Public Sentiment in Times of Terror

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January 2023

Abstract

How do public sentiments towards the government change following terror attacks? The literature has traditionally answered this question using temporally aggregated voting data. This paper proposes an alternative, fine-grained approach to explore the *short term* dynamics underlying public sentiments. I first use high-frequency, media-reported event data to quantify *Public Discontent*, for 135 countries, over the period 2002-2020. Comparing the change in *Public Discontent* in country-months with successful terror attacks against country-months with failed terror attacks, I find that the average level of *Public Discontent* increases by approximately 11% in the 11 months following a successful terror attack. Information on government capability, political institutions and exposure to violence are incorporated in the response. Interestingly, characteristics of the national leader, such as gender, age, length of tenure and military experience, also affect the public response. Findings highlight short term dynamics of public sentiments as a critical component in shaping the citizen-state relationship.

Keywords: Terrorism, public discontent, government, leader.
JEL classification: H11, H41, H56, D72

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1 Introduction

On 11 September 2001, in one of the most ruthless terror attacks in recent human history, 19 terrorists engaged in four coordinated suicide terror attacks targeted at key locations in the United States (US).[1] While the devastating effects of these terror attacks were felt across many sections of the society and for extended periods of time, one common observation was how strongly the public rallied around the government. A mammoth 60% of the adults interviewed in the month after the attack expressed trust in the government, the highest to be recorded in the US since the 1970's.[2] These developments are in stark contrast to the situation in Spain, where the same terror group executed the infamous 2004 Madrid train bombings, which killed 193 people and injured thousands more.[3] Countrywide anti-government protests and demonstrations arose in the following days, and the attacks have also been highlighted as a potential reason for the incumbent government's loss at the subsequent election (Bali, 2007; Montalvo, 2011).

These two terror attacks, *although different along many dimensions*, suggest that the public response to terror attacks can take different forms. While citizens rallied 'round the flag in the US, the level of public discontent rose insurmountably in Spain. What could explain these different responses? The aim of this paper is to disentangle the complex set of factors underlying public sentiments towards governments following terror attacks.

In doing so, this paper focuses specifically on the *short term* dynamics in public sentiments, which have been largely understudied in the academic literature. Thus far, the focus within the political economy literature has centered around elections as the key mechanism of government accountability (Healy and Malhotra, 2013). However, due to their aggregate and periodic nature, election data cannot capture the short-term variations in public sentiments following important events. The absence of alternative disaggregated data sources has been a major empirical barrier in exploring short term dynamics.

[1] See, for example, *BBC*, "September 11 attacks: What happened on 9/11?," 3 August 2021.

[2] Simultaneously, 86% of the adults interviewed approved George W. Bush's handling of the job as the President. See, for example, *Pew Research Center*, "Two decades later, the enduring legacy of 9/11," 2 September 2021.

[3] See, for example, *New York Times*, "Bombings in Madrid: The attack; 10 bombs shatter trains in Madrid, killing 192," 12 March 2004.

Despite such limited attention, short term public sentiments are crucial in shaping the behaviors of governments and the public alike. Continuous monitoring of public sentiments enables governments to respond to public concerns either via alleviation or strategic diversion (Lewandowsky, Jetter and Ecker, 2020; Amarasinghe, 2022), while the government's response can reciprocally affect public confidence and trust in the government as well (Sangnier and Zylberbeg, 2017).

The aim of this paper is to examine the short term dynamics in public sentiments, specifically in the aftermath of terror attacks. Departing from the traditional usage of election data, I generate a temporally granular, event-based indicator of *Public Discontent* which quantifies public sentiments towards the government, in a global representative sample of countries, at any given point in time. Combining this index with data on terror attacks in 135 countries, at the monthly level, over the years 2002-2020, I then examine whether and how short-term public sentiments towards the government change following terror attacks. In doing so, this paper provides, to the best of my knowledge, the first global-level causal estimates of the short term public response in the aftermath of terror attacks.

The *Public Discontent* index, which is the key outcome variable in this study, is based on the premise that, on a continuous basis, citizens engage in "events" through which they express their pleasure or displeasure with the government. These events, such as protests, demands or appeals targeting the government, are reported by news media. Such unstructured, media-reported event information can be used to generate a structured quantification of public sentiments, enabling the systematic study of the citizen-state relationship at fine levels of temporal granularity.

Accordingly, following Amarasinghe (2022), the *Public Discontent* index is constructed using textual data from millions of media-reported actual physical events, retrieved from the Global Database of Event, Language and Tone (GDELT). Each event in the data set receives a sentiment score as per the conflict-cooperation scale introduced by Goldstein (1992), with scores ranging from –10 to +10 based on the theoretical potential impact a particular event type can have on the political stability of a country. Using

these scores, along with information on the actors (i.e., initiator and target) involved in the reported event, the *Public Discontent* index expresses the number of "negative" domestic events targeted at the government in a given month, as a proportion of the total number of domestic events targeted at the government.[4] I then combine this index with data on terror attacks extracted from the Global Terrorism Database (GTD) to examine how *Public Discontent* behaves in the aftermath of terror attacks. For the purpose of the empirical exercise, I use the full set of terror attacks, targeted at any party, recording at least one fatality. *Ex-ante*, I hypothesize that *Public Discontent* will increase following terror attacks. However, I also hypothesize that rational citizens would incorporate relevant information such as the government's perceived/realized competence, government's response following terror attacks, as well as terrorists' fighting capacity, in to their expressed sentiments.

In the first part of the empirical strategy, I compare country-months where terror attacks occurred with country-months where no terror attacks occurred, and find that the occurrence of a terror attack is followed by a statistically and economically significant increase in *Public Discontent*. However, these estimates potentially suffer from selection bias, since the location and the timing of terror attacks are likely strategically decided by terrorists. To address this problem, I apply an alternate identification strategy building on the work of Brodeur (2018) who proposes that, conditional on the location and timing of terror events, and controlling for the type/weapon of the attack, the *success* or *failure* of the terror attack is as good as random.[5] Therefore, in this second identification strategy, I consider, not the occurrence of a terror attack, but the *outcome* of a terror attack, and establish that country-months with successful attacks are not statistically significantly different from country-months with failed attacks, along observable dimensions.[6] Based on this premise, I then provide causal estimates of the direction and magnitude of the

[4] More details on the *Public Discontent* Index are available in Sections 2.1 and A.1.

[5] This identification strategy was first introduced by Jones and Olken (2009), in the context of assassination attempts of political leaders.

[6] A country-month is defined as one with a successful attack if it recorded at least one successful attack. A country-month is identified as one with a failed attack if at least one failed attack, and no successful attacks, were recorded. While country-months with successful terror attacks may still differ from country-months with failed terror attacks along unobservable dimensions, within the empirical strategy I use a number of alternative vectors of fixed effects to account for this concern as comprehensively as possible.

change in public sentiment towards governments in the aftermath of terror attacks. I find that, conditional on the timing, location and weapon/attack type, *Public Discontent* increases by a sizable 11%, over the sample mean, in the 11 months following a *successful terror attack*. These estimates remain robust to a number of alternative specifications.

Next I explore the mechanisms underlying this effect. At the outset I acknowledge that, in the absence of specific data sets, pinning down the exact mechanism is a challenge. Nevertheless, within these empirical constraints, I examine a number of possibilities. I first check whether the increase in *Public Discontent* is a result of public anger with the government or of sympathy for terror groups. Using alternative indices of public sentiments targeting terror groups, I find no evidence of an increase in support for terrorists, thus eliminating the "sympathy with terrorists" channel. Next, I demonstrate that there is no "general increase is discontent in the society" following successful terror attacks, based on a falsification test which confirms that discontent at other major entities remain unaffected. Taken together, these two findings show that the increase in *Public Discontent* following terror attacks is *specifically targeted at the government*, suggesting that "government accountability" is a potential mechanism underlying this response.

Building on this finding, next I examine how information on government capability affect the public response. Considering country-specific characteristics, the increase in *Public Discontent* occurs specifically in countries where governments committed less resources to counter terrorism. The increase in *Public Discontent* is also more prominent in countries least exposed to terrorism and violence. The trend reverses in democratic countries, where the public become less condemning of the government following successful terror attacks. In terms of attack-specific characteristics, the government is criticized less if the attack was a lone wolf attack, which is intrinsically harder to predict and control, as opposed to an attack by an organized terror group. The response is stronger for domestic attacks, highlighting that in-group threats are more relevant for the public as opposed to out-group threats. Interestingly, I observe a reversal of the baseline effect depending on the characteristics of the national leader in power. Public criticism is lower if a female leader, young leader, new leader or military leader is in power. These heterogeneous

effects based on country-specific, attack-specific and leader specific characteristics further highlight public rationality in holding the government accountable, and eliminate "fear due to insecurity" as a potential mechanism.

Taken together, these findings have important policy implications. First, they establish that the government and its performance is scrutinized by the public not only during elections, but continuously and consistently throughout its tenure. The analyses on mechanisms eliminate a number of alternative hypotheses and strongly suggest government accountability as a potential mechanism. Such continued 'rational' public scrutiny in the short term acts as a system of checks and balances on government performance, and can even shape its trajectory in the long run. These findings are also important in light of the literature suggesting that increased public discontent may induce governments to strategically engage in aggressive diversionary tactics (Morgan and Anderson, 1999; Lewandowsky, Jetter and Ecker, 2020; Amarasinghe, 2022) which can lead to instability in the domestic or international space. As such, understanding the short term causes and consequences of *Public Discontent* is a critical component in determining the behaviors of actors in the citizen-state relationship.

This paper contributes to several strands of the literature. Primarily, it relates to the broad political economy literature that examines terrorism as an important socioeconomic phenomenon. One portion of this literature focuses on the *causes* of terrorism, ranging from economic to non-economic conditions (Krueger and Malečkova, 2003; Dreher and Gassebner, 2008; Enders and Hoover, 2012; Jetter, 2017; Mahmood and Jetter, 2022). A second portion focuses on the *consequences* of terrorism, such as on employment and wages (Benmelech, Berrebi and Klor, 2010; Brodeur, 2018), economic growth (Blomberg, Hess and Orphanides, 2004; Abadie and Gardeazabal, 2008), bilateral trade (De Sousa, Mirza, and Verdier, 2018), migration (Dreher, Krieger and Meierrieks, 2011), cabinet duration (Gassebner, Jong-A-Pin and Mierau, 2008), immigrant assimilation (Gould and Klor, 2016) and asylum approval (Brodeur and Wright, 2019). In general terms, my paper contributes to this second portion of the literature by exploring the short term consequences of terror attacks on public sentiment, specifically targeted at governments.

As such, this paper complements Brodeur (2018) who examines the effect of terror attacks on consumer sentiments in terms of business conditions and buying conditions, although in my paper the focus is specifically on sentiments targeted at the government.

Within this specific portion of the literature studying consequences of terror attacks, there is growing academic interest in studying the effects of terror attacks on political preferences. Bali (2007) and Montalvo (2011) find that the 2004 Madrid train bombings contributed to replacing the incumbent government. Berrebi and Klor (2008) and Elster (2019) show that terror attacks increase right-bloc parties' vote share in Israel, while Rehman and Vanin (2017) find that exposure to terrorism is associated with lower support for democratic values. This portion of the literature also relates to the broad political economy literature exploring government accountability for socioeconomic outcomes, typically focusing on retrospective voting as a tool,[7] in relation to economic performance (Margalit, 2011; Reeves and Gimpel, 2012), as well as for the delivery of non-economic public goods (Karol and Miguel, 2007; Healy and Malhotra, 2009; Gasper and Reeves, 2011). Achen and Bartels (2004) find that voters punish governments for "acts of god" i.e., droughts, flu and shark attacks, while Fowler and Hall (2018) dispute this claim in relation to shark attacks. Interestingly, Hassell, Holbein and Baldwin (2020) and Baccini, Brodeur, Nossek and Shor (2021) find no effect of school shooting events and terrorist attacks, respectively, on voting outcomes in the US.

While electoral accountability is a critical component in the citizen-state relationship, the temporal gap between elections is a major empirical barrier in using voting data to explore the short term variations in public sentiments.[8] Moreover within the election cycle, events that occurred closer to the election receive higher salience in voters' minds, thereby crowding out important events with a higher temporal distance (Herrnstadt and Muehlegger, 2014; Adida, Gottlieb, Kramon, and McClendon, 2020). My paper contributes to and advances this literature by exploring the short term dynamics in government account-

[7]For an overview of the literature on retrospective voting, see Healy and Malhotra (2013).

[8]Some studies attempt to circumvent this limitation by measuring public sentiment towards government via public opinion surveys (Arnold and Carnes, 2012; Sangnier and Zylberberg, 2017). However, similar to elections, survey responses are not available at a global scale and at consistent time intervals. In particular, global surveys capturing the public's attitudes on governments, such as the World Values Survey (WVS) or the Afrobarometer survey, take place in waves, and are available in 2-3 year intervals.

ability, not being limited to periodic voting data. Building on the work in Amarasinghe (2022), I use a quantified, event-based *Public Discontent* index, which can be used as a consistent and continuous indicator of public sentiment at fine degrees of temporal granularity, and for the world as a whole. To the best of my knowledge, this is the first paper to explore the *short term dynamics* surrounding public sentiments towards governments in the aftermath of terror attacks, for a globally representative sample of countries.

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 the underlying mechanisms. Section 5 concludes.

2 Data

The unit of analysis is a country-month. The final sample consists of monthly observations for 135 countries, over the years 2002-2020. Within the sample, 6,451 country-month observations record a terror attack.

2.1 Data on public discontent

Recent developments in natural language processing (NLP) algorithms have led to the increased availability of new, massive databases that capture event data from worldwide news media reports. These high-frequency data sets can be used to uncover sentiments of the broader public at fine levels of spatial and temporal granularity, thereby transcending many empirical barriers that have constrained quantitative social scientists for years.

Following Amarasinghe (2022), I leverage on such high-frequency event data extracted from the GDELT project to generate an index of *Public Discontent* that quantifies public sentiments towards governments. GDELT is a real time open data global graph of the human society, analyzed using print, broadcast, and web news media in over 100 languages across every country in the world, in 15 minute intervals (Leetaru and Schrodt, 2013). It applies NLP algorithms to extract over 300 categories of physical activities based on

Conflict and Mediation Event Observations (CAMEO) event codes (Gerner, Schrodt and Yilmaz, 2009), ranging from 'make a public statement' to 'appeal', 'demand', 'threaten', and 'engage in unconventional mass violence'. For each event, it provides information on approximately 60 attributes, including the type of actors involved, as well as the location of the actors and the event itself. Accordingly, this is a massive and detailed database of millions of media-reported events across the world.[9]

To generate the index of *Public Discontent*, I follow the step-wise procedure proposed in Amarasinghe (2022). I first identify all the 'domestic' events that occurred in a country over the sample period.[10] Next, based on information on the 'target', I extract the sub-sample of domestic events *specifically targeting the government*.[11] I then identify the sentiment attached to each event using the reported score on the Goldstein scale (Goldstein, 1992), which captures the theoretical potential impact posed by each event type on the stability of a country. On the Goldstein scale, each event type is assigned a score on a range of –10 (extreme conflict) to 10 (extreme cooperation), based on its inherent intensity of conflict and/or cooperation.[12] Since the objective is to quantify *Public Discontent*, my focus is primarily on events that receive a *negative* score on the Goldstein scale.

I estimate the index of *Public Discontent* using Equation 1,

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

where $Dom_{iymG\leq -5}$ refers to the number of domestic events targeting the government, recording a maximum Goldstein value of –5.[13] The denominator $Dom_{iym-10\leq G\leq 10}$ refers to

[9]Detailed information on the nature and content of this data set can be found in Section A.1.

[10]For the purpose of identification, all events where the locations of the source, the target and the event itself are within the same country are classified as 'domestic'. To sustain the integrity of the index, baseline estimates are based on the set of events which were recorded in at least 3 media reports. In Figure B.6 I provide estimates for alternative cutoffs.

[11]In GDELT the target category "government" refers mainly to the executive branch of the government, which is what I use in the baseline estimates. In Table B.2, I examine the effects on the legislature and the judiciary, as well as on the composite.

[12]A summary list of CAMEO event types and associated Goldstein scores are available in Table A.1.1.

