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Public Sentiment in Times of Terror

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September 2021

Abstract

Do citizens hold their government accountable for the delivery of public goods? 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 towards governments. Focusing on terror attacks as a government accountability shock, and using high-frequency, text-based event data to quantify public sentiments, I find that the average level of *Public Discontent* increases by approximately 14% in the 11 months following a successful terror attack. This effect is not merely driven by fear, and is influenced by information on government competence and attack-specific features. Citizens are less reproachful if the government made a reasonable effort to keep the public safe, and for events that may be beyond the government's control. Interestingly, young leaders and new leaders demonstrate an ability to mobilize the masses to rally 'round the flag in the aftermath of terror attacks.

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

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1 Introduction

On 15 March 2019, in one of the most brutal events in the country's history, a single gunman opened fire at two mosques in Christchurch, New Zealand, killing 50 people and injuring another 40.[1] In the aftermath, the Prime Minister of New Zealand, Jacinda Ardern, received widespread local and global praise for her handling of the situation, with her popularity reaching an all-time high.[2] These developments are in stark contrast to the situation in Spain following the 2004 Madrid train bombings, where a series of coordinated terror attacks on the commuter train system killed 193 people and injured thousands more.[3] Countrywide protests and demonstrations arose in the following days, and the attacks have been highlighted as a potential reason for the incumbent government's loss at the subsequent election (Montalvo, 2011).

These two terror attacks, although different along many dimensions, are examples of government accountability shocks, where the expectation that the public good of "national security" will be delivered by the government did not materialize. However, the public response differed remarkably between the two events. While citizens rallied 'round the flag in New Zealand, the level of public discontent rose insurmountably in Spain. What could explain these different responses? This paper aims to disentangle the complex set of factors underlying the public's sentiments towards government accountability shocks, in the specific form of terror attacks.

In doing so, this paper focuses specifically on the *short term, immediate* dynamics in public sentiments, which have been largely understudied in the political economy literature. Within this literature, the focus has typically centered around elections as the key mechanism of government accountability (Healy and Malhotra, 2013). Due to their aggregate and periodic nature, election data cannot capture the immediate variations in

[1] See *ABC News* , "Christchurch shooting death toll rises to 50 after one more victim discovered at mosque," 17 March 2019.

[2] See, for example, *SBS News*, "Jacinda Ardern's popularity at all-time high after mosque attacks," 15 April 2019. See also, *Time*, "A year after Christchurch, Jacinda Ardern has the world's attention. How will she use it?," 20 February 2020.

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

public sentiments following important events, and the absence of alternative disaggregated data sources has been a major empirical barrier in exploring these short term dynamics. Despite the limited attention however, short term public sentiments are crucial in shaping the behavior of governments and the public alike. Understanding public sentiments enables governments to respond to the public's concerns on a continuous basis, either via alleviation or strategic diversion (Amarasinghe, 2021; Lewandowsky, Jetter and Ecker, 2020), while the government's response can reciprocally affect the public's confidence and trust in the government (Sangnier and Zylberbeg, 2017).

Amidst such a setting, this paper proposes an alternative, fine-grained approach to examine the *short term dynamics* in public sentiments following government accountability shocks. Departing from the traditional usage of election data, I generate a temporally granular, text-based indicator of *Public Discontent* which quantifies public sentiments towards the government, in a global representative sample of countries, and at any given point in time. Combining this index with data on approximately 5,000 terror attacks, in 132 countries, over the years 2002-2016, I then examine whether and how the public sentiments towards the government change immediately 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 immediate aftermath of government accountability shocks.

The *Public Discontent* index, which is the key outcome variable in this study, is based on the premise that on a daily basis citizens engage in "events" through which they continuously 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 sentiment, enabling the systematic study of the citizen-state relationship at a very fine degree of temporal granularity. Accordingly, following Amarasinghe (2021), the *Public Discontent* index is constructed using textual data from approximately 100 million media-reported actual physical events, retrieved from the Global Database of

Event, Language and Tone (GDELT).[4]

I then combine this index with data on terror attacks extracted from the Global Terrorism Database (GTD) to examine how *Public Discontent* behaves following government accountability shocks in the form of terror attacks. Considering national security as a public good that lies within the domain of government responsibility, *Public Discontent* is primarily expected to increase following terror attacks. However, I hypothesize that rational citizens would also incorporate relevant information such as the government's perceived/realized competence, as well as terrorists' fighting capacity, in to their sentiments.

In the first part of the empirical strategy, I compare country-month units where a terror attack occurred with country-month units 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*. This is a first signal that the public criticize the government immediately following terror attacks. However, this definition of the treatment potentially suffers from selection bias, since the location and the timing of terror attacks are likely to be strategically decided by terrorists. To address this problem, I apply an alternate identification strategy building on the work by 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]

Combining this identifying assumption with GTD's own interpretation on whether a terror attack was a success or failure, I am able to provide causal estimates of the direction and magnitude of the change in public sentiment towards governments in the immediate aftermath of terror attacks. I find that, conditional on the timing, location

[4]This 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. Sentiment scores attached to events are identified as per the conflict-cooperation scale introduced by Goldstein (1992), which assigns a score ranging from -10 to $+10$ to each event category, based on the theoretical potential impact a particular event type can have on the political stability of a country. A positive (negative) score identifies the particular event category as theoretically strengthening (weakening) the country's political stability. More details on the construction of 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.

and weapon/attack type, a successful terror attack increases the *Public Discontent* index by 0.14 points, confirming that the public does indeed criticize the government, in the short run, for not keeping them safe. The effect is a sizable 14% increase over the sample mean, and is robust to a number of alternate specifications.

Next I explore whether this public reaction is based on fear or on available information, by using a series of indicators on perceived/realized government competence as well as attack-specific characteristics. Primarily, I find that the effect is stronger for countries with governments that committed less resources to counter terrorism. I also find that the effect is weaker if the attack was committed by an individual unaffiliated with an organized terror group, i.e. lone wolf attacks, or by a foreign terror group, suggesting that the public is less critical of the government if the attacks were reasonably beyond the governments' control. Interestingly, I observe a reversal of the baseline effect if the attack occurred when a young (i.e., less than 40 years old) or new (i.e., in office for less than 3 years) national leader was in office, suggesting that such leaders are able to mobilize the masses towards solidarity with the government in the aftermath of a terror attack, consistent with a "rallying 'round the flag" effect.

Taken together, these findings have important policy implications. First, these results establish that the government and its performance is scrutinized by the public not only during elections, but is continuously and consistently monitored throughout its tenure. The findings also suggest that the public response is not merely driven by fear, but is based on the set of available information on leader and government competence. Evidence of such continued 'rational' public scrutiny in the short term would act as a system of checks and balances on government performance, and can even shape the trajectory of the citizen-state relationship 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 (Amarasinghe, 2021; Lewandowsky, Jetter and Ecker, 2020; Morgan and Anderson, 1999) which can lead to further instability in the domestic or international space. Therefore, understanding the short term causes and consequences of *Public Discontent* is a critical component in determining the behaviors of the actors in the citizen-state relationship.

This paper contributes to several strands of the literature. Primarily, it relates to the broad literature in political science and economics 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; Enders and Hoover, 2012; Mahmood and Jetter, 2020; Dreher and Gassebner, 2008; Jetter, 2017). A second portion focuses on the *consequences* of terrorism, such as on employment, wages and consumer sentiment (Brodeur, 2018; Benmelech, Berrebi and Klor, 2010), 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) and asylum approval (Brodeur and Wright, 2019). Closely related to my work, and using voting data, Montalvo (2011) finds that terror events increase the probability of replacing the incumbent government, although Baccini, Brodeur, Nossek and Shor (2021) find no effect of terror events on voting outcomes.

My paper contributes to and expands on this second portion of the literature by exploring the immediate, short term consequences of terrorist events on public sentiment towards governments, going beyond the traditionally usage of periodic voting data. In a context where existing studies, based on voting data, find mixed evidence on the effects of terror attacks, this paper provides a complementary and temporally disaggregated view which can clearly filter out the immediate effects of terror attacks on public sentiments.

Next, this paper contributes to the broad political economy literature exploring government accountability for socioeconomic outcomes. This literature typically focuses on retrospective voting as the tool for such accountability,[6] in relation to economic performance (Reeves and Gimpel, 2012; Margalit, 2011), as well as for the delivery of non-economic public goods (Gasper and Reeves, 2011; Healy and Malhotra, 2009; Karol and Miguel, 2007). 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

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

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 large temporal gap between elections is a major empirical barrier in using voting data to explore the short term variations in public sentiments.[7] 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 accountability, not limited to periodic voting data. Building on the work in Amarasinghe (2021), I use a quantified, text-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 government accountability in the immediate aftermath of terror attacks, for a globally representative sample of countries.

Finally, this paper contributes to the literature examining the importance of national leaders in shaping country level outcomes. Famously, Jones and Olken (2005) and Besley, Montalvo and Reynal-Querol (2011) examine how national leader transitions and education levels, respectively, affect economic growth. A score of studies examine how the leader's gender, age and period of tenure affect aggregate outcomes (Chattopadhyay and Duflo, 2004; Spisak, Grabo, Arvey and Vugt, 2014; Bienen and van de Walle, 1989). To the best of my knowledge, my paper is the first to examine how terror attacks form an immediate signal about the leader's competence and how these effects vary depending on a range of leader-specific characteristics.

