2)), as proposed by Manacorda and Tesei (2020). The unit of analysis is a country-year. Sample is limited to countries in the African continent due to data constraints. The mean (standard deviation) of $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$ are 0.7050 (0.1798), 0.0478 (0.0372), 0.0711(0.0571) and 0.0439 (0.0420), respectively. The average value of $Domestic\ Turmoil$ is 0.2143, with a standard deviation of 0.1675. Robust standard errors are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.15: Heterogeneous effects of DT on diversionary foreign interactions

	(1) $Verb\ Coop_{iym}$	(2) $Mat\ Coop_{iym}$	(3) $Verb\ Conf_{iym}$	(4) $Mat\ Conf_{iym}$
Panel A: Political Institutions				
$Domestic\ Turmoil_{iym} \times Anocracy_i$	-0.2054	0.0960	0.3460*	0.2509
	(0.2866)	(0.1281)	(0.1780)	(0.1565)
$Domestic\ Turmoil_{iym} \times Autocracy_i$	-0.4497	0.3965	0.0343	-0.3149
	(0.6323)	(0.3373)	(0.2735)	(0.3497)
$Domestic\ Turmoil_{iym} \times Democracy_i$	0.5329	-0.3332	0.2644	-0.1840
	(0.5657)	(0.2828)	(0.2895)	(0.2443)
$Domestic\ Turmoil_{iym} \times Anocracy_i +$ $Domestic\ Turmoil_{iym} \times Autocracy_i +$ $Domestic\ Turmoil_{iym} \times Democracy_i$	-0.1222	0.1594	0.6447*	-0.2479
	(0.7037)	(0.3638)	(0.3500)	(0.3233)
First–stage F-statistic	3.24;2.51;1.76	3.24;2.51;1.76	3.24;2.51;1.76	3.24;2.51;1.76
No. of Observations	34,776	34,776	34,776	34,776
No. of countries	161	161	161	161
Panel B: Income Level				
$Domestic\ Turmoil_{iym}$	-0.2874	0.1565	0.3015*	0.0010
	(0.3604)	(0.1735)	(0.1827)	(0.1297)
$Domestic\ Turmoil_{iym} \times Income_i$	1.043	-0.7334	-0.1628	-0.1613
	(1.4869)	(0.9468)	(0.6304)	(0.5050)
$Domestic\ Turmoil_{iym} +$	0.7554	-0.5770	0.1386	-1603
$Domestic\ Turmoil_{iym} \times Income_i$	(1.244)	(0.8266)	(0.5107)	(0.4232)
First–stage F-statistic	7.07;1.09	7.07;1.09	7.07;1.09	7.07;1.09
Observations	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190
Panel C: Human Development				
$Domestic\ Turmoil_{iym}$	-0.7168	0.2877	0.3490*	0.0592
	(0.4560)	(0.2054)	(0.2088)	(0.1439)
$Domestic\ Turmoil_{iym} \times HDI_i$	1.210	-0.5801	-0.1765	-0.1888
	(0.7698)	(0.3516)	(0.3555)	(0.2594)
$Domestic\ Turmoil_{iym} +$	0.4933	-0.2924	0.1725	-0.1296
$Domestic\ Turmoil_{iym} \times HDI_i$	(0.4763)	(0.2260)	(0.2220)	(0.1764)
First–stage F-statistic	7.55;3.26	7.55;3.26	7.55;3.26	7.55;3.26
Observations	38,316	38,316	38,316	38,316
No. of countries	181	181	181	181
Panel D: Election Cycle				
$Domestic\ Turmoil_{iym}$	-0.0477	-0.0140	0.2685**	-0.0351
	(0.2248)	(0.0910)	(0.1286)	(0.0920)
$Domestic\ Turmoil_{iym} \times Election_{iym}$	-0.2093	0.0744	0.2114	0.0709
	(0.2054)	(0.0630)	(0.1461)	(0.1446)
$Domestic\ Turmoil_{iym} +$	-0.2570	0.0605	0.4800**	0.0358
$Domestic\ Turmoil_{iym} \times Election_{iym}$	(0.3532)	(0.1156)	(0.2184)	(0.1906)
First–stage F-statistic	7.19;22.77	7.19;22.77	7.19;22.77	7.19;22.77
Observations	41,040	41,040	41,040	41,040
No. of countries	190	190	190	190
Controls:				
Country-Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Football Match	YES	YES	YES	YES
Maximum Goldstein Score	-5	-5	-5	-5