[13]By using a threshold of –5 and below in the baseline specification, I exclude events with scores near zero, which could be perceived as being more 'neutral' instead of 'negative'. The results are robust to alternative thresholds, as indicated in Figure B.5.

the total number of domestic events targeting the government, on the full spectrum of the Goldstein scale (-10 $\leq$ G $\leq$ 10). Accordingly, $PublicDiscontent_{iymG\leq -5}$ is a standardized indicator that captures people's resentment towards their government, expressing the proportion of events attached with a negative sentiment score, relative to all events, targeted at the government.

Using event data to quantify the level of *Public Discontent* towards governments provides several advantages. First, it allows me to consistently quantify public sentiments towards governments, in a globally representative sample of countries, and at a fine degree of temporal granularity, enabling me to surpass empirical challenges associated with the usage of periodic voting data. Second, as demonstrated in Table A.1.1, the *Public Discontent* index transcends the boundaries of traditional data sets by capturing a broad range of event types underlying public sentiments, such as demands, threats, coercion and the use of force, instead of being limited to a single event type. Additionally, being a standardized index as opposed to a simple count variable, it captures the change in negative sentiment towards the government *relative* to the change in positive sentiment, during each period, thereby making it comparable across time and space.[14]

Given the novelty of this *Public Discontent* index, it is necessary to examine how well it represents existing, albeit imperfect, indicators of public sentiment. Section A.1 provides detailed information and a number of tests that strengthen the validity of this measure as an indicator of public sentiment towards governments. Specifically, in Table A.1.2 I show that the *Public Discontent* index is strongly correlated (in the expected direction) with other measures of public sentiments such as presidential approval ratings and public protests. Interestingly, I observe that the *Public Discontent* index is correlated with outcomes of the formal voting process i.e., *Public Discontent* in election years can strongly predict the incumbent party's loss at the election, further strengthening the index's validity. Moreover, using data from the WVS and the Afrobarometer Survey, in Figure A.1.2 I show that *Public Discontent*, measured in the weeks leading up to the

[14]Nevertheless, it is important to note that a number of factors, ranging from a country's level of political institutions to cultural norms and media behavior, could affect the levels and variation of *Public Discontent* within and between countries. These need to be appropriately addressed in the design of the empirical identification strategy, and are discussed in Section 3.

survey, can strongly predict people's sentiments towards the government, at the interview. These verification exercises provide confidence in ability of the *Public Discontent* index to accurately capture people's negative sentiments towards the government.

2.2 Data on terror attacks

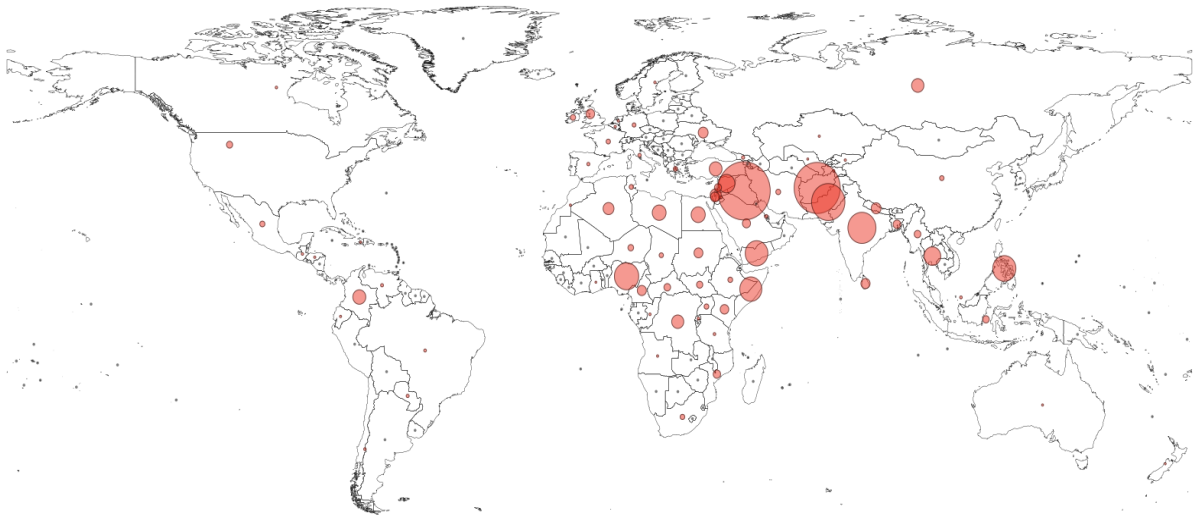
I obtain data on terror attacks from the Global Terrorism Database (GTD), which is published by the National Consortium for the Study of Terrorism and Responses to Terrorism and Responses to Terrorism (START) at the University of Maryland. It is currently one of the most widely used data sets on global terrorism (see, for example, Kis-Katos, Liebert, and Schulze, 2011; Brodeur, 2018; Baccini, Brodeur, Nossek and Shor, 2021).

The GTD defines a terror attack as *"the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation."* In order to be included in the data set, the event *must* (a) be intentional, (b) entail some level of violence or threat of violence, and (c) involve subnational perpetrators. Additionally, at least two of the following three criteria must be fulfilled - the act must be aimed at attaining an economic, political, religious, or social goal; there must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience than the immediate victims; and the action must be outside the context of legitimate war activities.

The database provides detailed information on terror attacks, including the date, location, weapon/method used, the number of fatalities and the target type. For the purpose of my analysis, I use all terror attacks, irrespective of the target, which recorded at least one fatality. Figure 1 shows the geographic distribution of these terror events within the sample period.

Importantly for the purpose of my analysis, the GTD provides, for each terror event, an indication of whether the attack was successful or not. This is arguably a complicated decision, and the GTD conducts this classification based on an objective criterion that captures the tangible effects of each attack. In particular, success is not judged based on the terrorists' larger goals, but on the attack type, and by determining whether *the*

Figure 1: Global distribution of terror attacks



Note: Figure shows the global distribution of terror attacks across the world over the sample period. Circle size is proportional to the number of terror attacks.

attack type took place. For example, an assassination attack is considered successful only if the target itself is killed. If the target is not killed but numerous others are killed in the process, this would be classified as a failed assassination attack. Likewise, a bombing attack is only considered successful if the device exploded. If not, it would be considered as a failed attack. Table A.2.1 provides the details on how each attack type is determined to be a success or failure. It is further important to note, as demonstrated in Table A.2.2, that the success rate of an attack varies by the type of attack/weapon used. For example, in the data set, the success rate of an armed assault is 94%, while the success rate of an assassination is 78%. To account for this distinction, in my preferred estimates I include a set of weapon/attack type fixed effects, which allows me to estimate the *within weapon/attack type* effects of successful and failed terror attacks on public sentiment towards governments.

2.3 Other data

Data on military expenditure is sourced from the SIPRI Military Expenditure Database (SIPRI, 2021), while data on national elections and regime changes is sourced from Bjørnskov and Rode (2020). I use data from the Polity IV project (Marshall, Gurr and Jaggers, 2019) to generate indicators of a country's level of democratic political institutions. Data on whether or not the country was engaged in a conflict is sourced from the Uppsala Conflict Data Program (UCDP). Data on the age and gender of country leaders is from the Political Leaders' Affiliation database (Dreher et al, 2020), while data on leaders' tenure and the presence of military influence in government is sourced from the Database of Political Institutions (Cruz, Keefer and Scartascini, 2020).

As an alternative outcome variable, I use data on public protests from the Mass Mobilization Project (Clark and Regan, 2016), which is a global data set of protests where 50 or more protesters publicly demonstrate *against the government*. The data set includes information on the location and size of the protest, as well as on protester demands and government responses. I also conduct a placebo test using country-level data on natural disasters from the EM-DAT database.

3 Empirical framework

To empirically examine the effect of terror attacks on *Public Discontent*, I employ a dual approach. The first approach uses a standard difference-in-differences strategy where I directly compare country-month units that experienced terror attacks with those that did not. However, these estimates may suffer from selection bias due to the non-random nature of the timing and location of terror attacks. To address this concern, in the second approach I specifically focus on the inherent "random" nature of the *outcome* of the terror attack, where a comparison is made between country-months that experienced a *successful* terror attack against those that experienced a *failed* terror attack. In the ensuing sections, I discuss these two empirical strategies in more detail.

3.1 Identification strategy 1: "Attacks vs no attacks" comparison

3.1.1 Event study estimates

I start with the naive "attacks vs no attacks" comparison. To examine how *Public Discontent* reacts in country-month units that experienced a terror attack, relative to those that did not, I first estimate the event study specification in Equation 2.

$$PublicDiscontent_{iym} = \sum_{t=-11}^{11} \alpha_t Attack_{iym-t} + \beta X_{iym} + \mathbf{FE_i} + \mathbf{FE_y} + \mathbf{FE_m} + \epsilon_{iym} \quad (2)$$

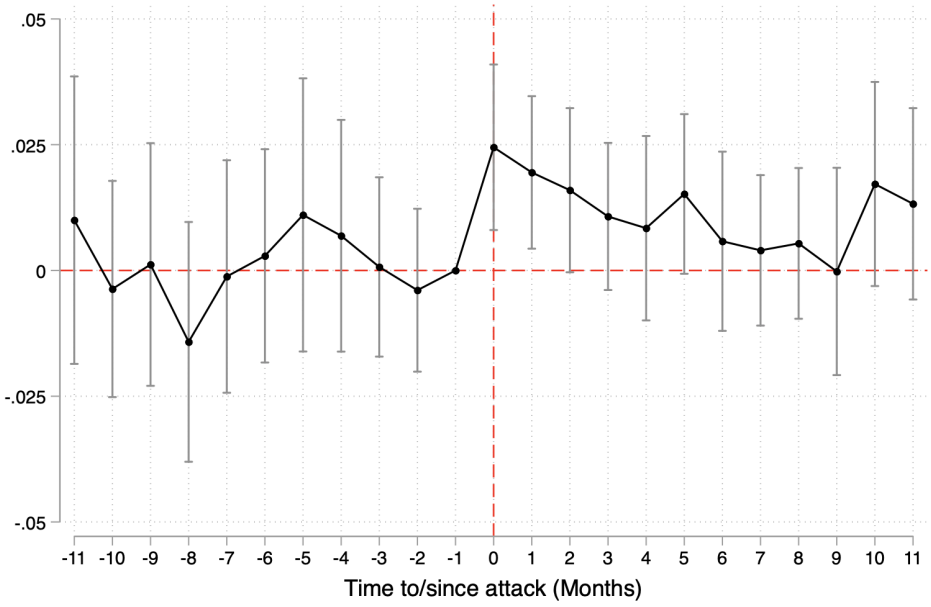
Here, $Public\ Discontent_{iym}$ is the index of public discontent in country i in month m of year y, calculated as per Equation 1. $Attack_{iym}$ is a binary indicator equal to one if a terror attack occurred in country i, in month m of year y, and zero otherwise. I include up to 11 monthly lags and leads of this variable to identify the temporal distance from the terror event. This temporal distance is negative for the months before the event, and positive for the months after the event. Moreover, inspired by Brodeur (2018), the variables are constructed in a manner such that the clock resets to zero each time an attack occurs. For example, if a country experiences terror attacks in consecutive months, both months will receive a score of 1 for the attack indicator, and the lags and leads will be set to zero for that month. The month before the attack is the omitted category.

The vector X incorporates a set of fixed effects to capture the attack type and the weapon type. I also include a vector of country fixed effects, $\mathbf{FE_i}$, which accounts for any time-invariant country-specific features. The vector of year fixed effects, $\mathbf{FE_y}$, accounts for any time-variant unobservables in a given year, while the vector of month–of–the–year fixed effects, $\mathbf{FE_m}$, accounts for unobserved seasonal variation that can simultaneously affect the relationship.

Figure 2 graphically illustrates the results of this estimation exercise. I observe that, conditional on country, year and month fixed effects, there exist no differential trends

in *Public Discontent* across countries in the 11 months leading up to the terror attack. There is a sharp and instantaneous rise in *Public Discontent* following terror attacks, which persists up to two months following the attack. This result conveys two key messages. First, it suggests that the reaction of the public following a terror attack is one of "discontent" against the government. Second, it portrays that the public reaction is visible even at this fine level of temporal granularity, i.e. at the month level, highlighting the importance of examining the short term dynamics in the relationship between the public and the government.

Figure 2: Effect of terror attacks on *Public Discontent*



Note: Figure shows the effect of terror attacks on *Public Discontent*, estimated as per Equation 2. The unit of observation is a country-month. Standard errors are clustered at the country level. Vertical lines depict the 95% confidence intervals.

3.1.2 Difference-in-differences estimates

Next, I quantify the effect of terror attacks on *Public Discontent* using the following difference-in-differences estimation strategy, where I compare country-months with terror attacks against those with no terror attacks.

$$PublicDiscontent_{iym} = \rho Post_{iym} + \beta X_{iym} + \mathbf{FE_i} + \mathbf{FE_y} + \mathbf{FE_m} + \epsilon_{iym} \tag{3}$$

Here, *Post* is a binary variable equal to one for the 11 months following a terror attack. It is equal to zero for all months before a terror attack, and for country-months with no terror attacks. The vectors of control variables and fixed effects remain the same as with Equation 2.

The coefficient of interest, ρ, captures the change in *Public Discontent* following a terror attack, relative to country-month units that did not experience a terror attack. It is important to note that *ex-ante* the sign of ρ can be positive or negative. A terror attack may lead the public to criticize the government (i.e, an increase in *Public Discontent*) which would be represented by a positive value of ρ. It may also be that people express solidarity with the government in the aftermath of a terror attack (i.e. a decrease in *Public Discontent*) which would be represented by a negative value of ρ. The ultimate direction of ρ will depend on which of these effects dominates.

The estimates of this difference-in-differences exercise are presented in Table 1. In Column (1) I present the basic model with no fixed effects. In Columns (2), (3) and (4), I add vectors of country, year and month fixed effects, respectively. In Column (5) I additionally control for attack type and weapon type fixed effects. Across the various specifications, I observe that *Public Discontent* targeted at governments increases following terror attacks. In terms of magnitude, the point estimate in Column (5) reflects an approximately 8% increase over the sample mean of the *Public Discontent* index.

3.1.3 Threats to identification

While the estimates presented in Sections 3.1.1 and 3.1.2 show that *Public Discontent* increases following terror attacks, non-trivial endogeneity concerns prevent these effects from being interpreted causally. A key threat to this identification strategy is that country-months where terror attacks occur could be systematically different from country-months in which no terror attacks take place. This threat is heightened by concerns on potential reverse causality, where an increase in *Public Discontent* at the beginning of the month may affect the probability of terror attacks later in the month. There may also exist unobservables that simultaneously affect *Public Discontent* and terror attacks. For ex-

Table 1: Effect of terror attacks on *Public Discontent*

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$	(4) *Public Discontent*$_{iym}$	(5) *Public Discontent*$_{iym}$
Post$_{iym}$	0.0463***	0.0302***	0.0202***	0.0202***	0.0088**
	(0.0045)	(0.0049)	(0.0044)	(0.0044)	(0.0037)
Observations	30,780	30,780	30,780	30,780	30,780
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Month FE	No	No	No	Yes	Yes
Attack/Weapon FE	No	No	No	No	Yes
Mean *Public Discontent*	0.1022	0.1022	0.1022	0.1022	0.1022

Notes: The unit of measurement is a country-month. The dependent variable *Public Discontent*$_{iym}$ 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. *Post* is a binary variable =1 for all country-months where a terror attack occurred and for up to 11 monthly lags, and zero for all other country-months. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

ample, a regime change that deteriorates the level of political institutions may increase both *Public Discontent* and the probability of terror attacks, leading to an upward bias. Likewise, a sudden increase in incomes due to a positive global commodity market shock could simultaneously decrease *Public Discontent* and the probability of terror attacks, thereby leading to a downward bias.

By using a stringent set of fixed effects incorporating time-invariant and time-variant unobservables, the empirical strategy already accounts for most of the unobserved variation that can lead to such bias. Moreover, the event study plot in Figure 2 finds no evidence of a differential trend in the outcome variable between the treated and untreated units prior to treatment. Nevertheless, in the next steps I conduct a prediction exercise, using a number of relevant variables for which data was available for a large majority of the countries in my sample, to systematically examine whether country-months where terror attacks occur are systematically different from country-months where no terror attacks occur. The list of considered variables include (a) indicators varying at country×year×month level (such as *Public Discontent*$_{iy,m-1}$, *Attack Count*$_{iy,m-1}$ and *Natural Disaster Count*$_{iy,m-1}$); (b) indicators varying at the country×year level (such as *GDP*$_{iy}$, *Population Density*$_{iy}$); and (c) time-invariant country-specific indicators (such as *Land Area*$_i$ and *Ruggedness*$_i$).