[7] 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.

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 mechanisms underlying the public response. Section 5 concludes.

2 Data

The unit of analysis is a country-month. The final sample consists of 5,009 terror attacks that occurred in 132 countries, over the years 2002-2016.

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 the 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 (2021), I leverage on such high-frequency event data extracted from the GDELT project to generate an index of *Public Discontent* that quantifies public sentiment towards governments for each country-month unit. 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 all media-reported events across the world, consisting of approximately 100 million events over the sample period.[8]

To generate the index of *Public Discontent*, I follow the step-wise procedure proposed in Amarasinghe (2021). I first identify all the 'domestic' events that occurred in a country over the sample period.[9] Next, based on the 'target', I extract the sub-sample of domestic events *specifically targeting the government*. 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.[10] Since the objective of this study is to quantify *Public Discontent*, my focus is primarily on events that receive a *negative* score on the Goldstein scale.

Accordingly, for each time period, I obtain the number of domestic events targeting the government, which scored less than a threshold value of -5 on the Goldstein score, to 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.[11] The denominator $Dom_{iym-10\leq G\leq 10}$ refers to the total number of domestic events targeting the government, on the full spectrum of the Goldstein scale (-10 $\leq$ G $\leq$ 10). Accordingly, $PublicDiscontent_{iymG\leq -5}$ is a standardized indicator that captures people's resentment towards their government, quantifying the proportion of events attached with a negative sentiment score relative to all events targeted at the government.

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

[9]For the purpose of identification, all events where the locations of the source, the target and the incident itself are within the same country are classified as 'domestic'. To sustain the integrity of the index, I only retain the set of events which were recorded in at least 3 media reports.

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

[11]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.1.

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. This means that I am able to explore the *short term* dynamics of the relationship between the public and their governments, surpassing 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.[12]

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 in the Online Appendix provides detailed information and a number of tests that strengthen the validity of this measure as a universally applicable indicator of public sentiment towards governments.

2.2 Data on terror attacks

Data on terror attacks is sourced 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*

[12]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 explain 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.

fear, coercion, or intimidation." In order to be included in the dataset, 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.

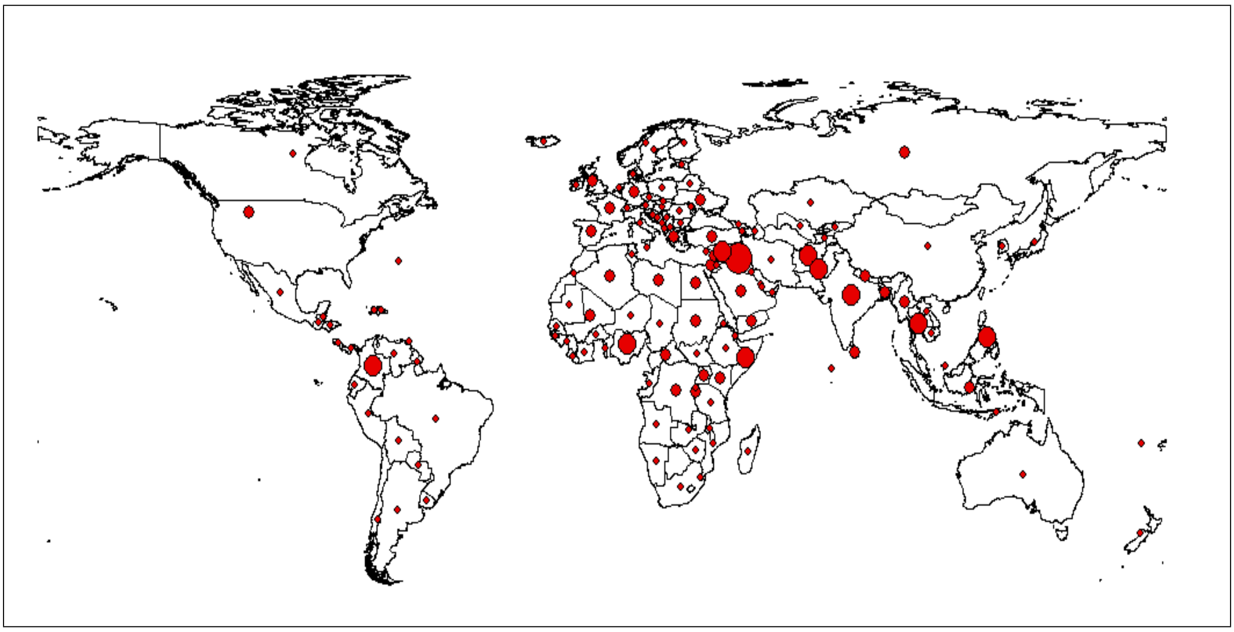
The database provides detailed information on terror attacks which occurred throughout the globe since 1970, including the date, location, weapon/method used, the number affected and the target type. For the purpose of my analysis, I only use the set of terror attacks targeted at civilians. Accordingly, terror attacks against the government or government agencies such as the military or police forces, are outside the scope of this study.[13] Figure 1 shows the geographic distribution of 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 criteria 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 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.

Within my analysis, I use the information provided by GTD to generate binary indicators to identify occurrences of (a) any terror attack (b) a successful terror attack and (c)

[13]This restriction is important because the question addressed in this paper is whether the public hold the government accountable for terror attacks. Including attacks against the government may bias the estimates, for example if the government uses an attack against itself to gain sympathy from the public.

Figure 1: Geographic distribution of terror events



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

a failed terror attack. I also generate a count variable that captures the total number of terror events that occurred in a given country-month, which I use as a control variable in my preferred estimates to capture the country's general atmosphere related to terrorism.

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 97%, while the success rate of an assassination is 79%. 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

To confirm the validity of the baseline results, I use an alternative outcome variable based on the number of protest events that occurred in a country in a given month. For this purpose, I obtain data on public protests from the Mass Mobilization Project (Clark and Regan, 2016). This is a global data set of protests where 50 or more protesters publicly demonstrate *against the government*, and includes information on the location, size of the protest, protester demands, and government responses. Using this data set, I generate a variable capturing the number of protests that occurred within a country-month unit, which is then used as an alternative outcome variable to corroborate the validity of the baseline estimates.

Additionally, I use data from the Polity IV project (Marshall, Gurr and Jaggers, 2019) to generate time-invariant binary indicators that classify countries as democratic and non-democratic. Countries with an average polity score ≥ 5 over the sample period are identified as democracies, while those with scores < 5 are identified as non-democratic countries. Data on the age and gender of country leaders is from the Archigos database of leaders (Goemans, Gelditsch and Chiozza, 2009), 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, 2018). Data on military expenditure and military personnel is sourced from the Correlates of War Project (Singer, 1987), while data on national elections is sourced from Bjørnskov and Rode (2020).

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 empircal strategies in more detail.

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

3.1.1 Event study estimates

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.

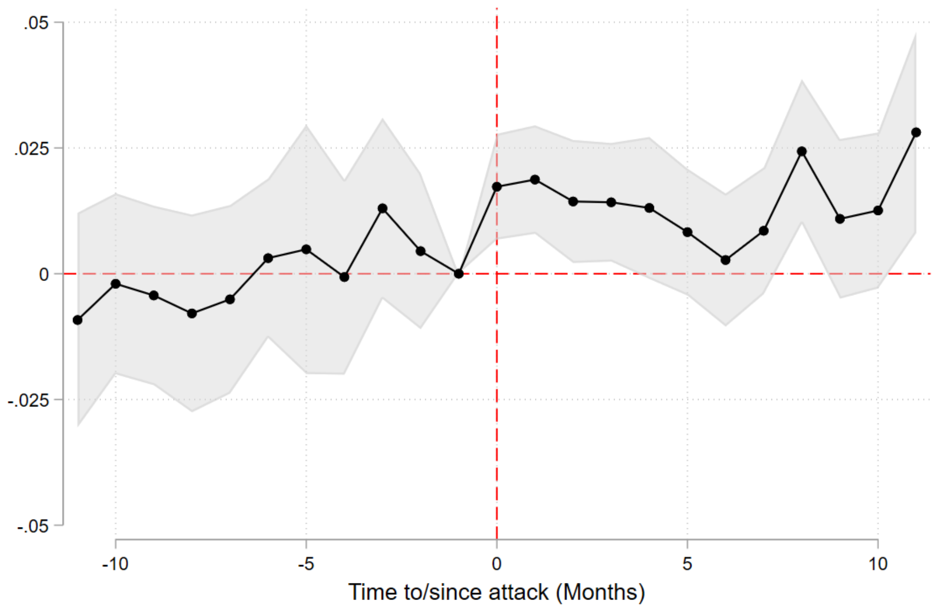
$$PublicDiscontent_{iym} = \sum_{t=-11}^{11} \alpha_t Attack_{iym-t} + \beta X_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_m} + \epsilon_{iym} \quad (2)$$

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 the country, 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.[14] The vector X incorporates a set of other control variables. This includes a variable on the number of terror attacks that occurred in the country in the given month, which captures the country's general climate towards terrorist activities, as well as fixed effects to capture the attack type and the weapon type. Additionally, I include a vector of country×year fixed effects, $\mathbf{FE_{iy}}$, which accounts for any time-variant unobservables affecting a given country in a given year, as well as time-invariant country-specific features. The vector of month–of–the–year fixed effects, $\mathbf{FE_m}$, accounts for unobserved seasonal variation that can simultaneously affect the relationship.