Notes: Second–stage IV estimates are reported. $Anocracy_i$ is a time-invariant indicator that equals 1 if the average polity score over the sample period was $\geq$ -5 to $\leq$ 5. $Democracy_i$ ($Autocracy_i$) is a time-invariant indicator that equals 1 if average polity score over the sample period was $\geq$ 6 ($\leq$ -6). $Income_i$ is a time-invariant that equals 1 if the country was classified as a high or upper-middle income country in at least one of the sample years. HDI_i is a time-invariant that equals 1 if the average HDI score over the sample period was $\geq$ 0.5 (on a scale of 0–1). $Election_{iym}$ is a binary indicator that equals 1 if the country reported an election in the given month of the given year. All specifications include country$\times$ year fixed effects and month fixed effects. Both stages additionally control for $Football\ Match_{iym}$.The unit of measurement is a country-month. Sample size is determined by data availability. The joint estimate for the variables is reported at the bottom of the table. When multiple F-statistics are reported, they are from the first-stage regression with $Domestic\ Turmoil_{iym}$ and the interaction terms as the dependent variable, respectively. The mean (standard deviation) of $Verb\ Coop$, $Mat\ Coop$, $Verb\ Conf$ and $Mat\ Conf$ are 0.6835 (0.3483), 0.0478 (0.1036), 0.0692 (0.1249) and 0.0420 (0.1018), respectively. The average value of $Domestic\ Turmoil$ is 0.2179, with a standard deviation of 0.3113. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.16: Target countries by features

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		$Verb\ Coop_{ijym}$			$Mat\ Coop_{ijym}$			$Verb\ Conf_{ijym}$			$Mat\ Conf_{ijym}$	
$Domestic\ Turmoil_{iym}$	-0.0207	-0.0262	0.0117	-0.0073	-0.0340	0.0171	0.0430**	0.0699***	-0.0175	0.0028	-0.0225	0.0036
	(0.0166)	(0.0216)	(0.0125)	(0.0190)	(0.0341)	(0.0161)	(0.0341)	(0.0262)	(0.0136)	(0.0235)	(0.0366)	(0.0202)
$Domestic\ Turmoil_{iym} \times Population_j$	0.0025			0.0010			-0.0042**			-0.0005		
	(0.0019)			(0.0022)			(0.0021)			(0.0029)		
$Domestic\ Turmoil_{iym} \times Mil.Exp_j$		0.0021			0.0028			-0.0050**			0.0017	
		(0.0017)			(0.0027)			(0.0021)			(0.0030)	
$Domestic\ Turmoil_{iym} \times Capability_j$			0.0016			0.0022			-0.0032*			0.0007
			(0.0017)			(0.0021)			(0.0018)			(0.0026)
Controls:												
Dyad×Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of Observations	5,564,160	5,149,440	5,564,160	5,564,160	5,149,440	5,564,160	5,564,160	5,149,440	5,564,160	5,564,160	5,149,440	5,564,160
Mean DV	0.0048	0.0048	0.0048	0.0026	0.0026	0.0026	0.0028	0.0028	0.0028	0.0024	0.0024	0.0024
Standard deviation of DV	0.0406	0.0406	0.0406	0.0401	0.0401	0.0401	0.0416	0.0416	0.0416	0.0397	0.0397	0.0397