Results of this prediction exercise are graphically represented in Figure B.1. Here, the outcome variable is a binary indicator = 1 if any terror attack occurred in country i is year y of month m, and 0 otherwise. The sample consists of country-months with any terror attack (treatment) and country-months with no terror attacks (control). I observe that temporally granular variables such as $Public\ Discontent_{iy,m-1}$ as well as $Total\ Attack\ Count_{iy,m-1}$ can statistically significantly predict the occurrence of a terror attack in month m of year y. Of the perused variables at other levels of temporal variation, $GDP(iy)$ as well as $\%Forest_i$ also emerge as having statistically significant predictive power. These findings therefore violate the pre-requisite that country-months with terror attacks be statistically indistinguishable from country-months with no terror attacks, thereby restricting above estimates from being interpreted causally.

3.2 Identification strategy 2: "Successful vs failed terror attacks" comparison

The discussion in Section 3.1.3, in combination with the recent literature on the strategic timing and location choices of terror groups (for example, Brodeur, 2018; Brodeur and Yousaf, 2020; Yousaf, 2021) necessitate that concerns related to such biases be alleviated through an alternative identification strategy. For this purpose, I build on the work of Brodeur (2018) who proposes that, conditional on the timing and location, the *success* or *failure* of a terror attack is of a random nature.[15] In this paper, I escalate the proposition in Brodeur (2018) to the country level and for a temporally disaggregated unit of analysis, i.e. month level. In this identification strategy I restrict the analysis to country-months that experienced a successful/failed terror attack only, which allows me to filter out any non-random location or timing choices made by terrorists that could lead to selection bias, enabling the causal interpretation of these estimates. Accordingly, here the comparison is between country-months that experienced a *successful* terror attack against country-

[15]Using a set of key observable variables, Brodeur (2018) empirically establishes that the US counties where a successful terror attack occurred are not statistically significantly different from those where a failed attack occurred. This identifying assumption has since been applied, in the specific context of the US, in a number of other studies as well. For example, see Brodeur and Yousaf (2020), Baccini, Brodeur, Nossek and Shor (2021) and Yousaf (2021).

months that experienced a *failed* terror attack.

3.2.1 Event study estimates

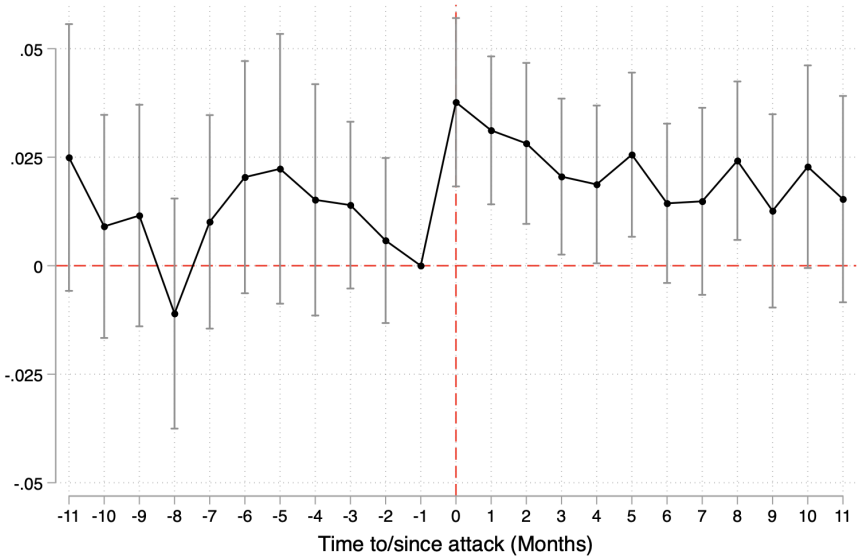
I first examine the differential effects of successful and failed terror attacks on *Public Discontent*. For this event study estimation, I use the generalized form of the equation presented in Equation 4, and limit the sample to country-months where the outcome occurred, and their respective temporal lags and leads

$$PublicDiscontent_{iym} = \sum_{t=-11}^{11} \alpha_t AttackOutcome_{iym-t} + \beta X_{iym} + \mathbf{FE_i} + \mathbf{FE_y} + \mathbf{FE_m} + \epsilon_{iym} \tag{4}$$

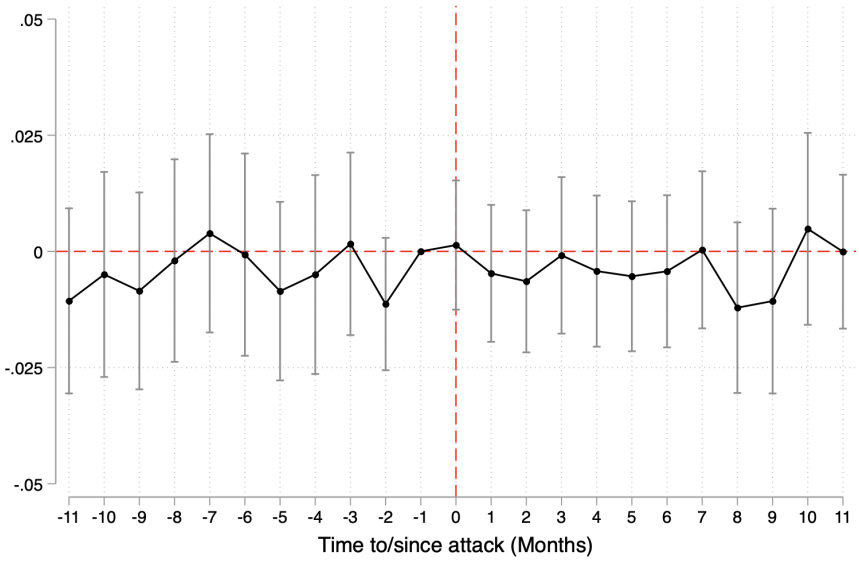
Here, *Public Discontent*$_{iym}$ is the level of public discontent in country i in month m of year y, calculated as per Equation 1. *AttackOutcome* is either (a) *Success*, a binary indicator equal to one if a successful terror attack occurred in the country, in month m of year y, or (b) *Failure*, a binary indicator equal to one if a failed terror attack occurred in the country, in month m of year y. I include up to 11 monthly lags and leads of this variable to identify the temporal distance from the terror event. This temporal distance is negative for the months before the event, and positive for the months after the event. As discussed before, the variables are constructed in a manner such that the clock resets to zero each time an attack occurs. For example, if a country experiences terror attacks in consecutive months, both months will receive a score of 1 for the attack indicator, and the lags and leads will be set to zero for that month. As with Equation 2, I include a vector of attack type/weapon type fixed effects, as well as country, year and month fixed effects. The month before the attack is the omitted category.

Panels (a) and (b) in Figure 3 show the behavior of *Public Discontent* before and after a successful and failed terror attack, respectively. In both plots, I do not observe any pre-trends. In Panel (a), I observe that successful terror attacks are followed by a sharp and instantaneous increase in *Public Discontent*, which persists up to 5 months following the successful attack. Accordingly, I note here that the effects under this 'cleaner' identification strategy are observed for longer than the effects observed under the "attack

Figure 3: Effects of successful and failed terror attacks on *Public Discontent*



(a) Successful Attacks



(b) Failed Attacks

Note: Figure shows the effect of the success and failure of terror attacks on *Public Discontent*, as per Equation 4. The unit of observation is a country-month. The sample in Panel (a) is limited to country-months with successful terror attacks and relevant lags and leads, while the sample in Panel (b) is limited to country-months with failed terror attacks and relevant lags and leads. Standard errors are clustered at the country level. Vertical lines depict 95% confidence intervals.

vs no attack" identification strategy in Figure 2.[16] By contrast, in Panel (b) I observe no statistically significant effects of failed terror attacks on *Public Discontent*.

3.2.2 Identifying assumptions

The identifying assumption here is that country-month observations with *successful* terror attacks are not statistically significantly different from country-month observations with *failed* terror attacks. To confirm the validity of this assumption, I investigate whether there are observable differences between the treatment and control groups, using the same 20 variables used in Section 3.1.3, for which data was available for a large majority of the countries in the sample. Here, a country-month is defined as one with a successful attack if it recorded at least one successful attack.[17] A country-month is identified as one with a failed attack if at least one failed attack, and no successful attack, was recorded.

Results of this prediction exercise are graphically represented in Figure B.2. Here, the outcome variable is a binary indicator = 1 if a successful terror attack (and no failed terror attack) occurred in country i is year y of month m, and 0 otherwise. The sample is restricted to country-months with successful terror attacks (treatment) and country-months with failed terror attacks (control). I observe here that none of the perused variables, irrespective of the level of temporal variation, have strong predictive power over the occurrence of a successful terror attack. (Only OECD membership is weakly significant at the 10% level, and while it seems plausible that one out of 20 variables may

[16] I further observe in Panel (a) that statistically significant effects resurface once the initial effect has worn off. Considering the level of temporal disaggregation applied in these estimates, it is possible that feedback loops continue to be observed some months after the initial effects have subsided. For example, the Gjørv Report on the investigation in to the 2011 Norway terror attacks, which was released 12 months after the attack occurred, found that the government could have prevented the attack from occurring. (See, for example, *The Star Online*, "Norway PM under pressure to quit after Breivik report," 14 August 2012.) A report released 6 months after the 2019 Easter Sunday bombings in Sri Lanka blamed government officials for failure to prevent the attack. (See, for example, *The Guardian*, "Sri Lanka bombings: spy chief lambasted in damning report," 24 October 2019.) In situations such as these, *Public Discontent* might re-ignite month later. Similarly, *Public Discontent*/interest in a terror attack may resurface when perpetrators are arrested, produced before courts, or sentenced, all of which may occur even after the initial effect of the attack has subsided. Such feedback loops are likely unobserved when using temporally aggregate (for example, yearly) data but become more prominent when considering temporally granular (for example, monthly, as in this paper) units of observation. These findings further highlight how temporally disaggregated empirical analyses can shed more light on the reciprocal relationship between the public and their governments.

[17] As such, if a country-month recorded both a successful and a failed attack, it would be classified as a country-month with a successful attack.

be weakly statistically significant, within the baseline estimates I account for this using the set of country fixed effects.) This prediction exercise therefore provides confidence that country-months with successful terror attacks are not statistically significantly different from country-months with failed terror attacks along observable features. I acknowledge however, that country-months with successful terror attacks may still differ from country-months with failed terror attacks along unobservable dimensions, and in the estimates I use a number of alternative vectors of fixed effects to appropriately account for this possibility.

3.2.3 Difference-in-differences estimates

Now I move to the core of my analysis, where I employ a difference-in-differences approach directly comparing country-months with successful attacks against country-months with failed attacks. As discussed, the comparison is *not* between country-months with and without terror attacks. Rather, I am leveraging on the *random* nature of the *outcome* of terror attacks, by essentially comparing country-months which were targeted by terrorists, but where, due to unforeseen reasons, the attack was successful in some, while unsuccessful in others.

$$PublicDiscontent_{iym} = \gamma Successful_{iym} + \tau Post_{iym} + \beta X_{iym} + \mathbf{FE_i} + \mathbf{FE_y} + \mathbf{FE_m} + \epsilon_{iym} \quad (5)$$

The estimation equation is presented in Equation 5. Here, $Successful$ is a binary variable equal to 1 if at least one successful attack occurred in country i in month m of year y, as well as for the 11 months following the successful terror attack. It assumes a value of zero for the 11 months prior to the successful attack. $Post$ is a variable equal to 1 for 11 months following any attack (successful or failed) in country i, including the month of the attack. For the 11 months preceding any attack, it assumes a value of zero.[18] As before, I include weapon/attack type fixed effects as well as country, year and month fixed effects in the estimates.

[18] In the baseline estimates, the variables $Successful$ and $Post$ include the month of the attack. In Table B.7 I exclude the effect of the month of the attack, and the results remain qualitatively and quantitatively similar.

The coefficient of interest, γ, captures the change in *Public Discontent* following successful terror attacks, relative to failed terror attacks. It could assume a positive value if the public criticizes the government following a successful terror attack, or a negative value if the public become more supportive of the government. The final direction of the coefficient depends on which of these effects dominates in the aggregate.[19]

Table 2 provides the baseline estimation results as per Equation 5. In Column (1) I first include the variable $Post_{iym}$ in isolation. The coefficient indicates that terror attacks, whether successful or failed, increase *Public Discontent*. In Column (2) I disentangle whether this increase is driven by successful attacks or failed attacks. I find that the increase in *Public Discontent* is almost entirely explained by successful terror attacks. The effect of failed terror attacks on *Public Discontent*, as captured by *Post*, is statistically insignificant. My preferred estimates appear in Column (3) where I additionally control for the type of the attack and the weapon, which allows me to compare the within-weapon/attack-type effects of successful vs failed terror attacks i.e., effects of attacks of the same type and where the same weapon was used, but where some were successful while others failed. The results remain quantitatively and qualitatively similar when this stringent set of controls is included as well. In terms of magnitude, the coefficients suggest that the occurrence of a successful terror attack increases the *Public Discontent* index by 0.0135 points, which is approximately a 11% increase over the sample mean.

The results in Table 2 demonstrate, within a causally interpretable framework, that *Public Discontent* towards the government increases following successful terror attacks. This finding is particularly interesting when considering the inconclusive nature of the existing literature on citizen competence, which is mainly based on voting data. For example, while Karol and Miguel (2007) and Reeves and Gimpel (2012) find evidence in favour of citizen competence, Hassell, Holbeing and Baldwin (2020) and Baccini, Brodeur, Nossek and Shor (2021) do not find evidence of governments being penalized for failure to deliver public goods. By contrast, based on a microscopic view of the public response

[19]It is important to note that successful attacks potentially receive more attention (among the public and the media) than failed attacks. Therefore, failed attacks are likely underreported in the GTD and as such, the estimated effects represent a lower bound of the true effect.

Table 2: Effect of successful vs failed terror attacks on *Public Discontent*

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$
$Successful_{iym}$		0.0157***	0.0135***
		(0.0036)	(0.0034)
$Post_{iym}$	0.0169***	0.0068	0.0043
	(0.0043)	(0.0044)	(0.0042)
Observations	17,282	17,282	17,282
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes
Mean *Public Discontent*	0.1212	0.1212	0.1212

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable *Public Discontent*$_{iym}$ 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. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

following terror attacks, the exercise undertaken in this paper highlights that citizens respond to shocks even at this temporally disaggregated level, and that public sentiment towards governments is therefore a highly-responsive, continuously-evolving phenomenon.

3.2.4 Diagnostic tests

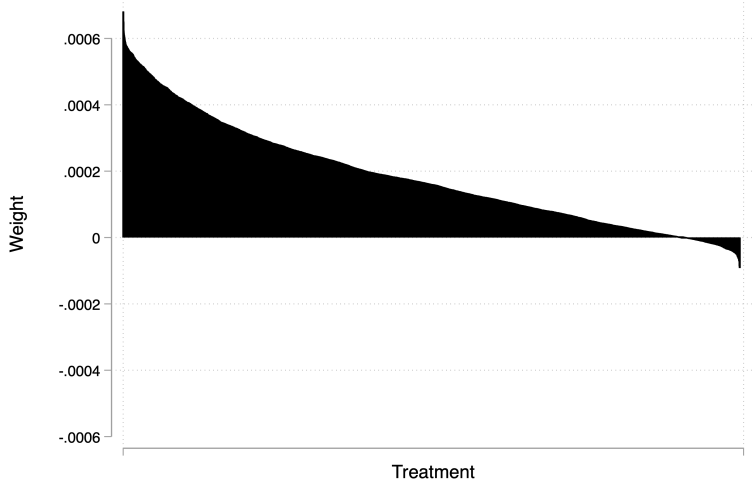
The recent literature on two-way fixed effects (TWFE) estimators has highlighted a key threat to this estimation strategy. Typically, the TWFE estimator is a weighted sum of the average treatment effects (ATE) in each group and period. However, when some such weights are negative, it may lead to a situation where the the linear regression coefficient is negative while all the ATEs are positive, and vice versa.[20]

To examine the relevance of this issue within the current setting, I follow the procedure suggested by De Chaisemartin and D'Haultfœuille (2020) to check if the weights attached to any of the treatments in this study are negative. Figure 4 demonstrates the distribution of weights for each treatment in the baseline identification strategy comparing successful

[20]For a detailed discussion on this issue and the related literature, see Baker, Larcker and Yang (2021).

vs failed terror attacks.[21] Here, 91% of the treatments receive positive weights, and the sum of the positive weights of ATEs clearly outweigh the sum of the negative weights on ATE.