[14]This temporal distance is negative for the months before the event, and positive for the months after the event. Moreover, the variables are constructed in a manner that the clock resets to zero each time an attack occurs. Therefore, 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.

Figure 2 graphically illustrates the results of this estimation exercise. I observe that, conditional on country×year fixed effects and month fixed effects, there exists 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* which persists up to 3 months following a terror attack, suggesting that citizens do indeed criticize their government following terror attacks. Moreover, I observe some statistically significant effects resurfacing even after the immediate effects have worn off, potentially indicative of a back-and-forth reaction to the government response following a terror attack. This result further suggests that the public reaction occurs even at very fine levels of temporal granularity, 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 90% confidence intervals.

3.1.2 Difference-in-differences estimates

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

$$PublicDiscontent_{iym} = \rho Post_{iym} + \beta X_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \tag{3}$$

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.[15] 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 is not clear cut. A terror attack may lead the public to criticize the government for failing to provide the public good of security (i.e, an increase in *Public Discontent* as represented by a positive value of ρ). It may also be that in the aftermath of a terror attack, the public expresses solidarity with the government, in line with the rallying 'round the flag hypothesis (a decrease in *Public Discontent*, represented by a negative value of ρ). The ultimate direction and magnitude of the coefficient 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 include the basic model with no control variables. In Columns (2) and (3) I add controls in the form of the number of terror attacks in the given period and weapon/attack type fixed effects, respectively. In all specifications, the occurrence of a terror attack increases *Public Discontent* targeted at governments, reconfirming that the public expresses their discontent at the government following terror attacks. The point estimates remain relatively stable across specifications, reflecting an approximately 11% increase over the sample mean of the *Public Discontent* index.

[15] I consider a time horizon of 11 months since Figure 2 indicates that the effects of terror attacks are visible in the 11 months following the attack.

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

	(1) *Public* $Discontent_{iym}$	(2) *Public* $Discontent_{iym}$	(3) *Public* $Discontent_{iym}$
$Post_{iym}$	0.0090**	0.0090**	0.0092**
	(0.0041)	(0.0041)	(0.0042)
Observations	27,900	27,900	27,900
No. of Countries	132	132	132
Month FE	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes
Attack Count	No	Yes	Yes
Weapon/Attack FE	No	No	Yes
Mean *Public Discontent*	0.0810	0.0810	0.0810

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.

3.1.3 Threats to identification

The key threat to this identification strategy, however, is that country-months where terror attacks occur could be systematically different from country-months in which no terror attacks take place. Of course, by using a stringent set of fixed effects incorporating (a) time-invariant country-specific unobservables, (b) time-variant country-specific unobservables as wells as (c) seasonal 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 Panel A of Table B.1, I conduct a quick balance test between the treated (i.e with terror attacks) and untreated (i.e without any terror attacks) units, using the two key variables that are consistently observed for all countries i.e., *Public Discontent* and *Attack Count*. I do not observe a statistically significant difference between the two groups in the key outcome variable i.e., *Public Discontent*. However, I observe that *Attack Count* is statistically significantly different between the two groups. Next in Panel B, I undertake a prediction exercise, where the objective is to examine if the values of these two key variables in the *previous* period can predict the occurrence of a terror attack in the *current* period. Again I observe that while *Public Discontent* in the previous period cannot statistically significantly predict the occurrence of a terror attack in the current period, *Attack Count* in the previous period can indeed predict the occurrence of a terror attack in the current period.

It is important to note however that the estimation results displayed in Figure 2 and in Column (2) of Table 1 already account for *Attack Count*, which was included as a control variable. Therefore, differential trends with respect to this variable are already accommodated within these estimates. Nevertheless, these diagnostic checks, in combination with the recent literature on the strategic timing and location choices of terror groups (for example, Brodeur, 2018; Brodeur and Youssaf, 2020; Youssaf, 2021) necessitate that concerns related to such bias be alleviated through an alternative identification strategy.

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

In this section I utilize an alternative identification strategy that addresses concerns related to selection bias discussed in Section 3.1.3 above. 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.[16] In this paper, I further escalate the proposition in Brodeur (2018) to the country level and for the world as a whole, by comparing country-months that experienced a *successful* terror attack against country-months that experienced a *failed* terror attack. By restricting the analysis to country-months that experienced a successful/failed terror attack only, I am able to fil-

[16]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 Baccini, Brodeur, Nossek and Shor (2021), Brodeur and Yousaf (2020) and Yousaf (2021).

ter out any non-random location or timing choices made by terrorists that could lead to selection bias, thereby enabling the causal interpretation of these estimates.

3.2.1 Identifying assumptions

For the identifying assumptions to hold, it is imperative 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 first investigate whether there are observable differences between the treatment and control groups, using two key variables that are consistently observed for all countries in the sample, i.e. *Public Discontent* and the *Attack Count*. In Panel A of Table B.2, I compare the means of these key variables for country-months with successful attacks (Column (1)) vs country-months with failed attacks and no successful attacks (Column (2)). Column (3) provides the difference in the means for the two samples. I observe that the treatment and control groups are not statistically significantly different along these relevant variables, thereby providing confidence on the valididty of the identifying assumption.

Next, in Panel B of Table B.2, I undertake a prediction exercise, where I combine these observable variables with a large set of fixed effects to investigate their ability in predicting the *success* of a terror attack.[17] I commence the prediction exercise using *Public Discontent* in isolation (Column (1)) and in the next step additionally include *Attack Count* as a predictor. However, none of these variables are able to predict the success of a terror attack. Since the success of a terror attack may depend on the weapon/type of the attack, in Column (3) I add weapon and attack type fixed effects as predictors. The inclusion of attack and weapon type fixed effects does not further improve the observable variables' ability to predict the success of a terror attack, thereby providing further

[17]Due to the unavailability of other consistent and comparable between-country-month data, in line with the large number of countries in the sample and the fine temporal granularity pursued in this paper, this exercise is limited to these two key variables. However, by including a large set of country $\times$ year and month fixed effects, I am able to absorb any time-variant and time-invariant unobservables as well as seasonal factors that could affect the relationship. This provides a high level of confidence on the comprehensiveness of this prediction. To enable the inclusion of these large sets of fixed effects, I use a linear probability estimator for this prediction exercise.

confidence on the validity of the identifying assumption.

3.2.2 Event study estimates

Having thus established that country-months with successful terror attacks are not statistically significantly different from country-months with failed attacks, I now 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 up to 11 months.

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

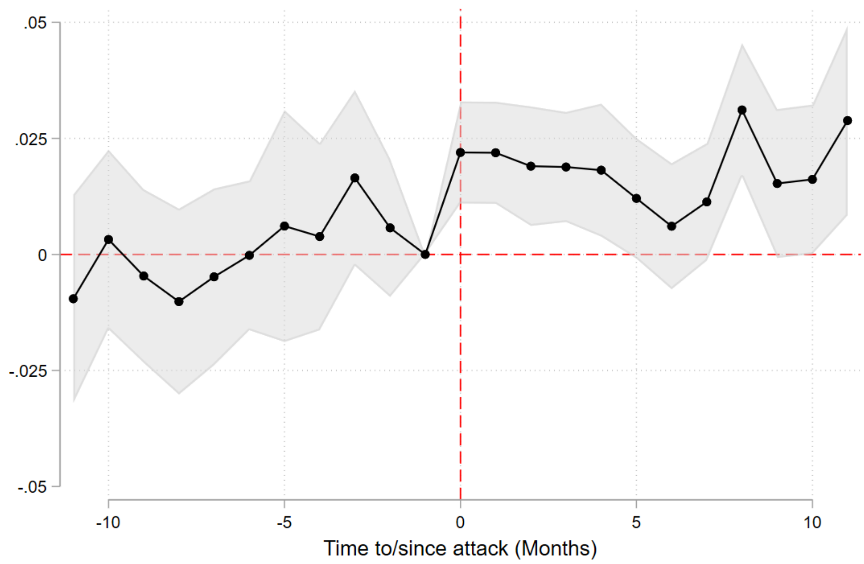
Here, *Public Discontent*$_{iym}$ is the level of public discontent in country i in month m of year y, calculated as per Equation 1. *AttackOutcome* is either (a) *Success*, a binary indicator equal to one if a successful terror attack occurred in the country, in month m of year y, or (b) *Failure*, a binary indicator equal to one if a failed terror attack occurred in the country, in month m of year y. The data set includes 11 monthly lags and leads of the explanatory variable. As with Equation 2, I include a vector of control variables as well as country×year and month fixed effects.