Notes: The Table depicts the second stage estimates at the dyad-month level. Columns (1)-(3), (4)-(6), (7)-(9) and (10)-(12) are estimated with $Verb\ Coop_{ijym}$, $Mat\ Coop_{ijym}$, $Verb\ Conf_{ijym}$ and $Mat\ Conf_{ijym}$ as the dependent variable, respectively. $Population_j$ and $Mil.Exp_j$ are natural logarithms of country j's population and Military Expenditure levels for the year 1997, i.e. the first year of the sample. $Capability_j$ is the Composite Index of National Capability (Singer, 1987) which is an index of the national material capabilities of government that takes in to account a country's demographic, economic, and military strength. Sample size is dependent on data availability. All specifications include dyad× year fixed effects and month fixed effects. Both stages additionally control for *Football Match*. The average value of *Domestic Turmoil* is 0.2340, with a standard deviation of 0.3138. Standard errors, clustered at the target country level, are in parenthesis.The unit of measurement is a dyad-month.

Table B.17: Effectiveness of diversionary foreign interactions

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	3SLS	OLS	3SLS	OLS	3SLS
	DT_{iym+1} (GDELT)		DT_{iym+1} (ICEWS)		$Protest_{iym+1}$	
$Verb\ Conf_{iym}$	0.0350***	-0.1485	0.0084	0.0363	0.0204*	-0.7598
	(0.0117)	(1.0125)	(0.0139)	(1.1792)	(0.0122)	(0.7732)
	[0.0126]	[1.0698]	[0.0132]	[1.1532]	[0.0114]	[0.8203]
Controls:						
Country-Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Football Match	YES	YES	YES	YES	YES	YES
No. of observations	40,850	40,850	38,915	38,915	27,950	27,950
No. of countries	190	190	181	181	130	130

Notes: Odd Columns present the OLS results while the even columns present the 3SLS results. The dependent variable in Columns (1) and (2) is the GDELT-based *Domestic Turmoil* index in month $m+1$, while the dependent variable in Columns (3) and (4) is the ICEWS-based *Domestic Turmoil* index in month $m+1$. In Columns (5) and (6), the dependent variable is the ihs-transformed number of protests targeted at the government, in month $m+1$. Mean (standard deviation) of the dependent variable in Columns (1)-(2), (3)-(4) and (5)-(6) are 0.2183 (0.3114), 0.2378 (0.3969) and 0.0533 (0.2376), respectively. Average value of $Verb\ Conf$ is 0.0692, with a standard deviation of 0.1249. The unit of measurement is a country-month. ( ) and [ ] display robust standard errors and jackknife bootstrapped standard errors, respectively. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.18: Target countries' response

	(1) OLS	(2) 3SLS	(3) OLS	(4) 3SLS	(5) OLS	(6) 3SLS	(7) OLS	(8) 3SLS
	$VerbCoop_{jiym+1}$		$MatCoop_{jiym+1}$		$VerbConf_{jiym+1}$		$MatConf_{jiym+1}$	
$Verb\ Conf_{ijym}$	0.0047***	0.6374	0.0061***	0.3850	0.0114***	-0.2073	0.0086***	-0.8260
	(0.0004)	(0.6450)	(0.0004)	(0.5868)	(0.0004)	(0.5551)	(0.0004)	(0.7027))
	[0.0009]	[0.8242]	[0.0014]	[0.6249]	[0.0019]	[0.8289]	[0.0017]	[1.0481]
Controls:								
Dyad-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Football Match	YES	YES	YES	YES	YES	YES	YES	YES
No. of observations	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650	7,720,650
No. of countries	190	190	190	190	190	190	190	190

Notes: Odd columns present the OLS results while the even columns present the 3SLS results. The dependent variables are indicators of country j's interactions towards country i in month $m+1$, classified as Verbal Cooperation, Material cooperation, Verbal Conflict and Material Conflict. The mean (standard deviation) of the dependent variables in Columns (1)-(2), (3)-(4), (5)-(6) and (7)-(8) are 0.0040 (0.0381), 0.0021 (0.03660), 0.0023 (0.0378) and 0.0020 (0.0361), respectively. The average value of $Verb\ Conf_{ijym}$ is 0.0023, with a standard deviation of 0.0378. The unit of measurement is a dyad-month. ( ) and [ ] display robust standard errors and jackknife bootstrapped standard errors, respectively. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.