Figure 4: Diagnostic tests - Weights attached to each treatment as per De Chaisemartin and D'Haultfœuille (2020)



Note: Figure shows the distribution of the weights attached to each ATE, when considering 'successful terror attack" as the treatment. This procedure was conducted using Stata's *twowayfeweights* estimator developed in line with De Chaisemartin and D'Haultfœuille (2020).

An analysis of the weights reveal that negative weights are attached specifically to country-months where successful attacks occur in close proximity to one another.[22] To further alleviate any concern that the baseline estimates may be affected by the treatments with negative weights, in Table 3 I re-estimate the baseline specification by excluding all treatments recording negative weights. I observe that the estimates remain quantitatively and qualitatively similar to baseline estimates even when such treatments are excluded.

[21] The equivalent for the "attack vs no attack" identification strategy appears in Figure B.3.

[22] Treatments belonging to terror-prone countries such as Afghanistan, India, Iraq, Libya and Pakistan make up 81% of the treatments with negative weights. The remainder is made up of treatments belonging to Colombia, Philippines, Russia, Somalia and Thailand, again where attacks occur in close temporal proximity to others.

Table 3: Excluding treatments with negative weights

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$
Successful$_{iym}$		0.0155***	0.0133***
		(0.0036)	(0.0034)
Post$_{iym}$	0.0165***	0.0064	0.0040
	(0.0042)	(0.0043)	(0.0041)
Observations	17,265	17,265	17,265
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes
Mean *Public Discontent*	0.1211	0.1211	0.1211

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. Treatments receiving negative weights for the ATE as per De Chaisemartin and D'Haultfœuille (2020) are excluded. The dependent variable *Public Discontent*$_{iym}$ 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. *Successful* is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both *Successful* and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

3.2.5 Symmetric effects of failed attacks on positive public sentiments

Just as successful terror attacks increase the public's negative sentiments towards the government, do failed attacks lead the public to praise the government? Although failed attacks are not necessarily "prevented" attacks, as per the definition of failed attacks in Table A.2.1, examining this symmetry is important in understanding the differential effects of successful and failed terror attacks on the public response. For this purpose, I define an alternative outcome variable, *Public Content*$_{iym}$, which expresses the number of events targeting the government with a positive Goldstein score of more than +5, as a proportion of the total number of events targeting the government. This variable therefore captures the other end of the sentiment spectrum and quantifies the public's *positive sentiments* towards the government.

I then apply this new indicator as the outcome variable in Equation 5 to examine how positive public sentiments behave following successful vs failed terror attacks. Table 4 provides the estimates. I observe no statistically significant effect of successful terror

attacks on *Public Content*. Interestingly, the coefficient on the variable $Post_{iym}$, which captures the effect of failed attacks, is also statistically insignificant (albeit negative).[23] These estimates therefore rule out the possibility that the public perceive failed terror attacks as a signal that the government keeps them safe, and "praise" the government following failed terror attacks.

Table 4: Effect of successful vs failed terror attacks on *Public Content*

	(1) *Public Content*$_{iym}$	(2) *Public Content*$_{iym}$	(3) *Public Content*$_{iym}$
$Successful_{iym}$		0.0001	0.0002
		(0.0034)	(0.0036)
$Post_{iym}$	-0.0024	-0.0024	-0.0011
	(0.0043)	(0.0051)	(0.0050)
Observations	17,282	17,282	17,282
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes
Mean *Public Content*	0.1491	0.1491	0.1491

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable *Public Content*$_{iym}$ expresses all domestic events targeting the government that record a Goldstein score of +5 or more, as a fraction of all domestic events targeting the government. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

3.3 Robustness checks

I now discuss a number of robustness checks.

In the first set of robustness checks, I explore alternative outcome variables. In Figure B.5, I show that the results remain quantitatively and qualitatively similar when using *Public Discontent* indices based on alternative Goldstein score thresholds of –3, –4, –5 and –6. In Figure B.6, I show that the estimates remain robust when using events reported

[23] Figure B.4 presents the event study estimates of failed terror attacks on *Public Content* where, again, no effect is observed.

in 1 news article as well as 10 news articles to generate *Public Discontent*, as opposed to the cutoff of 3 articles used in the baseline estimates. In Table B.1, I use the numerator and the denominator of the *Public Discontent* index as the outcome variables separately, and observe that the increase in *Public Discontent* is predominantly attributable to the increase in the number of *negative* interactions targeting the government. While the baseline estimates examined *Public Discontent* on the executive branch of the government, in Table B.2 I observe no effects on the legislature or judiciary. In Table B.3, I show that results are robust to using the number of protests against the government, retrieved from the Mass Mobilization project (Clark and Regan, 2016), as the outcome variable.

Next, I examine alternative versions of the treatment variable. In the baseline estimates, the treatment was defined as successful terror attacks with *at least one* fatality. In Figure B.7 I consider successful terror attacks with at least 5, 10 and 100 fatalities, and I find that the magnitude of the effect increases as the number of fatalities increases. In Table B.4, I dissect the effects based on the targets of terror attacks. I consider terror attacks on targets *excluding the government* (Panel A), terror attacks targeting the *government* (Panel B), terror attacks on *businesses* (Panel C) and terror attacks on *private citizens* (Panel D). Effects persist for terror attacks at targets excluding the government, as well as at targets related to the government and businesses. With respect to terror attacks targeted at private citizens and property (Panel D), I observe that the increase in *Public Discontent* observed in Column (2) disappears once attack/weapon type fixed effects are accounted for (Column (3)). This observation makes intuitive sense as aggregate effects on *Public Discontent* are unlikely to materialize in response to attacks targeted at nondescript individuals/property.

Does *Public Discontent* increase following other economic shocks as well? In Table B.5, I conduct a placebo test using natural disasters as an alternative treatment. In Column (1) I present the estimates for all natural disasters, while in Columns (2), (3), (4) and (5), I consider floods, storms, earthquakes and landslides, respectively. I do not observe any statistically significant effects, suggesting that the public response following a natural disaster is different from that following a successful terror attack. As to why such

a difference may occur, I draw on Choe and Raschky (2016) who discuss the concepts of "preventive effort" (i.e. efforts to reduce the likelihood of event occurrence) vs "palliative efforts" (i.e. efforts to reduce damages after the event). With natural disasters, due to their "natural" occurrence, and accounting for country, year and month fixed effects, palliative efforts of the government may be more important than preventive efforts. However, in the case of terror attacks, the importance of both preventive and palliative efforts may be equally heightened, which is a potential reason why the public response is more prominent in the case of terror attacks.

In Table B.6, I use the simple attack count as the main dependent variable. Column (1) applies the full sample consisting of country-months with any terror attack as well as country months with no terror attack (consistent with the "attack vs no attack" identification strategy). In Column (2), I restrict the sample to country-months where successful/failed terror attacks occurred, consistent with the "successful vs failed attack" identification strategy. In both sets of estimates, $Public\ Discontent_{iym}$ increases following terror attacks.[24] In Table B.7, I separate the effect on *Public Discontent* in the month of the attack, and the effects remain robust.

In Figure B.8, I plot the baseline estimates, along with estimates including three alternative sets of fixed effects, i.e. (a) country, year and month fixed effects; (b) country×year and month fixed effects; (c) country and year×month fixed effects; and (d)continent×year, country and month fixed effects. Point estimates remain qualitatively and quantitatively similar. To ensure that the baseline results are not driven by a particular country, in Figure B.9, I plot the estimates when dropping one country at a time.

One concern within the country-year-month panel is that in some countries terror attacks occur in close temporal proximity where the time periods of interest for each attack (i.e., 11 months before and after the event) may overlap. To circumvent this issue, in Table B.8 I use an event-level data set where, for each event, the full 11 months before and after the event are identified. Using this event-level panel too I observe that successful terror

[24]While these estimates provide an intuitive overview of the effects of terror attacks on $Public\ Discontent_{iym}$, they only present the effects in the month in which the terror attack occurs. It is to obtain a more holistic view of the lasting effects of terror attacks that I resort to the difference-in-differences strategy adopted in the baseline estimates.

attacks increase *Public Discontent*. Although the effects are less precisely estimated when attack/weapon type fixed effects are included within this event-level panel, baseline findings remain robust.

In Table B.9, I use alternative time horizons, i.e. 3, 6 and 9 months before and after the attack, as opposed to 11 months used in baseline estimates. I observe that in the first three months, *Public Discontent* increases following both successful and failed terror attacks. This is potentially because it takes time for the relevant information to trickle down to the public. However, the effect becomes more cleanly estimated as I incorporate 6 months and 9 months following attacks as the period of interest. A similar observation is made in Table B.10, which presents estimates at the country-week level.

4 Mechanisms underlying Public Discontent

The baseline estimates suggest that *Public Discontent* against the government increases following successful terror attacks. What mechanisms could underlie this effect?

Anecdotal evidence demonstrates that people turn to their governments, either with positive or negative sentiments, following terror attacks. For example, following the 9/11 attack in the US, people strongly rallied around the government. The same rallying effect was witnessed in New Zealand following the Christchurch massacre.[25] On the other end of the spectrum, the 2004 terror attacks in Spain and the 2019 Easter Sunday attacks in Sri Lanka saw people expressing tremendous angst towards the government.[26]

While acknowledging that identifying the the exact mechanism is a challenging exercise, in the ensuing sections I engage in specific empirical exercises that can shed some light in this regard. In summary, these exercise establish that *Public Discontent* following terror attacks are *specifically targeted at the government*, while eliminating "sympathy with terrorists", "general increase in discontent" and "fear due to insecurity" as potential mechanisms. Further, I find that available information on government capability are

[25] See, for example, *SBS News*, "Jacinda Ardern's popularity at all-time high after mosque attacks," 15 April 2019.

[26] Montalvo (2011); See also, *Financial Times*, "Sri Lanka: How Easter attacks shaped presidential election," 14 November 2019.

incorporated in to the public response. Consistent with Cowen (1985) who identifies national security as a public good that governments are expected to provide, and Bali (2007) who finds that the incumbent party's handling of the 2004 Madrid train bombings led to their defeat at the next election, these findings therefore provide suggestive evidence in favour of the "government accountability" mechanism.

However, these exercises are not without caveats. The first caveat is that within the data I cannot strictly identify whether the government accountability is attributed towards its inability to prevent the attack or for its response following the attack. Following Montalvo (2011), any references to the impact of the terrorist attacks therefore relates to "a composite event" incorporating both the event itself and the government's response. Second, while government accountability is one plausible mechanism, there may be other context-specific mechanisms driving these estimates, especially when considering the large number of countries and the length of the sample period, and this should be borne in mind when interpreting these findings.

4.1 Faulting the government vs sympathizing with terrorists?

One possible alternative scenario consistent with the baseline estimates is that through the attacks, the terror group delivered a convincing message, leading to the public sympathizing with the terrorists and opposing the government. This is an interesting distinction that can, to some extent, be empirically investigated with the available data.

While it is not possible, within GDELT, to pinpoint public sentiments towards the *exact* perpetrator of each terror attack, it is possible to identify sentiments towards *terror groups in general*. GDELT identifies three "actor" categories that may be generally grouped as terrorists, i.e. rebels, separatists and insurgents. Using events targeting these actor categories, I generate a proxy of *Public Discontent* towards terror groups in general. I also define *Public Content*, i.e. a proxy of *positive public sentiments* targeted at terror groups. I then apply these two indicators as the outcome variables, to examine the effects of successful vs failed terror attacks on public sentiments towards terrorists in general.

Table 5 presents the estimates. In Column (1), I observe that *Public Discontent*

Table 5: Public sentiments at terror groups

	(1) $Public\ Discontent_{iym}$	(2) $Public\ Content_{iym}$
$Successful_{iym}$	0.0107**	0.0041
	(0.0054)	(0.0035)
$Post_{iym}$	0.0023	0.0011
	(0.0050)	(0.0032)
Observations	17,282	17,282
Country FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
Weapon/Attack FE	Yes	Yes
Mean Dep. Var.	0.0990	0.0483

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack, along with 11 temporal lags and leads. Dependent variables in Columns (1) and (2) quantify negative and positive public sentiments against terror groups, with a Goldstein score cutoff of -5 and +5, respectively. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

against terror groups increases following successful terror attacks, while in Column (2) I observe no effect of successful terror attacks on positive public sentiments towards terror groups. Although these estimates are likely to be less precisely estimated as compared to an ideal situation where matched data on sentiments against the exact perpetrator group is available, they do provide suggestive evidence that the public response towards terror groups following attacks is not one of support, but of displeasure, thus eliminating "sympathy with terrorists" as a potential channel.

4.2 Public Discontent targeted at alternative entities

Is the increase in *Public Discontent* targeted specifically at the government, or is there a general increase in *Public Discontent* in the society, following terror attacks? If an increase in *Public Discontent* against other, unrelated entities is observed, it would suggest a general increase in public unrest, which can weaken the government accountability mechanism.

To examine this possibility, I build on the same approach followed in Section 4.1 above and conduct a falsification test based on public sentiments targeted at four key alternative entities included in GDELT, i.e. political opposition, elites, education entities, and international entities. I generate indices of *Public Discontent* targeted at each of these entities and use them as the outcome variable. Table 6 presents the estimates. Reassuringly, I do not observe any effect of successful terror attacks on these alternative target categories. This finding further strengthens the proposition that public discontent following terror attacks is targeted *specifically at the government.*

Table 6: *Public Discontent* targeting alternative entities

	(1) *Public* $Discontent_{iym}$ (*Political Opposition*)	(2) *Public* $Discontent_{iym}$ (*Elites*)	(3) *Public* $Discontent_{iym}$ (*Education Entities*)	(4) *Public* $Discontent_{iym}$ (*International Entities*)
$Successful_{iym}$	0.0086	0.0076	0.0047	-0.0003
	(0.0081)	(0.0068)	(0.0047)	(0.0030)
$Post_{iym}$	-0.0089	0.0095	0.0010	0.0036
	(0.0073)	(0.0063)	(0.0050)	(0.0028)
Observations	17,282	17,282	17,282	17,282
Month FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes	Yes
Mean *Public Discontent*	0.1566	0.1093	0.0969	0.0218

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable *Public* $Discontent_{iym}$ expresses all domestic events directed at the specified target, that record a Goldstein score of -5 or less, as a fraction of all domestic events directed at the target. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. All estimates additionally include a binary indicator for the month of the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

4.3 Do country-specific or attack-specific characteristics matter?

Having thus established that the *Public Discontent* following terror attacks is specifically targeted at governments, I now examine whether and how available information on perceived/realized government capacity can affect the public response. If the public incorporate such information to their response, it could be argued that the increase in *Public*

Discontent is an informed response of government accountability, thereby eliminating "fear due to insecurity" as a potential mechanism.

For this purpose, I use a range of country-specific, attack specific and leader-specific characteristics that can affect people's response. I modify the baseline specification as presented in Equation 6 where, in addition to the key variables $Successful$ and $Post$, I now include two interaction terms to identify heterogeneous effects.

$$\begin{aligned} PublicDiscontent_{iym} = \gamma_1 Successful_{iym} + \gamma_2(Successful_{iym} \times ClassificationType) \\ + \quad \tau_1 Post_{iym} + \tau_2(Post_{iym} \times ClassificationType) \\ + \quad \beta X_{iym} + \mathbf{FE_i} + \mathbf{FE_y} + \mathbf{FE_m} + \epsilon_{iym} \end{aligned} \tag{6}$$

In this generic specification, $ClassificationType$ is an indicator that represents a relevant (time-variant/invariant) characteristic. Coefficients γ_2 and τ_2 would capture the public response to successful and failed terror attacks, respectively, for attacks sharing this characteristic.