Panels (a) and (b) in Figure 3 show the behavior of *Public Discontent* before and after a successful and failed terror attack, respectively. 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 attack, longer than the 3 month effect observed under the "attack vs no attack" identification strategy.[18] By contrast, in Panel (b) I observe no statistically significant effect of failed terror attacks on *Public Discontent*.[19]

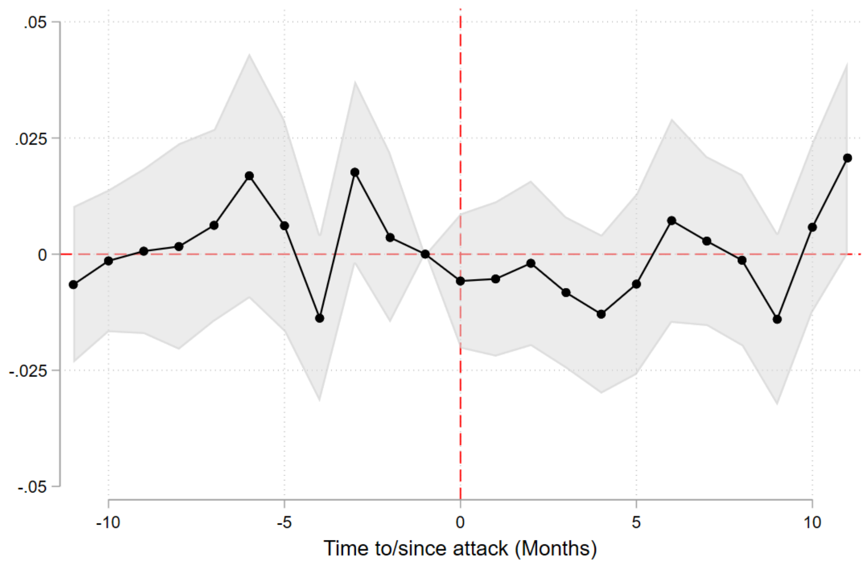
[18] I further observe, as with Figure 2, that statistically significant effects resurface once the immediate effect has worn off, potentially indicating a back-and-forth reaction to the government response.

[19] These estimates therefore rule out the possibility that the public may perceive failed terror attacks as a signal that the government keeps them safe, and "praise" the government following failed terror attacks, in which case a statistically significant decline in *Public Discontent* would have been observed. Moreover, such an argument implicitly equates failed attacks with "prevented" attacks, which is inconsistent with the definition of failed attacks in Table A.2.1.

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. Sample is limited to country-months with successful/failed terror attacks and their relevant lags and leads. Standard errors are clustered at the country level. Grey area shows the 90% confidence intervals.

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 againts country-months with failed attacks. As discussed, the comparison is *not* between country-months with terror attacks and country-months 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.

$$PublicDiscontent_{iym} = \gamma Successful_{iym} + \tau Post_{iym} + \beta X_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \quad (5)$$

The estimation equation is presented in Equation 5. Here, $Successful$ is a variable equal to 1 for the 11 months following a successful attack in country i, including the month of the attack.[20] 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. For the 11 months preceding any attack, it assumes a value of zero.[21] As before, I include country×year fixed effects and month fixed effects in the estimations.[22] In my preferred specification, I also control for weapon/attack type fixed effects as well as for the number of terror attacks in the period, $Attack\ Count$.

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 for failing to deliver national security, or a negative value if the public rallies 'round the government following a successful terror attack. The final direction of the coefficient depends on which of these effects dominates

[20] In the baseline estimates, the variables $Successful$ and $Post$ include the month of the attack. However, in Table B.4 I separate the effect of the month of the attack, and the results remain robust.

[21] The choice of a time horizon of 11 months is based on Panel (a) of Figure 3 where effects of terror attacks are observed within 11 months of the attack's occurrence. However, these baseline results remain robust when considering alternative time horizons, i.e., 9, 6 and 3 months before and after the attack, as indicated in Table B.5.

[22] In Figure B.3 I show the robustness of these baseline results to the inclusion of alternative sets of fixed effects.

in the aggregate.[23]

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 the period up to 11 months after the attack. In Column (2) I disentangle whether this increase is driven by successful attacks or failed attacks, by including the variable $Successful$ in the specification. 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 both statistically and economically insignificant. In Column (3) I control for the total number of terror attacks recorded in the period, to account for any unobservables related to the general climate towards terrorism, and the results do not change drastically. My preferred estimates appear in Column (4) where I additionally control for the type of the event and the weapon used in the attack. By controlling for weapon/attack type fixed effects, I am able 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 are robust and remain quantitatively and qualitatively similar when this stringent and very specific set of fixed effects 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 0.014 points, which is approximately a 14% increase over the sample mean.

The results in Table 2 confirms the findings under the "attack vs no attack" identification strategy demonstrated in Table 1. Under both identification strategies, I find that the public does indeed express their resentment towards the government for failing to deliver the public good of national security. This finding is particularly interesting when considering the inconclusive nature of the existing literature on government accountability and citizen competence, which is mainly based on election outcome data.[24] My paper, by

[23]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 the estimated effects represent a lower bound of the true effect.

[24]For example, while Reeves and Gimpel (2012) and Karol and Miguel (2007) find evidence in favour of government accountability, 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.

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

	(1) *Public* $Discontent_{iym}$	(2) *Public* $Discontent_{iym}$	(3) *Public* $Discontent_{iym}$	(4) *Public* $Discontent_{iym}$
$Successful_{iym}$		0.0139***	0.0137***	0.0139***
		(0.0039)	(0.0039)	(0.0039)
$Post_{iym}$	0.0126**	0.0003	0.0003	0.0007
	(0.0054)	(0.0055)	(0.0055)	(0.0055)
Observations	14,377	14,377	14,377	14,377
No. of Countries	132	132	132	132
Month FE	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes
Attack Count	No	No	Yes	Yes
Weapon/Attack FE	No	No	No	Yes
Mean *Public Discontent*	0.0997	0.0997	0.0997	0.0997

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. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

contrast, provides a novel perspective to this literature by taking a microscopic view of the instantaneous effects of government accountability shocks, using high-frequency, temporally disaggregated data, circumventing the empirical barriers associated with periodic voting data. This exercise highlights that the public's sentiment towards governments is a highly-responsive, continuously-evolving phenomenon that needs to be adequately monitored throughout the government's tenure.

3.3 Robustness checks

3.3.1 Alternative outcome variables

The outcome variable in the baseline estimates is the *Public Discontent* index, which was constructed using high-frequency event data from the GDELT database. I now conduct a robustness check using an alternative outcome variable, to ensure that the observed relationship is not simply driven by the nature of the data used to construct the *Public Discontent* index. I obtain data on public protests from the Mass Mobilization project (Clark and Regan, 2016). This data set is especially suitable for the purpose of this paper as it only reports public protests *against the government*. I generate a simple count variable of the protests that occurred in each country in month m of year y, and use this measure of public protests as the outcome variable in Equation 5. Consistent with the baseline estimates, results in Table B.3 show that successful terror attacks do increase public discontent, even when discontent is measured through this alternative variable on public protests.

Next, I revert to exploring the robustness of the *Public Discontent* index. In the baseline specification, I calculate the *Public Discontent* index using domestic events targeted at governments, based on a threshold Goldstein score of –5 or less. Now, I examine the sensitivity of the estimates to this threshold. I generate separate indices of *Public Discontent* based on threshold Goldstein scores of –3, –4, –5, –6 and –7, and use these indices as the outcome variable in separate regression estimates. As demonstrated in Figure B.1, the results remain quantitatively and qualitatively similar.

3.3.2 Separating the effect of the month of the attack

The variables *Successful* and *Post* in the baseline estimates include the month of the attack. However, since the analysis is conducted at the month level, there is a possibility that attacks at the end of the month are considered as predicting public discontent at the beginning of the same month. To address this concern, in Table B.4, I separate out the effect on *Public Discontent* in the month of the attack, by additionally including a binary indicator that assumes a value of 1 for all months where an attack occurs. I observe that the estimated effects remain robust to this distinction.

3.3.3 Alternative time horizons

The baseline estimates are based on a time horizon of 11 months before and after a terror attack. Panels A, B and C in Table B.5, present the estimates when considering the period 9, 6 and 3 months before and after an attack, respectively. I find that the baseline result remains robust to these alternative time periods as well.

3.3.4 Intensity of treatment

In Figure B.2 I examine whether the magnitude of increase in *Public Discontent* varies with the intensity of the damage incurred by terror activities. Accordingly, I define the success of an attack based on the number of deaths and estimate the baseline specification separately for successful terror attacks that led to at least 1, 5 and 10 fatalities. I find that the increase in *Public Discontent* is higher when the number of fatalities is high.

3.3.5 Alternative sets of fixed effects

Recall that in the baseline estimates, I use country×year fixed effects along with month fixed effects. In Figure B.3, I plot the baseline estimates, along with estimates incorporating three alternative sets of fixed effects which control for time-variant and time-invariant unobservables at different degrees of granularity, i.e. (a) country, year and month fixed effects separately, (b) country and year×month fixed effects, as well as (c) continent×year×month fixed effects. Point estimates remain qualitatively and quantitatively similar irrespective of the set of fixed effect incorporated.

3.3.6 Sample checks

To ensure that the baseline results are not driven by a particular country, in Figure B.4, I plot the estimates when dropping one country at a time. The coefficients on $Successful$ and $Post$ remain consistent with the baseline results in this robustness check as well.

3.3.7 Diagnostic tests

The recent literature on two-way fixed effects (TWFE) estimators applied in this difference-in-differences setting 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.[25]

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. As demonstrated in Figure B.5, 94% of the treatments, under both estimation strategies, receive positive weights, while a marginal 6% receive negative weights. Accordingly, within the current setting, the sum of the positive weights of ATEs clearly outweigh the sum of the negative weights on ATE. Moreover, the minimal values of the standard deviation of the treatment effect, across the treated groups and time periods under which the estimated coefficient and the average treatment effect on the treated (ATT) could be of opposite signs, are within recommended ranges specified in points (i) and (ii) of Corolloray 1 in De Chaisemartin and D'Haultfœuille (2020), providing further confidence that this issue remains trivial within the current setting.[26]

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

[26] Specifically, the estimated minimal value of the standard deviation of the treatment effect, across the treated groups and time periods under which the coefficient and the average treatment effect on the treated (ATT) could be of opposite signs, is 0.01. The rule-of-thumb recommendation in De Chaisemartin

4 Mechanisms underlying *Public Discontent*

The public's response to a terror attack may well depend on how the government itself responds following the attack.Moreover, the set of available information on government capability and intentions may also have a bearing on the level of public sentiment following a terror attack. Exploring these avenues is important in understanding if the increase in *Public Dsicontent* observed in the baseline estimates is driven by fear, or by the public's evaluation of government competence.

4.1 Government's counter-terrorism efforts

Governments typically commit large amounts of funds on counter-terrorism exercises, which is a signal that the government acknowledges its responsibility towards ensuring public safety. Regardless of these efforts however, terror attacks do take place. 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. However in the absence of such data for the large number of countries scrutinized in this study, I rely on data on military capacity, sourced from the Correlates of War project (Singer, 1987), as a proxy for counter-terrorism efforts. I use two indicators, i.e. the absolute amount of military expenditure (in Millions of US Dollars) and per capita military expenditure. I split the sample in to low and high military capacity based on the median values of these indicators for 2001, i.e. the year just before the commencement of the sample period.[27] I then separately estimate Equation 5 on these two sub-samples, to identify if public reaction differs between countries with low military capacity and those with high military capacity.

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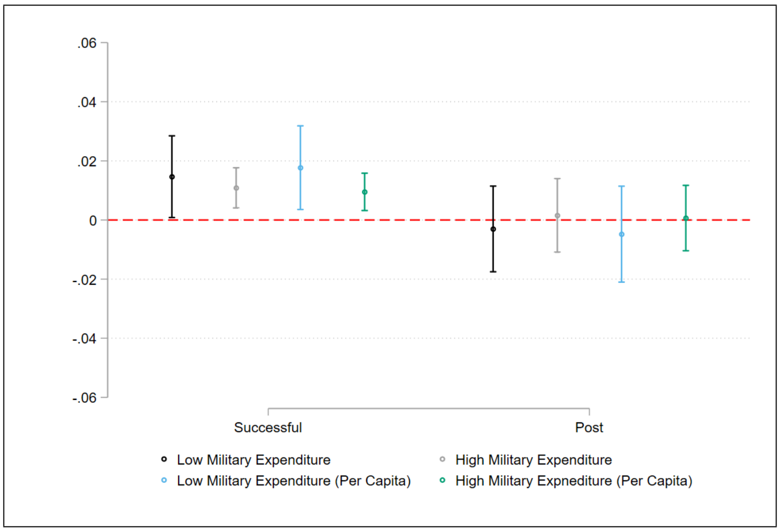
and D'Haultfœuille (2020) is that if the treatment effects of the treated groups and time periods are drawn from a normal distribution, then 95% of them will fall within the [-1.96x,1.96x] interval, where x is the minimal value of the standard deviations as disclosed above. In both estimation strategies, the estimated beta coefficient falls within this interval.

[27] Median values are: Military expenditure- 896 Million US Dollars; Per capita military expenditure - 58 US Dollars. I discretize these variables due to the lack of continuous data at the unit of analysis, i.e. country-month.

Figure 4: Effect of terror attacks on *Public Discontent* - The role of military capacity



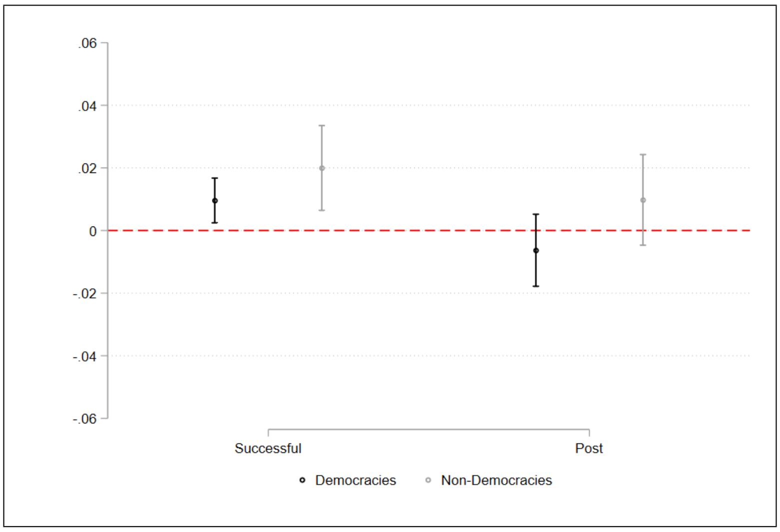
Note: Figure shows estimates as per Equation 5 when the sample is split under the indicated criteria. The dependent variable is *Public Discontent*$_{iym}$. *Successful* is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a 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. Countries have been classified as recording *Low* or *High* values of the military expenditure/military personnel based on the median values for the countries in the sample in the year 2001. Median values are: Military expenditure- 896 Million US Dollars; Per capita military expenditure - 58 US Dollars. Dots and vertical lines of similar colour represent a single regression estimate. The unit of measurement is a country-month. All specifications include country×year fixed effects and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure 4 displays the results of this split-sample analysis, which consists for four separate regression estimates i.e. one each for high/low levels of absolute and per capita military expenditure. I first observe that *Post* is always statistically insignificant, across the four estimates, which indicates that failed terror attacks do not trigger public discontent. However, I observe an interesting distinction in the coefficient on *Successful* between countries with high military capability, and those with low military capability. Although the effect of successful terror attacks on *Public Discontent* is always positive, the increase in countries with low military capability is almost two times higher than the increase in those with high military capability. This effect becomes more prominent when the classification is based on per capita military expenditure. These results therefore suggest that the public incorporates information on government efforts towards ensuring public safety in to their criticism in the aftermath of a successful terror attack.

4.2 Political institutions

Next I explore if the public's response varies by the level of political institutions in the country. Here, I classify countries as democratic and non-democratic based on the Polity IV score. A country is classified as a democracy if it recorded an average polity score of 5 or above (on a scale of -10 to 10) over the sample period. If the average polity score was less than 5 over the sample period, the country is classified as a non-democratic country. Figure 5 provides the estimates for these two sub-samples. I find that although *Public Discontent* rises following successful terror attacks irrespective of the level of political institutions, the increase is higher in non-democratic countries. This suggests that the prevailing quality of political institutions is a relevant factor in the public's evaluation of government accountability.

Figure 5: Effect of terror attacks on *Public Discontent*- The role of political institutions

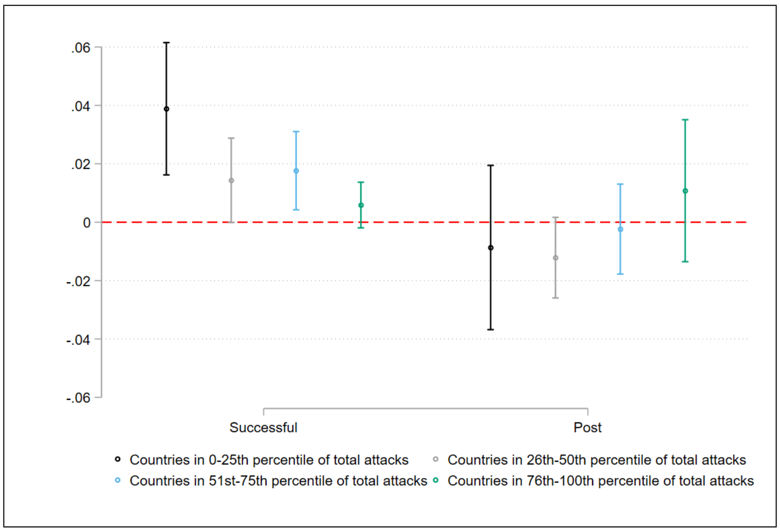


Note: Figure shows estimates as per Equation 5 when the sample is split under the indicated criteria. The dependent variable is $Public\ Discontent_{iym}$. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* is a 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. Countries have been classified as *Democracies* or $Non-democracies$ based on the average polity score recorded during the sample period. A country is classified as a democracy if it recorded an average polity score of 5 or above (on a scale of -10 to 10) over the sample period, and a non-democracy if the average polity score was less than 5 over the sample period. Dots and vertical lines of similar colour represent a single regression estimate. The unit of measurement is a country-month. All specifications include country×year fixed effects and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

4.3 The learning curve

What effect does the repeated exposure to terror attacks have on *Public Discontent*? Do citizens exhibit complacency in the face of more frequent terror attacks, or to they become increasingly critical of the government? To empirically investigate this question, I first group countries in to four groups based on the total number of attacks experienced over the sample period. I then estimate Equation 5 separately for each quantile. Results are shown in Figure 6.