4.3.1 Country-specific characteristics

In Table 7, I consider a set of country-specific characteristics that can affect the public response.[27]

Perhaps the most relevant information on a government's commitment to national security is their counter-terrorism efforts. Governments typically commit large amounts of funds on counter-terrorism activities, signalling their efforts to ensure public safety. A relevant question then is whether the public incorporate this information in their evaluation of government accountability. This question would have ideally been answered with country level data on counter-terrorism expenditure. In the absence of such data, I use data on military expenditure as a share of total government expenditure, sourced from the SIPRI Military Expenditure Database, as a proxy for counter-terrorism efforts.

[27]Table B.11 engages in a multiple hypothesis testing exercise for estimates presented in Table 7, and provides the false discovery rate (FDR) adjusted p-values as per Anderson (2008).

I define a binary indicator $Military\ Capacity_{iy}$, which assumes a value of one if the GDP share of military expenditure for country i in year y was higher than the median share, and zero otherwise. The interaction term $Successful \times Military\ Capacity_{iy}$ thereby identifies the effect of successful terror attacks on *Public Discontent* in countries with high levels of military capacity. In Column (1) of Table 7, while the coefficient on $Successful$ is positive and statistically significant, the effect is insignificant for countries with high levels of military capacity. As such, the increase in *Public Discontent* comes mainly from countries with low levels of military capacity, indicating that the public incorporates information on government efforts towards ensuring public safety in to their response in the aftermath of a successful terror attack.

Next, I examine the effect of the country's level of political institutions. The literature suggests that public trust and perceptions about leaders and institutions can affect the nature and intensity of civic engagement (Sangnier and Zylberberg, 2017). Interestingly, Grosjean and Senik (2011) find that democratization is a necessary condition to obtain public support for socio-economic reforms. How political institutions affect the public response following a crisis is then an interesting question to pursue within the context of this paper. Specifically, do strong political institutions enable the government to obtain a higher level of public support (or, symmetrically, a lower level of *Public Discontent*) following successful terror attacks?

To empirically investigate this question, I use annual data on country-level political institutions sourced from the Polity IV database. I generate a binary indicator equaling to one if the polity score of country i in year y is greater than 5 (on a scale of -10 to +10). I then interact this indicator with $Successful$ and $Post$ to examine how political institutions affect the public response. In Column (2) of Table 7, I observe that in non-democratic countries *Public Discontent* rises following successful terror attacks. Interestingly, I observe a reversal of this effect in the more democratic countries, suggesting that people are less critical of the government in the aftermath of the crisis. These findings suggest that the prevailing quality of political institutions is a relevant factor in the public's trust and perception of their government.

Table 7: *Public Discontent* and country characteristics

	(1) $Public\ Discontent_{iym}$	(2) $Public\ Discontent_{iym}$	(3) $Public\ Discontent_{iym}$	(4) $Public\ Discontent_{iym}$
$Successful_{iym}$	0.0141**	0.0246***	0.0145***	0.0139***
	(0.0058)	(0.0049)	(0.0039)	(0.0041)
$Post_{iym}$	0.0037	0.0009	0.0018	0.0040
	(0.0056)	(0.0060)	(0.0042)	(0.0045)
$Successful_{iym} \times Military\ Capacity_{iy}$	-0.0041			
	(0.0069)			
$Post_{iym} \times Military\ Capacity_{iy}$	0.0005			
	(0.0067)			
$Successful_{iym} \times Democracy_{iy}$		-0.0156**		
		(0.0075)		
$Post_{iym} \times Democracy_{iy}$		0.0005		
		(0.0080)		
$Successful_{iym} \times High\ Terror_{i}$			-0.0037	
			(0.0082)	
$Post_{iym} \times High\ Terror_{i}$			0.0126	
			(0.0123)	
$Successful_{iym} \times Conflict_{iy}$				-0.0064
				(0.0061)
$Post_{iym} \times Conflict_{iy}$				-0.0001
				(0.0102)
Observations	15,210	13,572	17,282	17,282
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes	Yes
Mean *Public Discontent*	0.1169	0.1174	0.1212	0.1212

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable $Public\ Discontent_{iym}$ 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. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. $Military\ Capacity_{iy}$ is a time-variant binary indicator =1 if the GDP share of military expenditure is above the sample median of 0.0165. $Democracy_{iy}$ is a time-variant binary indicator=1 if country i's polity score for year y is >= 5, and 0 otherwise. $High\ Terror_{i}$ is a time-invariant binary indicator=1 if country i experienced more than the sample median number of terror attacks, during the sample period, and 0 otherwise. The median number of terror attacks in the sample period is 115. $Conflict_{iy}$ is a time-variant binary indicator=1 if country i was engaged in a war during year y, and 0 otherwise. Sample size is determined by data availability. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

There is a large body of literature examining the effects of intense exposure to violence on a number of social indicators, such as social capital (Rohner, Theonig and Zilibotti, 2013); political participation (Bateson, 2012); market participation (Cassar, Grosjean and Whitt, 2013); and risk preferences (Callen, Isaqzadeh, Long and Sprenger, 2014). How then, does continuous exposure to violence affect *Public Discontent*? On the one hand, people may become more agitated with their government when terror attacks occur repeatedly. On the other hand, it could also be that they become more complacent with increased exposure, with focus being placed more on survival and less on expressing discontent.

I investigate the effects of intensity of exposure in Columns (3) and (4) of Table 7. First, in Column (3) I define a time-invariant binary indicator equal to 1 if the country recorded more than the median number of country-level terror attacks during the sample period, and 0 otherwise.[28] Results suggest that the increase in *Public Discontent* is driven by countries experiencing a low number of terror attacks. In Column (4), I use data from the UCDP geo-referenced conflict data set to generate a binary variable that identifies whether a country was engaged in a conflict in a given year or not. In line with the findings in Column (3), I observe no effect of successful terror attacks on *Public Discontent* in conflict-ridden countries, and the effect is entirely driven by terror attacks in peaceful countries. Taken together, these results suggest that the public is more likely to express discontent when terror attacks are an infrequent occurrence. Indeed, in a peaceful country, a single terror attack could create a massive sense of insecurity amongst the public, which will in turn materialize as negative sentiments directed towards governments. However, as terror attacks become increasingly frequent, citizens may internalize their exposure to violence, in line with a potential "learning" effect.

[28]The median number of attacks per country over the sample period is 115.

4.3.2 Attack-specific characteristics

In Table 8, I examine how attack-specific characteristics can affect the public response.[29]

An important distinction that can have an effect on *Public Discontent* is the domestic vs international nature of a terror attack. The literature suggests that a foreign terror attack (i.e. an attack from an out-group) may strengthen in-group unity and lead the public to rally around the government in solidarity (Pickering and Kisangani, 1998; Sobek, 2007). Using information provided by the GTD on the nationality of the perpetrators, I define a binary indicator, $ForeignAttack$, equalling to 1 if the attack was carried out by foreign nationals. In Column (1) of Table 8, I observe that the effect is primarily attributable to domestic terror attacks.

Next, I distinguish between attacks committed by organized terror groups and attacks committed by unaffiliated individuals (lone wolf attacks). This is an important distinction that again signals the government's control over national security. The literature identifies attacks by organized terror groups as being significantly different from lone wolf attacks in terms of lethality, security impacts and strategic considerations (Alakoc, 2017; Phillips, 2017). A successful attack carried out by an organized terror group would be a clear signal that the government failed to deliver the public good of national security. By contrast, following a lone wolf attack, the public may be more forgiving towards the government, as it likely had limited means of foreseeing and controlling it.

I generate a binary indicator, $Lonewolf Attack$, which assumes a value of 1 if the attack was carried out by an "unaffiliated individual", and zero otherwise.[30] In Column (2) of Table 8, I find that, while successful attacks by organized terror groups increase *Public Discontent*, successful attacks by lone wolves makes the public less condemning of the government. This finding again points towards the rationality of the public in holding the government accountable for actions deemed to be "within their scope of responsibility" and discounting for those beyond.

[29] Table B.12 engages in a multiple hypothesis testing exercise for estimates presented in Table 8, and provides the FDR adjusted p-values as per Anderson (2008).

[30] GTD defines an unaffiliated individual as someone "identified by name (or specific unnamed minors) and not known to be affiliated with a group or organization".

Table 8: *Public Discontent* and characteristics of terror attacks

	(1) $Public\ Discontent_{iym}$	(2) $Public\ Discontent_{iym}$	(3) $Public\ Discontent_{iym}$
$Successful_{iym}$	0.0131***	0.0150***	0.0123***
	(0.0035)	(0.0036)	(0.0036)
$Post_{iym}$	0.0038	0.0036	0.0040
	(0.0043)	(0.0043)	(0.0045)
$Successful_{iym} \times ForeignAttack$	-0.0016		
	(0.0047)		
$Post_{iym} \times ForeignAttack$	0.0011		
	(0.0046)		
$Successful_{iym} \times LonewolfAttack$		-0.0167***	
		(0.0062)	
$Post_{iym} \times LonewolfAttack$		0.0080	
		(0.0057)	
$Successful_{iym} \times CapitalAttack$			0.0039
			(0.0039)
$Post_{iym} \times CapitalAttack$			-0.0027
			(0.0041)
Observations	17,282	17,282	17,282
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes
Mean *Public Discontent*	0.1212	0.1212	0.1212

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable $Public\ Discontent_{iym}$ 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. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. $ForeignAttack$ is a binary variable =1 if the attack was carried out by a foreign terrorist organization, and zero otherwise. $LonewolfAttack$ is a binary variable =1 if the perpetrator of the attack is an individual unaffiliated to any terror group, and zero otherwise. $CapitalAttack$ is a binary variable =1 if the attack took place in a national capital city, and zero otherwise. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

In Column (3) of Table 8 I explore whether the location of the terror attack can drive *Public Discontent*. By virtue of their economic ripple effects, as well as heightened media coverage, successful attacks in urban areas may create a larger increase in *Public Discontent* as opposed to attacks in rural areas. Using information on locations provided in the GTD, I define a binary indicator *CapitalAttack* which assumes a value of 1 if the attack occurred in a national capital, and zero otherwise. Column (3) of Table 8 displays the results of this exercise. Somewhat counter-intuitively, I do not find any statistically significant evidence of capital city attacks increasing *Public Discontent*, although the coefficient is positive.[31]

4.3.3 The effect of national leaders on Public Discontent

Finally, I examine how characteristics of the national leader at the time of the attack can affect the public response. A broad literature explores the importance of the characteristics of the national leader on country level economic outcomes (Jones and Olken, 2005; Besley, Montalvo and Reynal-Querol, 2011). Leader characteristics such as gender, age and length of tenure have been identified in this literature as signals of leader competence. In Table 9, I examine whether these characteristics have an effect on the public's response following terror attacks.[32]

Female leaders are considered to have positive effects on the delivery of public goods (Chattopadhyay and Duflo, 2004; Clots-Figueras, 2012), but their evaluations suffer from gender bias due to perceptions of leading with 'emotion' (Brescoll, 2016; Gangadharan, Jain, Maitra and Vecci, 2016). In Column (1) of Table 9, I examine whether the gender of the leader affects the public response following terror attacks. I define a variable *FemaleLeader* which assumes a value of 1 if the leader at the time of the attack is female, and zero otherwise. Although I find some evidence that the public expresses less discontent towards the government when the leader in power is female, this effect

[31] It is important to note that the variable *CapitalAttack* only captures urban areas classified as *national capitals*. Expanding this classification to other economically important areas, instead of restricting to capital cities only, might increase the precision of these estimates. However, data limitations preclude me from conducting such an exercise.

[32] Table B.13 engages in a multiple hypothesis testing exercise for estimates presented in Table 9, and provides the FDR adjusted p-values as per Anderson (2008).

disappears when adjusted for multiple hypotheses, as demonstrated in Table B.13.

Next, I focus on the age of the leader in power. Horowitz, McDermott and Stam (2005) propose two alternative views on how the age of a leader can affect the stability of a country. First, it could be that due to biological reasons, younger leaders act with more aggression than older leaders. Alternatively, it could be that younger leaders have relatively longer time horizons to stay in power, thus having the ability to delay risky decisions and bring in more stability than older leaders. To examine which of these effects dominates, I generate a binary indicator to classify a leader as"young", based on the top 1% of the age distribution of the leaders within the sample. Accordingly, I define a variable $YoungLeader$, which equals to 1 if the leader in power is less than 40 years old, and zero otherwise. Interestingly, in Column (2) of Table 9, I find that the coefficient on the interaction term is negative and statistically significant, suggesting that the public is less likely to criticize the government if a young leader is in power at the time of the successful terror attack.

Length of leadership is another key characteristic of leader power (Bienen and van de Walle, 1989), as the leader is likely to have strong control over the country if they have been in power for a long period. In Column (3) of Table 9, I focus on the effect of the length of tenure of the national leader. I generate a binary indicator $NewLeader$ which assumes a value of 1 if the leader has been in office less than the median number of tenure for the sample (4 years), and zero otherwise.[33] I observe, again, a negative coefficient on the variable $Successful \times NewLeader$, suggesting that, following terror attacks, the public is *less* likely to criticize new leaders. This effect remains statistically significant when adjusted for multiple hypotheses, in Table B.13.

In the last set of estimates, I explore whether the military background of the leader affects the public response, as the literature finds that military regimes have enhanced capacity to face issues related to national security (Panel, 2017; Kim, 2019). Lever-

[33]It is important to note that the political maturity of the leader may depend not only on the number of years since she assumed office, but also on the number of years she has spent engaged in active politics before assuming office. However, in the absence of systematic data on the history of each national leader's political activism, I rely on the number of years since officially coming in to power as an indicator of leader's political experience.

Table 9: *Public Discontent* and leader characteristics

	(1) $Public\ Discontent_{iym}$	(2) $Public\ Discontent_{iym}$	(3) $Public\ Discontent_{iym}$	(4) $Public\ Discontent_{iym}$
$Successful_{iym}$	0.0146***	0.0134***	0.0157***	0.0146***
	(0.0037)	(0.0033)	(0.0039)	(0.0038)
$Post_{iym}$	0.0033	0.0051	0.0018	0.0018
	(0.0044)	(0.0042)	(0.0047)	(0.0050)
$Successful_{iym} \times FemaleLeader$	-0.0164*			
	(0.0084)			
$Post_{iym} \times FemaleLeader$	0.0075			
	(0.0092)			
$Successful_{iym} \times YoungLeader$		-0.0303**		
		(0.0121)		
$Post_{iym} \times YoungLeader$		0.0057		
		(0.0089)		
$Successful_{iym} \times NewLeader$			-0.0099*	
			(0.0058)	
$Post_{iym} \times NewLeader$			0.0015	
			(0.0059)	
$Successful_{iym} \times MilitaryLeader$				-0.0185**
				(0.0080)
$Post_{iym} \times MilitaryLeader$				0.0093
				(0.0083)
Observations	15,199	15,199	15,188	15,067
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes	Yes
Mean *Public Discontent*	0.1212	0.1212	0.1208	0.1219

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable $Public\ Discontent_{iym}$ 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. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. *FemaleLeader* is a binary variable =1 if the country's effective leader at the time of the attack was female, and zero otherwise. *YoungLeader* is a binary variable =1 if the country's effective leader at the time of the attack was less than 40 years old, and zero otherwise. *NewLeader* is a binary variable =1 if the country's effective leader at the time of the attack had been in office less than 4 years, and zero otherwise. *MilitaryLeader* is a binary variable =1 if the country's effective leader or defence minister at the time of the attack had a military background, and zero otherwise. Sample size is limited by data availability. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

aging on the information provided by the Database of Political Institutions, I define *MilitaryLeader*, a binary variable equal to one if the national leader or the defence minister at the time of the attack had a military background. Interestingly, in Column (4) of Table 9, I find that the public is *less* likely to express discontent when a military leader is in power at the time of the successful terror attack.

Across the four sets of estimates presented in Table 9, the message portrayed is that the information on the national leader at the time of the terror attack is an important factor feeding in to the public reaction. I note that further analyses are necessary to gauge whether this effect is driven by the public's perception of leader competence or the nature of the leader's response following the terror attack.

5 Conclusion

In this paper, I propose a novel, temporally granular approach that examines the effect of terror attacks on public sentiments towards the government. In line with Amarasinghe (2022), I use an indicator of *Public Discontent*, constructed based on millions of high-frequency event data retrieved from the GDELT database, to quantify negative public sentiments towards the government at any given point of time. I first compare country-month units that experienced a terror attack against country-month units that did not experience a terror attack, and find that *Public Discontent* increases following a terror attack.