Figure 6: Effect of terror attacks on *Public Discontent* - Frequency of attacks



Note: Figure shows estimates as per Equation 5 when the sample is split into four groups based on the number of terror attacks faced by a country over the sample period. The dependent variable is $Public\ Discontent_{iym}$. $Successful$ 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. Cutoff values of the total number of attacks used to determine the quantiles: 25th percentile - 5 attacks, 50th percentile - 16 attacks, 75th percentile - 146 attacks. Dots and vertical lines of similar colour represent a single regression estimate. The unit of measurement is a country-month. All specifications include country×year fixed effects and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

I find interesting heterogeneity in the level of public response between the four groups. The largest increase in public discontent is observed in countries least exposed to terror attacks. As the number of terror attacks increases, the magnitude of the response gradually declines, becoming statistically insignificant in the group with the largest number of attacks. These results suggest that *Public Discontent* is most responsive 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 the perceived incapacity of the government within their process of evaluation, as manifested by the less intense reaction in the face of repeated successful terror attacks.

4.4 Do attack-specific characteristics matter?

Next I consider whether information specific to the type of the attack could affect the public's response. For this purpose, I modify the baseline specification where, in addition to the variables $Successful$ and $Post$, I now include two interaction terms to identify the heterogeneous effects of attack types. The modified equation is as indicated in Equation 6.

$$\begin{aligned} PublicDiscontent_{iym} = \gamma_1 Successful_{iym} + \gamma_2 (Successful_{iym} \times AttackType) + \tau_1 Post_{iym} \\ + \tau_2 (Post_{iym} \times AttackType) + \beta X_{iym} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iym} \end{aligned} \tag{6}$$

Here, $AttackType$ is a binary indicator which equals to one if an attack exhibited the relevant characteristic, and zero otherwise. The coefficient on $Successful \times AttackType$ and $Post \times AttackType$ would capture the public's response to successful and failed terror attacks, respectively, for attacks sharing this characteristic. I provide more details on attack-specific characteristics below.

4.4.1 Domestic vs foreign terror attacks

First, I explore whether the domestic vs international nature of a terror attack could heterogeneously affect the change in public sentiments towards governments. One may expect, *ex ante*, that the public will be less critical of the government if the attack was carried out by foreign individuals, since they may be perceived as being beyond the government's control. It could also be 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, in which case a decline in *Public Discontent* may be observed (Sobek, 2007; Pickering and Kisangani, 1998).

To classify terror attacks as foreign, I rely on the information provided by the GTD on the nationality of the perpetrators. I define an "Attack Type" indicator $ForeignAttack$, which is a binary indicator equalling to 1 if the attack was carried out by foreign nationals. I then substitute this indicator for *AttackType* in Equation 6. Accordingly, the coefficients on the interaction terms $Successful \times ForeignAttack$ and $Post \times ForeignAttack$ capture the effects of successful and failed foreign attacks on *Public Discontent*, respectively. Column (1) of Table 3 presents the estimation results. I observe that the effect of failed attacks, whether foreign or domestic, is statistically insignificant. Between successful attacks, in line with my hypothesis, the larger effect on *Public Discontent* emanates from successful *domestic* terror attacks, as reflected via the coefficient of $Successful$. The coefficient of $Successful \times ForeignAttack$ is lower in magnitude and is statistically insignificant, suggesting that the public response is influenced by the available information on terror attacks, as opposed to being purely driven by fear.

4.4.2 Attacks by organized terror groups vs lone wolf attacks

Next I distinguish between attacks committed by organized terror groups and attacks committed by individuals unaffiliated with an organized terror group. This is an important distinction that again signals the government's control over national security. Attacks by organized terror groups are identified 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. However, if the attack is conducted by an unaffiliated individual, i.e. lone wolf, the public may be more forgiving towards the government, as it likely had limited means of foreseeing and controlling it.

For each attack listed on the database, GTD provides information on whether it was carried out by an "unaffiliated individual".[28] I use this information to generate a binary indicator, *LonewolfAttack*, which assumes a value of 1 if the attack was carried out by an unaffiliated individual, and zero otherwise. Column (2) in Table 3 displays the estimation results distinguishing lone wolf attacks. As expected, I do not find an effect of lone wolf attacks on *Public Discontent*, hinting at 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.

4.4.3 Attacks in the capital city vs other locations

Next I explore if 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.

To investigate this hypothesis, I combine information on national and provincial capital cities for each country in the sample, with the location data of each terror attack as provided by the GTD. I then define a binary indicator *CapitalAttack* which assumes a value of 1 if the attack occurred in a national or provincial capital, and zero otherwise. Column (3) of Table 3 displays the results of this exercise. Somewhat counter-intuitively, I find that the effect of terror attacks on *Public Discontent* is positive and statistically significant irrespective of the location, and the magnitude of the effect is not remarkably different between the two categories of successful terror attacks. However, it is important to note that the variable *CapitalAttack* only captures urban areas classified as national or provincial capitals, and this result may be driven by geographies which are economically important although not classified as a national/provincial capital.

[28] 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 3: *Public Discontent* and characteristics of terror attacks

	(1)	(2)	(3)
	Public	*Public*	*Public*
	$Discontent_{iym}$	$Discontent_{iym}$	$Discontent_{iym}$
$Successful_{iym}$	0.0136***	0.0131***	0.0114**
	(0.0040)	(0.0039)	(0.0045)
$Post_{iym}$	0.0009	0.0011	-0.0007
	(0.0056)	(0.0054)	(0.0064)
$Successful_{iym} \times ForeignAttack$	0.0046		
	(0.0097)		
$Post_{iym} \times ForeignAttack$	-0.0042		
	(0.0095)		
$Successful_{iym} \times LonewolfAttack$		0.0209	
		(0.0157)	
$Post_{iym} \times LonewolfAttack$		-0.0126	
		(0.0151)	
$Successful_{iym} \times CapitalAttack$			0.0081*
			(0.0046)
$Post_{iym} \times CapitalAttack$			0.0009
			(0.0048)
Observations	14,377	14,377	14,377
No. of Countries	132	132	132
Country ×year FE	YES	YES	YES
Month FE	YES	YES	YES
Attack Count	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 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/provincial 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.

4.5 The effect of national leaders on *Public Discontent*

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 the literature as signals of leader competence. For example, female leaders are considered to have positive effects on the delivery of public goods (Clots-Figueras, 2012; Chattopadhyay and Duflo, 2004), but their evaluations suffer from gender bias due to perceptions of leading with 'emotion' (Brescoll, 2016; Gangadharan, Jain, Maitra and Vecci, 2016). Young leaders are sought in time of change, while older leaders are preferred in times of stability (Spisak, Grabo, Arvey and Vugt, 2014). Length of leadership is a key characteristic of leader power (Bienen and van de Walle, 1989), while military regimes are perceived as having enhanced capacity to face issues related to national security (Kim, 2019; Panel, 2017). Based on such evidence from the literature, a relevant question within the scope of this study is whether perceived/realized signals of leader competence affect the public response following terror attacks. In the ensuing section, I examine this question in detail, combining data on a number of leader characteristics.

First, I examine whether the gender of the leader affects the public response. 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. Column (1) in Table 4 provides the estimation results. I find no statistically significant effect of successful terror attacks on *Public Discontent* when the national leader is female.

Next, I focus on the age of the leader in power. I generate a binary indicator $YoungLeader$ which equals to 1 if the leader in power is less than 40 years old, and zero otherwise. Interestingly, in Column (2) of Table 4, I find that the coefficient on the interaction term $Successful \times YoungLeader$ is negative and highly statistically significant. This indicates 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, suggesting that young leaders are able to mobilize the masses to rally 'round the flag in the aftermath of a terror attack. Although whether this is due to young leaders' empathetic reactions following an attack or their perceived competence in leading a counter-attack is unclear, what does seem strongly suggestive is that governments are less likely to be faced with negative sentiments if the leader in power is a *young* leader.

Could the period of time that the leader has been in power affect the public response? To examine this possibility, I generate a binary indicator $NewLeader$ which assumes a value of 1 if the leader has been in office less than 3 years, and zero otherwise.[29] In Column (3) of Table 4 I observe, again, a negative coefficient on the variable $Successful \times NewLeader$, suggesting that, following terror attacks, the public rallies 'round new leaders in solidarity. Moreover, when the effect of new leaders is accounted for, the coefficient on the variable $Successful$ (which captures the effect of *Public Discontent* for leaders in power for longer than 3 years) almost doubles in comparison to the baseline estimates, confirming that the public's expectations of government accountability are increasing in the time the government has been in power.

Finally, I explore whether the presence of a military leader affects the public response. Leveraging on the information provided by the Database of Political Institutions, I define $MilitaryLeader$ as a binary variable equal to one if the national leader or the defence minister at the time of the attack had a military background. However, in Column (4) of Table 4, I do not find a differential effect in the public response based on this distinction.

5 Conclusion

The existing literature on government accountability, which primarily focuses on periodic electoral outcomes as a measure of the public's evaluation of government performance, provides inconclusive evidence on whether or not the public holds their government accountable for failing to deliver key public goods. In this paper, I propose a novel, temporally granular approach that enables the quantification of public sentiments towards

[29] 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. The underlying assumption is that even if the leader has been an active politician long before assuming power, the public will only consider them accountable if they are in power at the time of the attack.

Table 4: *Public Discontent* and leader characteristics

	(1) Public $Discontent_{iym}$	(2) Public $Discontent_{iym}$	(3) Public $Discontent_{iym}$	(4) Public $Discontent_{iym}$
$Successful_{iym}$	0.0151***	0.0140***	0.0215***	0.0123***
	(0.0048)	(0.0044)	(0.0065)	(0.0041)
$Post_{iym}$	-0.0016	0.0005	-0.0013	-0.0021
	(0.0067)	(0.0061)	(0.0069)	(0.0061)
$Successful_{iym} \times FemaleLeader$	-0.0169			
	(0.0127)			
$Post_{iym} \times FemaleLeader$	0.0094			
	(0.0094)			
$Successful_{iym} \times YoungLeader$		-0.0429***		
		(0.0139)		
$Post_{iym} \times YoungLeader$		-0.0088		
		(0.0297)		
$Successful_{iym} \times NewLeader$			-0.0187**	
			(0.0089)	
$Post_{iym} \times NewLeader$			0.0040	
			(0.0084)	
$Successful_{iym} \times MilitaryLeader$				0.0046
				(0.0154)
$Post_{iym} \times MilitaryLeader$				0.0116
				(0.0174)
Observations	12,802	12,802	13,185	13,185
No. of Countries	129	129	131	131
Country-year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Attack Count	YES	YES	YES	YES
Weapon/Attack FE	YES	YES	YES	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 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 3 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.

their government at any given point of time. In line with Amarasinghe (2021), I use a text-based indicator of *Public Discontet*, constructed based on millions of high-frequency event data rerieved from the GDELT database, to examine whether the public criticizes their government for failing to deliver a key public good, i.e., national security.

Using terror attacks as a government accountability shock, and comparing country-month units that experienced a terror attack against the country-month units that did not experience a terror attack, I first show that *Public Discontent* increases immediately following a terror attack. However, the occurrence of terror attacks, by itself, is non-random in nature due to terrorists' strategic decisions on the timing and location of such attacks. To address endogeneity concerns arising from such selection bias, I follow the proposition in Brodeur (2018) in comparing, conditional on the location, timing as well as the attack/weapon type, country-months where successful attacks occurred against those where failed terror attacks occurred. Leveraging on this random nature of the *outcome* of the attack, I re-confirm that the public holds their governments accountable for national security. Specifically, a successful terror attack leads to a 14% increase in *Public Discontent* over the sample mean. This result is robust to a number of stringent robustness tests, and also holds when using public protests as an alternative outcome variable.

I find interesting heterogeneous effects underlying this public response based on realized/perceived signals on government competence and attack-specific characteristics. Importantly, governments with low military commitments are criticized more than governments exhibiting strong signals of military capability. The public is more forgiving towards the government if it is perceived as having made an effort at keeping the public safe, and for events that may be beyond their control, such as terror attacks by foreign perpetrators and lone wolves. The response is strongest in countries where terror attacks are infrequent occurrences. Interestingly, consistent with the rallying 'round the flag hypothesis, I find that young leaders and new leaders are able redirect the public response in a manner that unites the public with the government in the aftermath of successful terror attacks.

The findings of this empirical exercise provide important policy implications for the relationship between the public and their government. Primarily, this exercise shows that the performance of the government is consistently and continuously scrutinized by the public, even in the short term, and not only during elections. Moreover, the findings suggest that the public response is not merely driven by fear, but is based upon available information, and such 'rational' public scrutiny would act as a disincentive for governments to achieve sub-optimal levels of performance. Amidst recent empirical evidence that governments respond aggressively to short term public sentiment shocks (Amarasinghe, 2021; Lewandowsky, Jetter and Ecker, 2020), the temporally fine-grained approach suggested in this paper could be used to shed further light on these disaggregated dynamics, which are important for policy makers and the public alike.

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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 finely 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.

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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 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 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. 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 using country and time fixed effects. Moreover, a standardization of the indicators, for example by expressing as ratios, as opposed to taking a simple count of event occurrences, 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

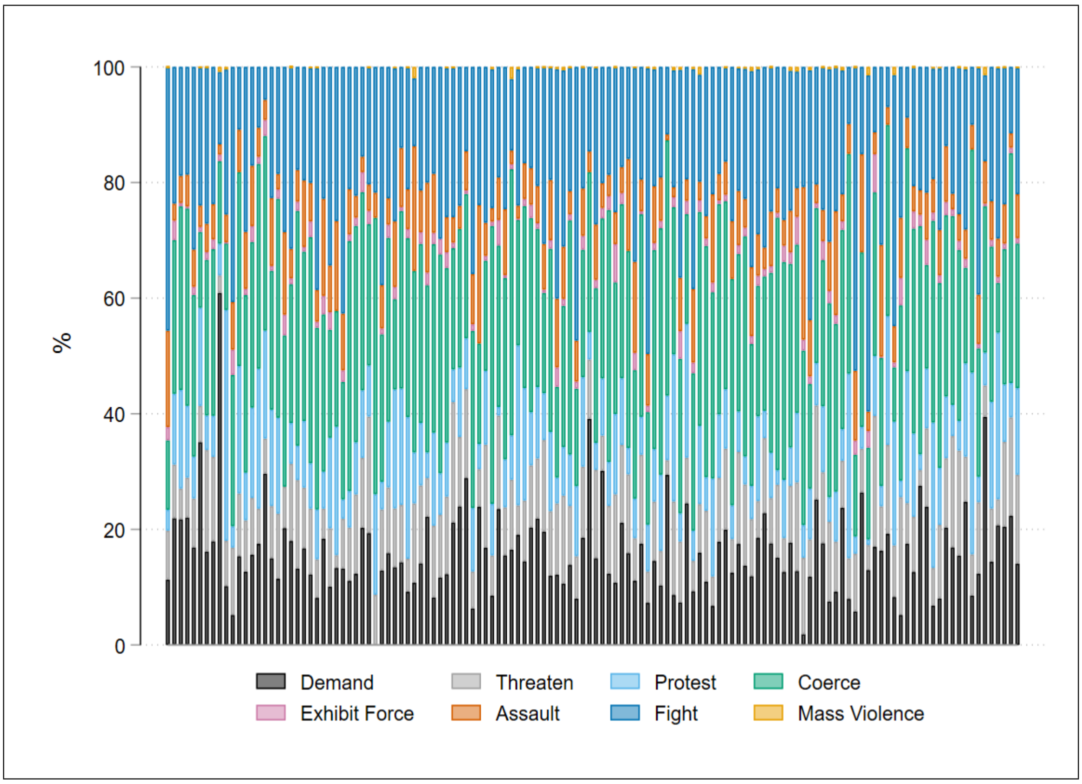
Source: The Computational Event Data System

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.1, the results are robust to alternative cutoffs on the Goldstein scale.

Which event categories typically show up in the *Public Discontent* index? To answer this question, 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 balanced within the index for each country, 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

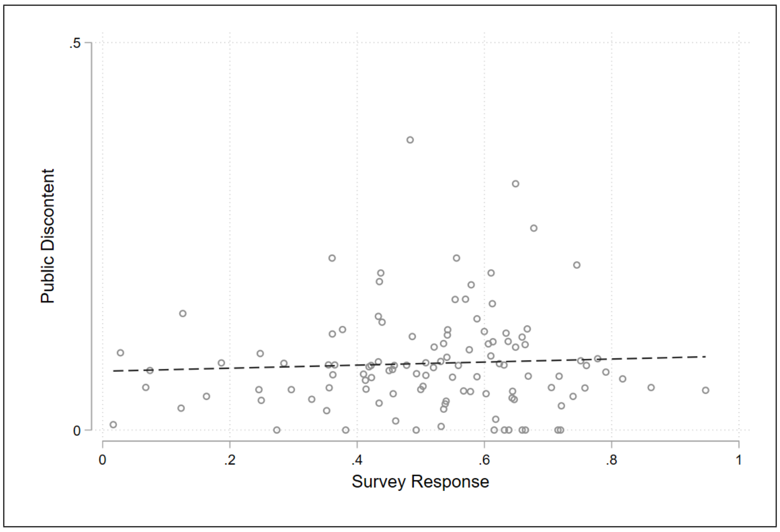
How well does the *Public Discontent* index represent the existing, albeit imperfect, measures of public sentiment? I approach this question using two types of data sets that are frequently used to assess sentiments towards governments.

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 4–6 of the World Values Survey (WVS) covering 77 countries, and waves 2–6 of the Afrobarometer survey covering 35 African countries, 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.

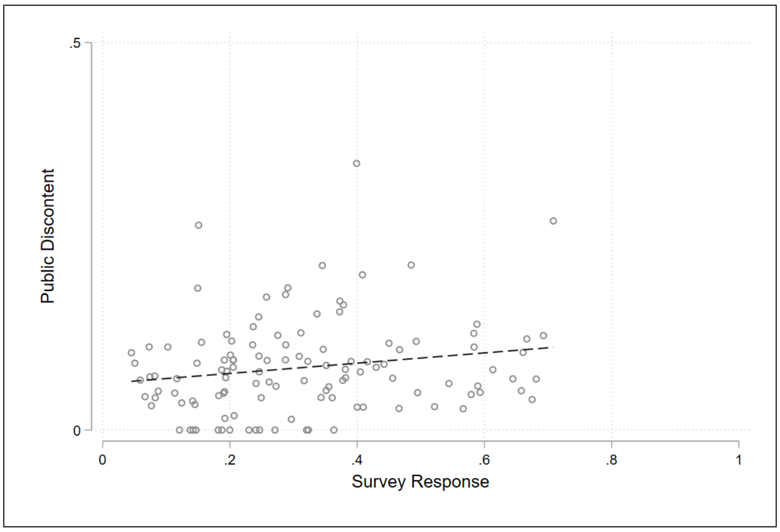
In the WVS, I focus on the question, 'How much confidence do you have in the government?' This question yields a range of categorized answers, which may be 'a great deal', 'quite a lot', 'not very much' or 'none at all'. I construct an indicator variable equal to 1 if the respondent replied 'not very 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. For both surveys, I then sum up the scores over a given country in a given year, and standardize this measure by expressing it as a proportion of the total number of respondents.