However, the occurrence of terror attacks, by itself, is non-random in nature due to terrorists' strategic decisions on their timing and location. To address endogeneity concerns arising from such selection bias, I follow the proposition in Brodeur (2018) in comparing country-months where successful attacks occurred against those where failed terror attacks occurred, conditional on the location, timing and attack/weapon type of terror attacks. Leveraging on this random nature of the *outcome* of the attack, I re-confirm that *Public Discontent* increases following successful terror attacks. Specifically, *Public Discontent* increases by 11% over the sample mean, in the 11 months following a successful terror attack. This result is robust to a number of stringent robustness tests,

and also holds when using public protests as an alternative outcome variable.

While it is empirically challenging to identify the exact mechanism underlying this effect, I engage in a number of exercises that highlights government accountability as a potential mechanism. First, through careful empirical explorations, I eliminate "sympathy with terrorists" and "general increase in discontent" as potential mechanisms, and identify that the increase in *Public Discontent* following terror attacks is specifically targeted at the government. I then use a number of country-specific, attack-specific and leader-specific characteristics that highlight the rationality of the public response, thereby also eliminating "fear" as a potential mechanism. I show that a government's commitment to national security and democracy, as well as the characteristics of the leaders, are key considerations feeding in to the public response. The public is less condemning if the government is perceived as having made an effort to keep the public safe, and for events that may be beyond their control.

The findings of this empirical exercise provide important policy implications for the relationship between the public and their governments. First, these results establish that the government and its performance is scrutinized by the public not only during elections, but continuously and consistently throughout its tenure. The analyses on mechanisms confirm that people hold their governments accountable for failing to ensure their security, and that relevant information is incorporated by the rational public in to their response. Such scrutiny and criticism is an important component in the system of checks and balances on government power and behaviours, acting as a disincentive for governments to achieve sub-optimal levels of performance. Further empirical analyses, based on temporally fine-grained data, can help improve our understanding of the dynamics of numerous other facets of the citizen-state relationship.

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Online Appendix
Public Sentiment in Times of Terror

Ashani Amarasinghe[1]

A Additional data description

A.1 Public Discontent index

In this section, I provide further details on the *Public Discontent* index used in this study.

A.1.1 High-frequency event data

The *Public Discontent* index is constructed using temporally granular, high-frequency event data sourced from the GDELT database. GDELT gathers information from global news media articles to provide a real time open data global graph of the human society (Leetaru and Schrodt, 2013).[2] It is updated every 15 minutes, and peruses print, broadcast, and web news media in over 100 languages across every country in the world, to keep track of a broad range of events across the world, as and when they occur.

It applies NLP algorithms on the text of each article, and extracts approximately 300 event categories based on the Conflict and Mediation Event Observations (CAMEO) event codes (Gerner, Schrodt and Yilmaz, 2009). As demonstrated in Table A.1.1, these events range from mildly/highly cooperative to mildly/highly aggressive. For example, event categories such as 'provide aid' or 'express intent to cooperate' are identified as cooperative events with different degrees of intensity (i.e. mildy/highly cooperative), while event categories such as 'appeal' or 'engage in unconventional mass violence' are identified as aggressive events, again with different levels of intensity.[3] Therefore this event data set provides a comprehensive view of the various types of interactions that occur in the human society, on a continuous basis.

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[2]www.gdeltproject.org.
[3]For further details on CAMEO event types, please see the CAMEO Codebook

For each reported event, GDELT provides information on over 60 attributes. It reports the two main actors, i.e. the target and source, as well as their primary location, and the location of the event itself, at the national and/or subnational level. Specifically relevant for the empirical exercise pursued in this paper, it reports, for each event, a related numeric score on the Goldstein scale (Goldstein, 1992). The Goldstein scale is a quantitative measure of the theoretical impact a particular event type poses on the political stability of a country. It takes in to consideration the inherent intensity of conflict and/or cooperation in the different event types, and each event type is assigned a score on a range of –10 (extreme conflict) to 10 (extreme cooperation).

Taken together, event data sets such as GDELT provide a wealth of information for empiricists to explore societal phenomenon which were previously overlooked due to data limitations. Whereas traditional data sets typically focus only on "key" events of interest, such as conflict (in its most extreme form) or protests, event data sets such as GDELT are the first attempts at categorizing the broad spectrum of important events occurring in society, including events such as demands, appeals or coercion. The use of such data therefore enables me to provide a comprehensive overview of the sentiments prevailing in the society at a given point of time.

However, the use of GDELT is not without caveats. First, the representation of countries within the data set might vary by their prominence within the news universe. While this is potentially a representation of the underlying distribution of newsworthy events itself, I nevertheless account for such unobservables within the empirical strategy by using country and time fixed effects. Usage of standardized indicators, such as ratios, as opposed to simple counts, is also effective in circumventing this issue. Another concern is the possibility of erroneous reporting and categorization of events, although such errors are not fully eliminated even in human-coded event sets, and are likely to be trivial and random. Nevertheless, to address any such concerns I only retain the set of events reported in at least three media articles. This filter provides corroboration of the occurrence of the event as well as confidence on the event classification.

Table A.1.1: 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

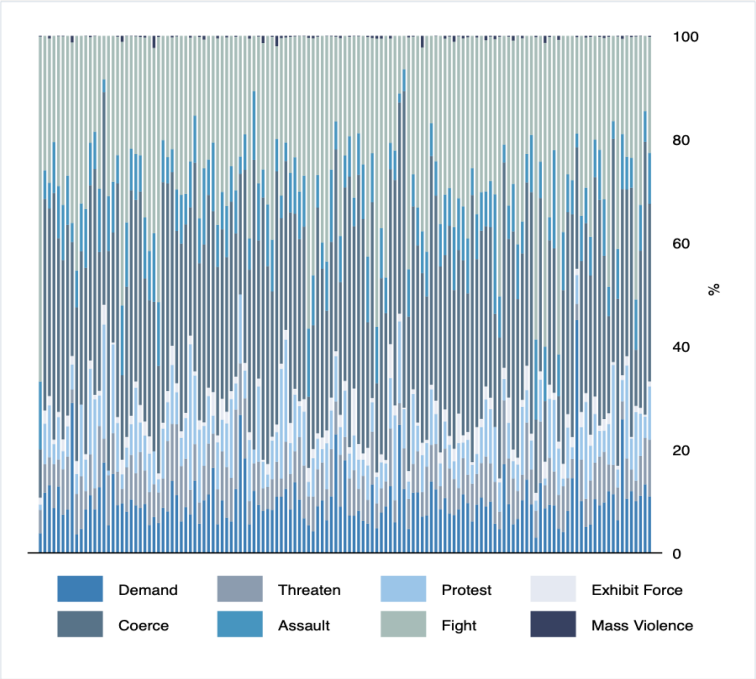
A.1.2 Events included in the Public Discontent index

As the objective of this study is to quantify *Public Discontent*, my focus is entirely on domestic events targeted at the government. To generate this index, I express the number of events targeting the government, with a Goldstein score of less than –5, as a proportion of the total number of domestic events targeting the government (Equation 1). I choose the cutoff of –5 on the goldstein scale for the baseline analysis because it represents the midpoint on the negative spectrum on the Goldstein scale. Moreover, as visible in Table A.1.1, this cutoff encompasses a broad range of event categories which are "intuitively" considered as associated with a negative sentiment. However, as exhibited in Figure B.5, the results are robust to alternative cutoffs on the Goldstein scale.

Which event categories typically constitute the *Public Discontent* index? Figure A.1.1 shows the composition of the *Public Discontent* index for each country over the sample period. Each bar represents a country, and the stacks within each bar show the weight received by each event category within the country's *Public Discontent* index. The representation of event categories appears fairly similar across countries, with the most

prominent event categories being "demand", "coerce" and "fight". This decomposition becomes particularly illuminating when considering that traditional data sets existent in the empirical domain typically focuses on the more "obvious" event categories, such as conflict/protest. Instead, this index captures both the obvious and subtle events on the full spectrum of interactions between the public and governments.

Figure A.1.1: Composition of *Public Discontent* by country



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

A.1.3 Relationship with existing indicators

How well does the *Public Discontent* index represent the existing, albeit imperfect, measures of public sentiment? I approach this question using two types of data sets that are frequently used to assess sentiments towards governments.

First I focus on data derived from public opinion surveys. I generate an indicator of people's sentiments towards their governments using data from waves 4–7 of the World Values Survey (WVS), and waves 2–7 of the Afrobarometer survey, which overlay with

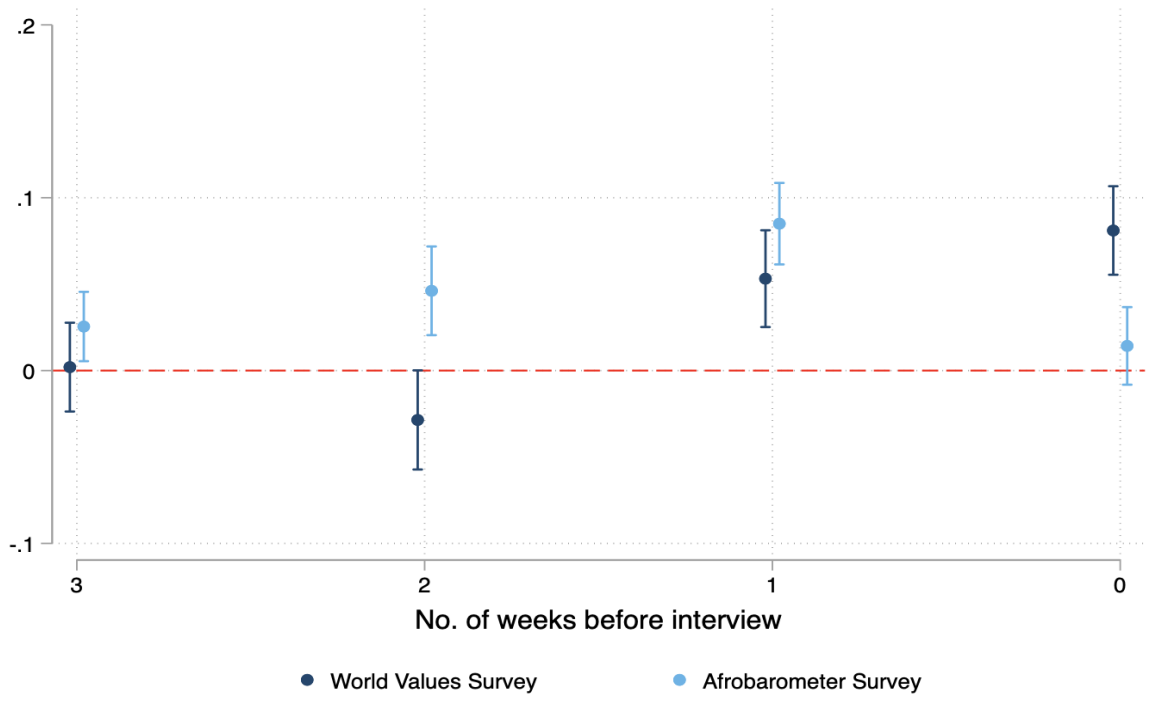
the sample period of this study. Inspired by Sangnier and Zylberberg (2017), for this exercise I use survey questions related to the level of the public's trust/confidence in their governments, and explore how closely such trust/confidence indicators mirror the *Public Discontent* index.

In the WVS, I focus on the question, 'How much confidence do you have in the government?' This question yields a range of categorized answers, which may be 'a great deal', 'quite a lot', 'not very much' or 'none at all'. I construct an indicator variable equal to 1 if the respondent replied 'not very much' or 'none at all', and 0 otherwise. Likewise 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' to quantify people's sentiment. This question also yields a set of hedonic answers (i.e., 'strongly disapprove', 'disapprove', 'approve', or 'strongly approve'). I assign a binary variable equal to 1 if the respondent answered 'strongly disapprove' or 'disapprove', and 0 otherwise.

Next, exploiting data on the exact date of the interview, I match the level of *Public Discontent* that persisted in the country in the weeks before the interview, with the response of each individual belonging to the same country. Based on this matching, I examine whether *Public Discontent* measured in the *weeks leading up to the interview* can predict individuals' attitudes towards the government *at the interview*. Since the survey responses are coded to quantify *negative* sentiments towards the government, as with the *Public Discontent* index, I expect the correlation to be positive. I plot the results of this exercise in Figure A.1.2. I observe that *Public Discontent* measured in the weeks prior to the interview is a strong predictor of expressed discontent with the government at the interview, for both the WVS and the Afrobarometer Survey.

I now examine the association between the *Public Discontent* index and other existing data sets on public sentiments. I first use data on US presidential approval ratings sourced from the American Presidency Project. Since the approval rating quantifies the *positive* sentiments towards the President, I expect its correlation with *Public Discontent* to be negative. As expected, in Column (1) Table A.1.2, I observe a strong negative association

Figure A.1.2: Effect of pre-interview *Public Discontent* on survey interview outcomes



Notes: Figure shows the effect of *Public Discontent* in the weeks before the survey interview, on expressed dissatisfaction with government/president at the interview. The unit of analysis is a respondent. Year×month fixed effects are included. The number of observations in 105,806 for the World Values Survey and 148,357 for the Afrobarometer survey. Vertical lines indicate 95% confidence intervals.

Table A.1.2: Correlation between *Public Discontent* and alternative indicators of public sentiment

	(1) *US Presidential Approval Rate*$_{iym}$	(2) *Mass Mobilization Protest*$_{iym}$	(3) *ACLED Protest*$_{iym}$	(4) *Incumbent Election Loss*$_{iy}$
Public Discontent$_{iym}$	-1.1923***	0.4446***	1.0544***	
	(0.3363)	(0.0562)	(0.2972)	
Public Discontent$_{iy}$				0.8199**
				(0.3651)
Observations	228	27,132	7,980	483

Notes: This table depicts the correlations between *Public Discontent* and alternative country level indicators of sentiments targeted at governments. Column (1) uses monthly data on US presidential approval rates. Columns (2) and (3) use monthly data on protests targeting the government from the Mass Mobilization Project and ACLED (which only covers the African continent), respectively. Column (4) uses a binary indicator on whether, conditional on the occurrence of a national election, the incumbent government suffered an electoral loss in the given year, as the outcome variable. Sample size is determined by data availability. ***, **, * indicate significance at the 1, 5 and 10% level.

between the presidential approval rating and *Public Discontent*. Next, I obtain data on public protests, particularly targeting the government, from the Mass Mobilization Project. I also obtain data on protests *in the African continent* from the Armed Conflict Location & Event Data (ACLED) Project. Columns (2) and (3) of Table A.1.2 displays the correlations between protests and *Public Discontent*. The *Public Discontent* index is highly correlated, both statistically and economically, with the number of protests occurring in the same period within a country. Finally, in Column (4) I examine the correlation between *Public Discontent* and regime changes, using data from Bjørnskov and Rode (2020). I generate a binary indicator that assumes a value of 1 where, conditional on the occurrence of a national election, the incumbent party recorded an election loss in a given year, and zero otherwise. I observe that the level of *Public Discontent* is highly predictive of the incumbent party's election loss as well.

Accordingly, these results highlight that the *Public Discontent* index is indeed representative of the existing, albeit imperfect, measures of public sentiment towards their governments. Therefore, in the absence of comprehensive and consistent global data that quantifies public sentiment at a very fine level of temporal granularity, this index can be confidently applied for academic and policy making purposes.

A.2 Data on terror events

Table A.2.1: GTD's approach in determining the success/failure of terror attacks

Attack Type	Successful	Failed
Assassination	Target is killed	Kills numerous people but not the target
Armed Assault	Assault takes place **and** a target is hit	Assault takes place **and** the target is not hit* Apprehended on the way to commit the assault*
Bombing/Explosion	Device detonates	Device does not detonate
Hijacking	Assume control of the vehicle	Fail to assume control of the vehicle
Hostage (Barricading/kidnapping)	Assume control of the individuals	Fail to assume control of the individuals
Facility/Infrastructure attack	Facility is damaged	Facility is not damaged
Unarmed assault	A victim was injured	No one was injured*

*S*ource: The Global Terrorism Database. *To make this determination, however, there must be information to indicate that an assault was imminent. If a case has multiple attack types, it is successful if any of the attack types are successful, with the exception of assassinations, which are only successful if the intended target is killed.

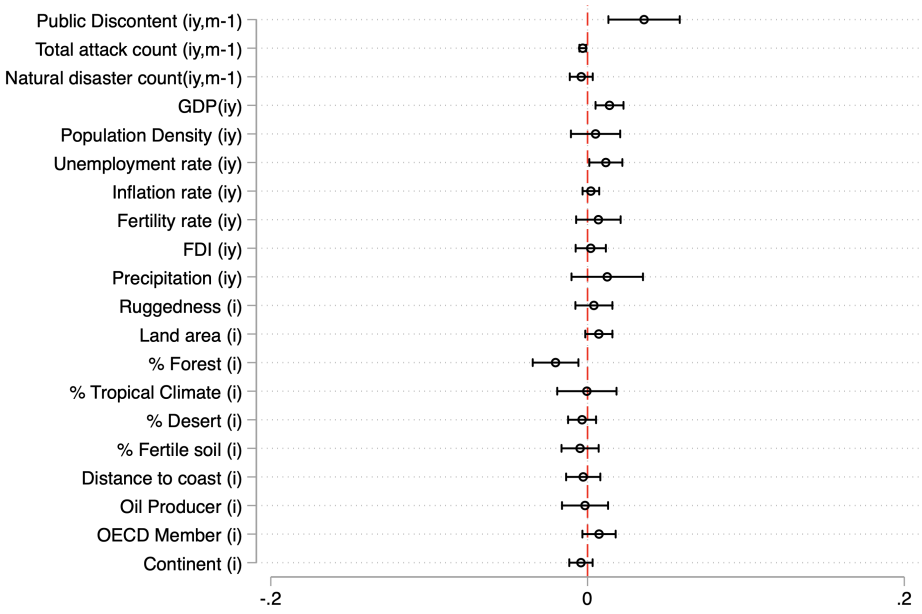
Table A.2.2: Descriptive statistics on terror attacks

Description	Observations	Percent of total	Success rate
Attack type			
Armed assault	4,239	66%	94%
Unarmed assault	161	3%	67%
Bombing	4,308	67%	79%
Infrastructure	474	7%	59%
Assassination	2,501	39%	78%
Other	2,341	36%	93%
Weapon type			
Explosives	4,308	67%	79%
Firearms	4,455	69%	93%
Incendiary	636	10%	60%
Melee	1,046	16%	90%
Other	1,912	30%	86%
Other attack-specific characteristics			
Foreign Attack	2,979	46%	85%
Lone Wolf Attack	231	4%	74%
Capital Attack	1,709	27%	75%
Characteristics of national leader at the time of attack			
Female Leader × Attack	461	7%	78%
Young Leader × Attack	69	1%	82%
New Leader × Attack	2,892	45%	84%
Military Leader × Attack	1,775	28%	94%
Total	6,451		85%

Notes: *Foreign Attack* is an attack carried out within a country by a foreign terrorist organization. *Lone Wolf Attack* is an attack where the perpetrator is an individual unaffiliated to any terror group. An attack is identified as a *Capital Attack* if it took place in a national capital city. *Female Leader* is a binary variable =1 if the country's effective leader at the time of the attack was female. *Young Leader* is a binary variable =1 if the country's effective leader at the time of the attack was less than 40 years old. *New Leader* is a binary variable =1 if the country's effective leader at the time of the attack had been in office less than 4 years. *Military Leader* is a binary variable =1 if the country's effective leader or defence minister at the time of the attack had a military background.

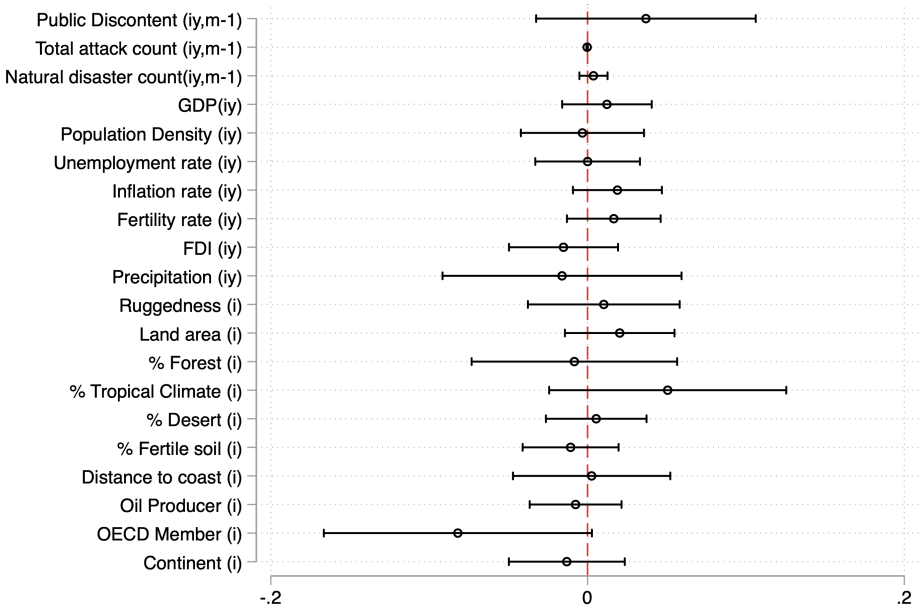
B Additional robustness tests

Figure B.1: Predicting the occurrence of terror attacks



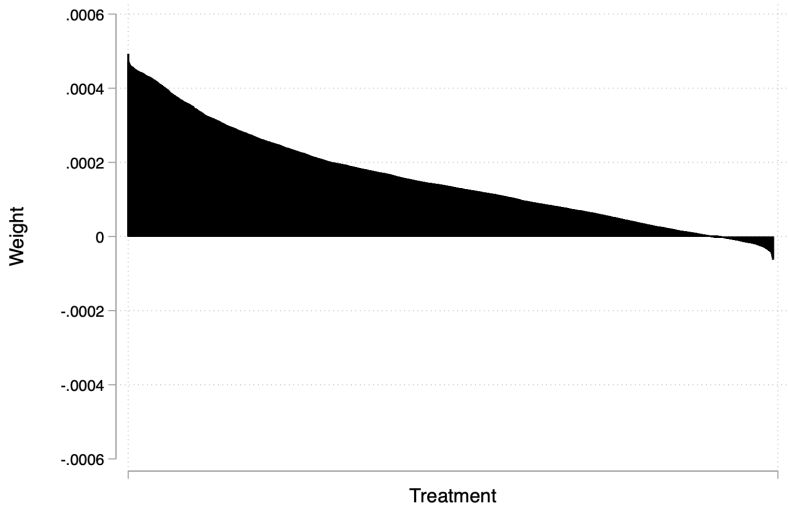
Note: Figure shows the predictability of the occurrence of terror attacks based on a number of time-variant and time-invariant variables. The sample consists of all country-months where any terror attack occurred as well as those where no terror attacks occurred. The dependent variable is a binary indicator = 1 if any terror attack occurred in country i is year y of month m, and 0 otherwise. The unit of observation is a country-month. Sample size is limited by data availability. Attack/weapon type fixed effects are included. Standard errors are clustered at the country level. Vertical lines depict 95% confidence intervals.

Figure B.2: Predicting the success of terror attacks



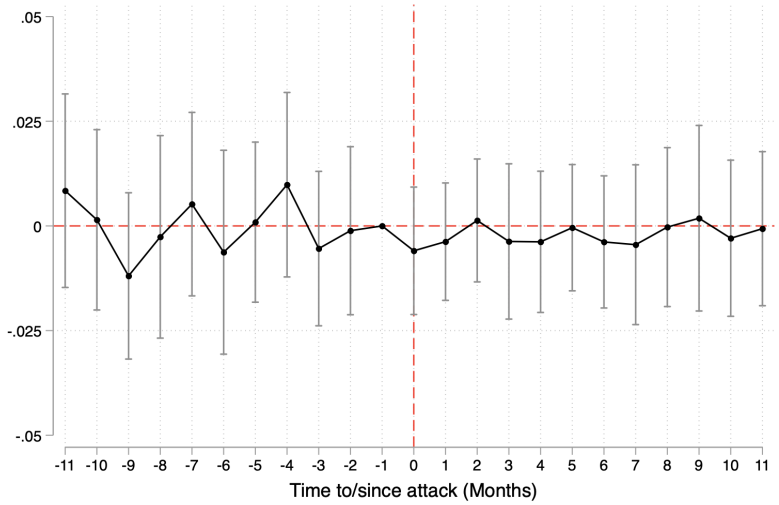
Note: Figure shows the predictability of the success of terror attacks based on a number of time-variant and time-invariant variables. The sample consists of country-months where a successful terror attack occurred and those where failed terror attacks occurred. The dependent variable is a binary indicator = 1 if a successful terror attack (and no failed terror attack) occurred in country i is year y of month m, and 0 otherwise. The unit of observation is a country-month. Sample size is limited by data availability. Attack/weapon type fixed effects are included. Standard errors are clustered at the country level. Vertical lines depict 95% confidence intervals.

Figure B.3: "Attack vs no attack" strategy: Treatment weights as per De Chaisemartin and D'Haultfœuille (2020)



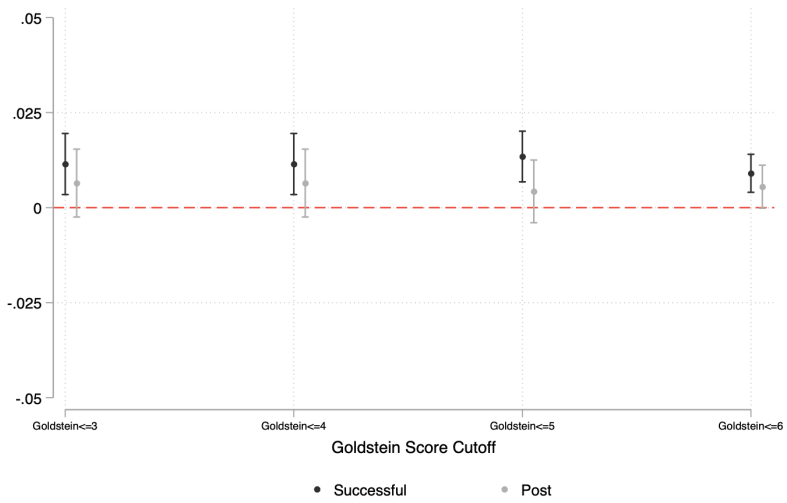
Note: Figure shows the distribution of the weights attached to each ATE when considering "any terror attack" as the treatment. This procedure was conducted using Stata's $twowayfeweights$ estimator developed in line with De Chaisemartin and D'Haultfœuille (2020).

Figure B.4: Effect of failed attacks on *Public Content*



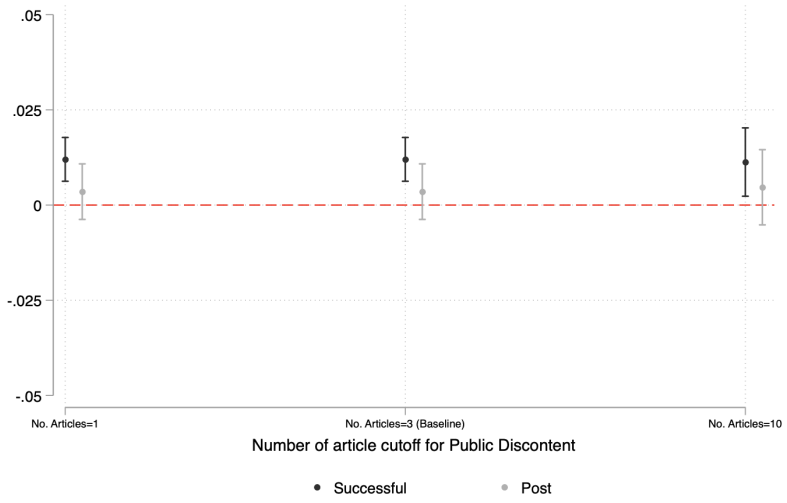
Note: Figure shows the effect of failed terror attacks on positive public sentiments. The outcome variable is *Public* $Content_{iym}$, which expresses the number of events targeting the government with a Goldstein score of more than 5, as a proportion of the total number of events targeting the government. The unit of observation is a country-month. Sample is limited to country-months with failed terror attacks and their relevant lags and leads. Standard errors are clustered at the country level. Vertical lines depict the 95% confidence intervals.

Figure B.5: Alternative definitions of *Public Discontent*



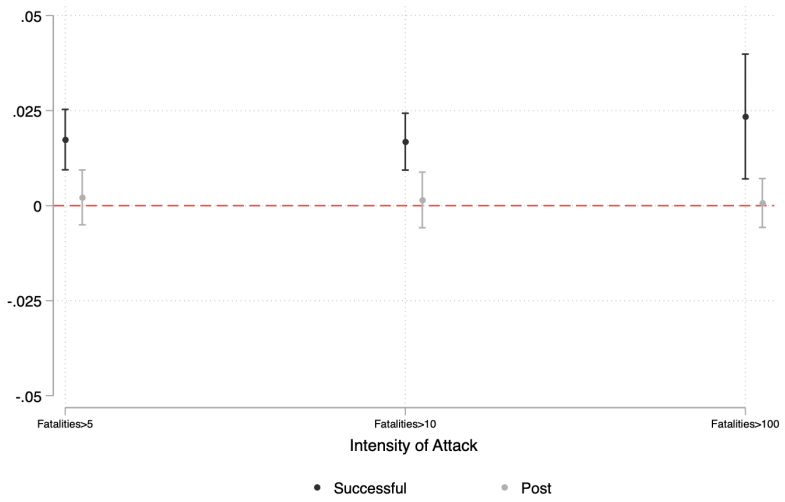
Note: Figure shows estimates as per Equation 5, but uses alternative cutoffs on the Goldstein scale when defining Public Discontent, which is the dependent variable. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. All specifications include country, year and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 95% confidence intervals.

Figure B.6: Alternative cutoff for number of articles for *Public Discontent*



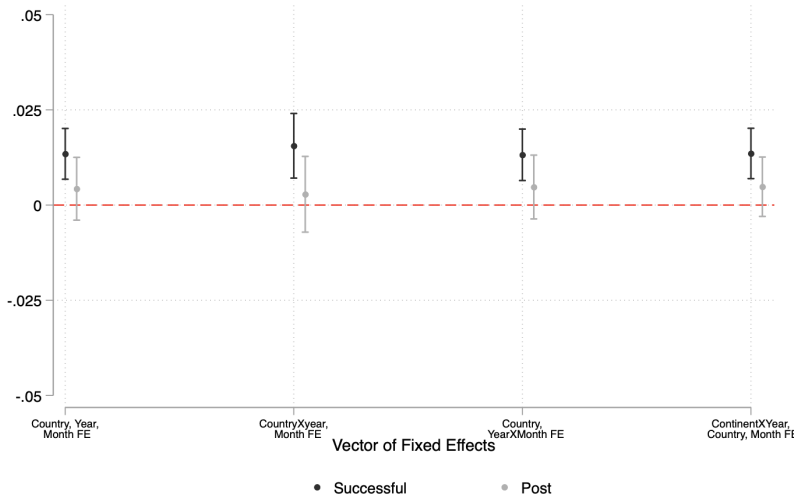
Note: Figure shows estimates as per Equation 5, but uses alternative cutoffs on the number of articles reporting events that constitute the *Public Discontent* index. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. All specifications include country, year and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 95% confidence intervals.

Figure B.7: Alternative definition of successful attacks based on the number of fatalities



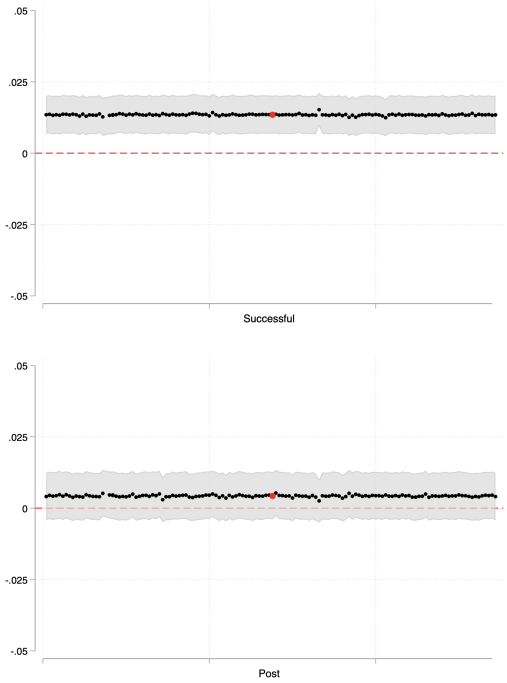
Note: Figure shows estimates as per Equation 5, but defines the success of an attack based on alternative number of fatalities. The dependent variable is DT_{iym}. $Successful$ is a binary variable =1 for all country-months where a successful terror attack (leading to 5,10, 100 fatalities, respectively) occurred and for up to 11 monthly lags. $Post$ is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and $Post$ assume a value of zero for the 11 months prior to the attack. The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. All specifications include country, year and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 95% confidence intervals.

Figure B.8: Alternative sets of fixed effects



Note: Figure shows estimates as per Equation 5, but uses alternative sets of fixed effects. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. $Post$ is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and $Post$ assume a value of zero for the 11 months prior to the attack. The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. Standard errors are clustered at the country level. Vertical lines indicate 95% confidence intervals.

Figure B.9: Dropping one country at a time



Note: Figure shows baseline estimates when excluding one country at a time from the sample. Each dot represents a separate regression estimate. The red dot in each panel indicates the baseline estimate for the full sample. All specifications include country, year and month fixed effects. The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. Standard errors are clustered at the country level. Shaded area indicates the 95% confidence interval.

Table B.1: Number of events targeting the government

	(1)	(2)	(3)
Panel A: Dep. var - Total no. of events targeting gov.			
$Successful_{iym}$		0.0540	0.0172
		(0.0380)	(0.0346)
$Post_{iym}$	0.0997***	0.0647	0.0508
	(0.0313)	(0.0408)	(0.0423)
Mean Dep. Var.	3.6572	3.6572	3.6572
Panel B: Dep. var - No. of negative events targeting gov.			
$Successful_{iym}$		0.1202***	0.0652*
		(0.0451)	(0.0390)
$Post_{iym}$	0.1389***	0.0611	0.0396
	(0.0364)	(0.0430)	(0.0422)
Mean Dep. Var.	1.8864	1.8864	1.8864
Observations	17,282	17,282	17,282
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful/failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable in Panel A is the natural logarithm of the total number of events targeting the government (i.e., denominator of the *Public Discontent* index). The dependent variable in Panel B is the natural logarithm of the number of events targeting the government recording a Goldstein Score of less than –5 (i.e., numerator of the *Public Discontent* index). $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.2: *Public Discontent* targeting other branches of government

	(1) *Public Discontent*$_{iym}$ *Executive* (*Baseline*)	(2) *Public Discontent*$_{iym}$ *Legislature*	(3) *Public Discontent*$_{iym}$ *Judiciary*	(4) *Public Public All*
$Successful_{iym}$	0.0135***	-0.0066	-0.0037	0.0119***
	(0.0034)	(0.0048)	(0.0064)	(0.0031)
$Post_{iym}$	0.0043	0.0046	0.0014	0.0048
	(0.0042)	(0.0051)	(0.0061)	(0.0040)
Observations	17,282	17,282	17,282	17,282
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes	Yes
Mean *Public Discontent*	0.1212	0.0753	0.0526	0.1232

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable *Public Discontent*$_{iym}$ expresses all domestic events targeting the relevant branch of government that record a Goldstein score of -5 or less, as a fraction of all domestic events targeting the same branch of government. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. All estimates additionally include a binary indicator for the month of the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.3: Public protests targeting the government

	(1) *Public Protests*$_{iym}$	(2) *Public Protests*$_{iym}$	(3) *Public Protests*$_{iym}$
$Successful_{iym}$		0.0884**	0.0721*
		(0.0423)	(0.0418)
$Post_{iym}$	0.0325	-0.0260	-0.0387
	(0.0373)	(0.0437)	(0.0410)
Observations	15,671	15,671	15,671
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes
Mean *Public Protest*	0.4164	0.4164	0.4164

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable *Public Protest*$_{iym}$ is the number of public protests that occurred in country c in month m of year y. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both $Successful$ and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.4: Effects by terror attack target type

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$
Panel A: Attacks on targets excluding government			
Successful$_{iym}$		0.0129***	0.0107***
		(0.0034)	(0.0031)
Post$_{iym}$	0.0135***	0.0048	0.0026
	(0.0043)	(0.0043)	(0.0042)
Observations	15,039	15,039	15,039
Mean *Public Discontent*	0.1254	0.1254	0.1254
Panel B: Attacks on government			
Successful$_{iym}$		0.0095**	0.0067*
		(0.0042)	(0.0040)
Post$_{iym}$	0.0127***	0.0065	0.0034
	(0.0042)	(0.0043)	(0.0040)
Observations	13,226	13,226	13,226
Mean *Public Discontent*	0.1272	0.1272	0.1272
Panel C: Attacks on businesses			
Successful$_{iym}$		0.0180***	0.0155***
		(0.0041)	(0.0043)
Post$_{iym}$	0.0148***	0.0021	0.0019
	(0.0042)	(0.0050)	(0.0046)
Observations	8,169	8,169	8,169
Mean *Public Discontent*	0.1362	0.1362	0.1362
Panel D: Attacks on private citizens			
Successful$_{iym}$		0.0104**	0.0073
		(0.0051)	(0.0046)
Post$_{iym}$	0.0158***	0.0078	0.0052
	(0.0046)	(0.0053)	(0.0051)
Observations	11,445	11,445	11,445
Mean *Public Discontent*	0.1325	0.1325	0.1325
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack against the specified target occurred, along with 11 temporal lags and leads. The dependent variable *Public Discontent*$_{iym}$ 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. *Successful* is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both *Successful* and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.5: Natural disasters and *Public Discontent*

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$	(4) *Public Discontent*$_{iym}$	(5) *Public Discontent*$_{iym}$
Post$_{iym}$	-0.0029	-0.0037	-0.0027	-0.0025	-0.0029
	(0.0026)	(0.0026)	(0.0024)	(0.0024)	(0.0025)
Observations	30,780	30,780	30,780	30,780	30,780
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Disaster Category	All	Flood	Storm	Earthquake	Landslide
Mean *Public Discontent*	0.1022	0.1022	0.1022	0.1022	0.1022

Notes: The unit of measurement is a country-month. The dependent variable *Public Discontent*$_{iym}$ 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. *Post* is a binary variable =1 for all country-months where a natural disaster occurred and for up to 11 monthly lags, and zero for all other country-months. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.6: Terror attack count and *Public Discontent*

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$
Any Attack Count$_{iym}$	0.0116***	
	(0.0035)	
Successful Attack Count$_{iym}$		0.0111***
		(0.0033)
Observations	30,780	6,451
Country FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
Weapon/Attack FE	Yes	Yes
Mean *Public Discontent*	0.1022	0.1473

Notes: The unit of measurement is a country-month. The sample in Columns (1) consists of the full set of country-months where any terror attack happened/did not happen. The sample in Column (2) consists of country-month observations where a successful terror attack or failed terror attack occurred. The dependent variable *Public Discontent*$_{iym}$ 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. The dependent variable in Column (1) is the natural logarithm of the total attack count, while the dependent variable in Column (2) is the natural logarithm of the successful attack count. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.7: Excluding the month of the attack

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$
Successful$_{iym}$		0.0144***	0.0129***
		(0.0035)	(0.0034)
Post$_{iym}$	0.0138***	0.0047	0.0030
	(0.0041)	(0.0044)	(0.0042)
Observations	17,282	17,282	17,282
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes
Indicator for month of attack	Yes	Yes	Yes
Mean *Public Discontent*	0.1212	0.1212	0.1212

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack occurred, along with 11 temporal lags and leads. The dependent variable *Public Discontent*$_{iym}$ 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. *Successful* is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both *Successful* and *Post* assume a value of zero for the 11 months prior to the attack. All estimates additionally include a binary indicator for the month of the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.8: Event-level panel

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$
Successful$_{iym}$		0.0047***	0.0021*
		(0.0013)	(0.0012)
Post$_{iym}$	0.0014***	-0.0026**	-0.0001
	(0.0005)	(0.0012)	(0.0011)
Observations	147,186	147,186	147,186
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes
Mean *Public Discontent*	0.1448	0.1448	0.1448

Notes: The unit of measurement is a event-country-month. The dependent variable *Public Discontent*$_{iym}$ 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. *Successful* is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 11 monthly lags. Both *Successful* and *Post* assume a value of zero for the 11 months prior to the attack. Standard errors, clustered at the year-month level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.9: Alternative time horizons

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$
Panel A: Time horizon – 3 months before and after the attack			
$Successful_{iym}$		0.0163***	0.0146***
		(0.0037)	(0.0036)
$Post_{iym}$	0.0198***	0.0087**	0.0075*
	(0.0036)	(0.0039)	(0.0038)
Observations	12,252	12,252	12,252
Mean *Public Discontent*	0.1307	0.1307	0.1307
Panel B: Time horizon – 6 months before and after the attack			
$Successful_{iym}$		0.0161***	0.0142***
		(0.0036)	(0.0034)
$Post_{iym}$	0.0166***	0.0060	0.0040
	(0.0041)	(0.0041)	(0.0040)
Observations	14,661	14,661	14,661
Mean *Public Discontent*	0.1260	0.1260	0.1260
Panel C: Time horizon – 9 months before and after the attack			
$Successful_{iym}$		0.0175***	0.0156***
		(0.0035)	(0.0032)
$Post_{iym}$	0.0159***	0.0044	0.0018
	(0.0041)	(0.0040)	(0.0038)
Observations	16,369	16,369	16,369
Mean *Public Discontent*	0.1224	0.1224	0.1224
Month FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes

Notes: The unit of measurement is a country-month. The sample consists of all country-months where a successful or failed terror attack occurred, along with 3, 6 and 9 temporal lags and leads, in Panels A, B and C, respectively. The dependent variable *Public Discontent*$_{iym}$ 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. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 3, 6 and 9 monthly lags, in Panels A, B and C, respectively. *Post* is a binary variable =1 for all country-months where a terror attack occurred (successful/failed) and for up to 3, 6 and 9 monthly lags, in Panels A, B and C, respectively. Both $Successful$ and *Post* assume a value of zero for the months prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.10: Country-week estimates

	(1) *Public Discontent*$_{iym}$	(2) *Public Discontent*$_{iym}$	(3) *Public Discontent*$_{iym}$
Panel A: 12 weeks before and after			
Successful$_{iym}$		0.0118***	0.0104***
		(0.0030)	(0.0028)
Post$_{iym}$	0.0148***	0.0067**	0.0045*
	(0.0024)	(0.0027)	(0.0026)
Observations	49,211	49,211	49,211
Mean *Public Discontent*	0.1097	0.1097	0.1097
Panel B: 26 weeks before and after			
Successful$_{iym}$		0.0118***	0.0103***
		(0.0029)	(0.0026)
Post$_{iym}$	0.0130***	0.0054*	0.0022
	(0.0030)	(0.0030)	(0.0028)
Observations	62,283	62,283	62,283
Mean *Public Discontent*	0.1038	0.1038	0.1038
Panel C: 52 weeks before and after			
Successful$_{iym}$		0.0114***	0.0095***
		(0.0029)	(0.0026)
Post$_{iym}$	0.0134***	0.0062*	0.0029
	(0.0033)	(0.0034)	(0.0031)
Observations	75,901	75,901	75,901
Mean *Public Discontent*	0.0980	0.0980	0.0980
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Weapon/Attack FE	No	No	Yes

Notes: The unit of measurement is a country-week. The sample consists of all country-weeks where a successful or failed terror attack occurred, along with the specified number of temporal lags and leads. The dependent variable *Public Discontent*$_{iym}$ 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. *Successful* is a binary variable =1 for all country-weeks where a successful terror attack occurred and for the specified number of weekly lags. *Post* is a binary variable =1 for all country-weeks where a terror attack occurred (successful/failed) and for the specified number of weekly lags. Both *Successful* and *Post* assume a value of zero for the weeks prior to the attack. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.11: FDR adjusted p-values: *Public Discontent* and country characteristics

	(1) $Public\ Discontent_{iym}$	(2) $Public\ Discontent_{iym}$	(3) $Public\ Discontent_{iym}$	(4) $Public\ Discontent_{iym}$
$Successful_{iym}$	0.0141*	0.0246***	0.0145***	0.0139***
	[0.086]	[0.001]	[0.002]	[0.005]
$Post_{iym}$	0.0037	0.0009	0.0018	0.0040
	[0.915]	[1.000]	[0.971]	[0.388]
$Successful_{iym} \times Military\ Capacity_{iy}$	-0.0041			
	[0.915]			
$Post_{iym} \times Military\ Capacity_{iy}$	0.0005			
	[1.000]			
$Successful_{iym} \times Democracy_{iy}$		-0.0156*		
		[0.086]		
$Post_{iym} \times Democracy_{iy}$		0.0005		
		[1.000]		
$Successful_{iym} \times High\ Terror_{i}$			-0.0037	
			[0.971]	
$Post_{iym} \times High\ Terror_{i}$			0.0126	
			[0.860]	
$Successful_{iym} \times Conflict_{iy}$				-0.0064
				[0.388]
$Post_{iym} \times Conflict_{iy}$				-0.0001
				[0.873]
Observations	15,210	13,572	17,282	17,282
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes	Yes
Mean *Public Discontent*	0.1162	0.1174	0.1212	0.1212

Notes: This table conducts the same exercise as per Table 7, and reports the FDR adjusted p-values for these estimates. This procedure is implemented as per Anderson (2008). Sample size is determined by data availability. [] present the FDR adjusted p-values. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.12: FDR adjusted p-values: *Public Discontent* and characteristics of terror attacks

	(1) *Public* $Discontent_{iym}$	(2) *Public* $Discontent_{iym}$	(3) *Public* $Discontent_{iym}$
$Successful_{iym}$	0.0131***	0.0150***	0.0123***
	[0.002]	[0.001]	[0.002]
$Post_{iym}$	0.0038	0.0036	0.0040
	[0.627]	[0.311]	[0.385]
$Successful_{iym} \times ForeignAttack$	-0.0016		
	[0.967]		
$Post_{iym} \times ForeignAttack$	0.0011		
	[0.967]		
$Successful_{iym} \times LonewolfAttack$		-0.0167**	
		[0.017]	
$Post_{iym} \times LonewolfAttack$		0.0080	
		[0.194]	
$Successful_{iym} \times CapitalAttack$			0.0039
			[0.385]
$Post_{iym} \times CapitalAttack$			-0.0027
			[0.455]
Observations	17,282	17,282	17,282
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes
Mean *Public Discontent*	0.1212	0.1212	0.1212

Notes: This table conducts the same exercise as per Table 8, and reports the FDR adjusted p-values for these estimates. This procedure is implemented as per Anderson (2008). [] present the FDR adjusted p-values. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.13: FDR adjusted p-values: *Public Discontent* and leader characteristics

	(1) $Public\ Discontent_{iym}$	(2) $Public\ Discontent_{iym}$	(3) $Public\ Discontent_{iym}$	(4) $Public\ Discontent_{iym}$
$Successful_{iym}$	0.0146***	0.0134***	0.0157***	0.0146***
	[0.001]	[0.001]	[0.001]	[0.001]
$Post_{iym}$	0.0033	0.0051	0.0018	0.0018
	[0.526]	[0.306]	[0.475]	[0.404]
$Successful_{iym} \times FemaleLeader$	-0.0164			
	[0.118]			
$Post_{iym} \times FemaleLeader$	0.0075			
	[0.526]			
$Successful_{iym} \times YoungLeader$		-0.0303**		
		[0.028]		
$Post_{iym} \times YoungLeader$		0.0057		
		[0.453]		
$Successful_{iym} \times NewLeader$			-0.0099*	
			[0.097]	
$Post_{iym} \times NewLeader$			0.0015	
			[0.475]	
$Successful_{iym} \times MilitaryLeader$				-0.0185**
				[0.024]
$Post_{iym} \times MilitaryLeader$				0.0093
				[0.153]
Observations	15,199	15,199	15,188	15,067
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Weapon/Attack FE	Yes	Yes	Yes	Yes
Mean *Public Discontent*	0.1212	0.1212	0.1215	0.1219

Notes: This table conducts the same exercise as per Table 9, and reports the FDR adjusted p-values for these estimates. This procedure is implemented as per Anderson (2008).Sample size is determined by data availability. [] present the FDR adjusted p-values. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.