Figure A.1.2 presents the correlation plots between the *Public Discontent* index and the survey responses. Consistent with the survey data, these correlations are reported at the country-year level. Panel (a) provides the scatter plot and line of best-fit for *Public Discontent* and WVS responses, while Panel (b) plots the responses from the Afrobarometer survey alongside *Public Discontent*. I observe that the survey indicators are indeed positively correlated with the *Public Discontent*, although the highly aggregated nature of survey data means that the number of observations is limited to country-years where surveys took place.[4]

Figure A.1.2: *Public Discontent* and Survey Indicators



(a) World Values Survey



(b) Afrobarometer Survey

Notes: Figure shows the relationship between *Public Discontent* and survey responses. Panels (a) and (b) plot *Public Discontent* against a standardized measure of expressed confidence in government/president as per the World Values Survey and the Afrobarometer survey, respectively. The unit of measurement is a country-year. Number of observations is 114 (Panel (a)) and 118 (Panel (b)).

Next, I examine the association between the *Public Discontent* index and other more disaggregated data sets on public unrest. For this purpose, I first use data on public

[4]Sangnier and Zylberberg (2017) use the variation in the timing of the survey rollout to identify how the public sentiments towards governments changes following exposure to protests. Unfortunately, the limited number of terror attacks coinciding with survey rollout dates precludes me from exploiting this identification strategy within the current setting.

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

	(1) *Mass Mobilization* $Protest_{iym}$	(2) *ACLED* $Protest_{iym}$	(3) *US Presidential* $Approval\ Rate_{iym}$	(4) *Incumbent* $Election\ Loss_{iym}$
$Public\ Discontent_{iym}$	0.4342***	3.1530***	-1.2615***	0.3467**
	(0.0517)	(0.7193)	(0.2679)	(0.1574)
Observations	22,500	7,380	180	471
No. of countries	125	41	1	135

Notes: This table depicts the correlations between *Public Discontent* and country level indicators of protests targeted at governments. Columns (1) and (2) use data on protests from the Mass Mobilization Project and ACLED (which only covers the African continent), respectively. Column (3) uses monthly data on US presidential approval rates. The unit of measurement is a country-month. 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 month, as the outcome variable. Standard errors, clustered at the country level, are in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level.

protests, particularly targeting the government, covering 125 countries, obtained from the Mass Mobilization Project. In addition, I obtain data on protests in the African continent from the Armed Conflict Location & Event Data (ACLED) Project, as well as data on US presidential approval ratings sourced from the American Presidency Project. Table A.1.2 displays the results of this exercise. In Columns (1) and (2), I show that the *Public Discontent* index is highly correlated, both statistically and economically, with the number of protests occurring in the same period within a country. In Column (3), I observe that, as expected, there is a negative correlation between *Public Discontent* and the US presidential approval rate. Finally, in Column (4) 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, 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*

Notes:Source: 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.

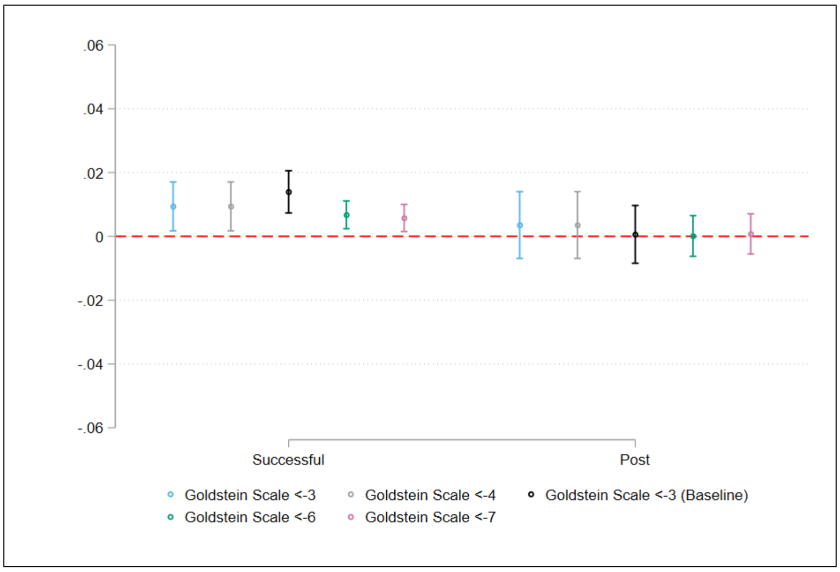
Table A.2.2: Descriptive statistics on terror attacks

Description	Observations	Percent of total	Success rate
Attack type			
Armed assault	2,459	24%	97%
Unarmed assault	226	2%	94%
Bombing	3,437	33%	93%
Infrastructure	1,402	13%	98%
Assassination	818	8%	79%
Other	1,841	18%	98%
Weapon type			
Explosives	3,437	36%	93%
Firearms	2,683	28%	98%
Incendiary	1,360	14%	97%
Melee	714	7%	97%
Other	1,342	14%	96%
Other attack-specific characteristics			
Foreign Attack	728	14%	90%
Lone Wolf Attack	128	3%	81%
Capital Attack	2,866	57%	79%
Characteristics of national leader at the time of attack			
Female Leader × Attack	391	8%	94%
Young Leader × Attack	60	1%	96%
New Leader × Attack	2,078	41%	95%
Military Leader × Attack	2,253	45%	58%
Total	5,009		96%

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/provincial 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 3 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.

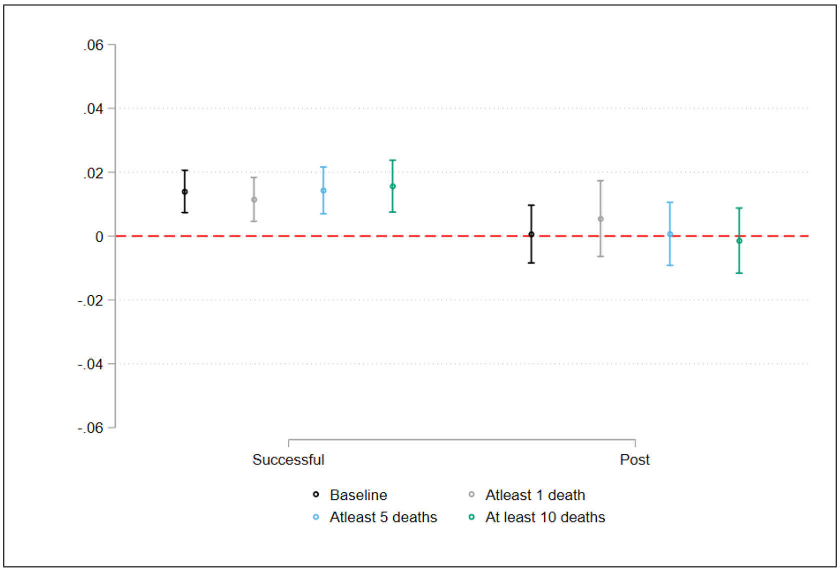
B Additional robustness tests

Figure B.1: Alternative definitions of *Public Discontent*



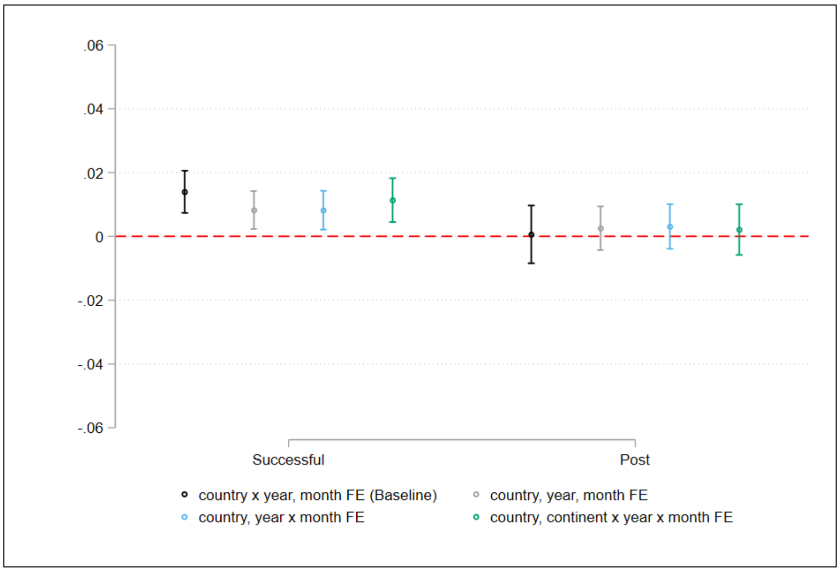
Note: Figure shows estimates as per Equation 5, but uses alternative cutoffs on the Goldstein scale when defining Public Discontent, which is the dependent variable. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. *Post* 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. Dots and vertical lines of similar colour represent a single regression estimate. The unit of measurement is a country-month. All specifications include country×year fixed effects and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure B.2: Alternative definition of successful attacks based on the number of fatalities



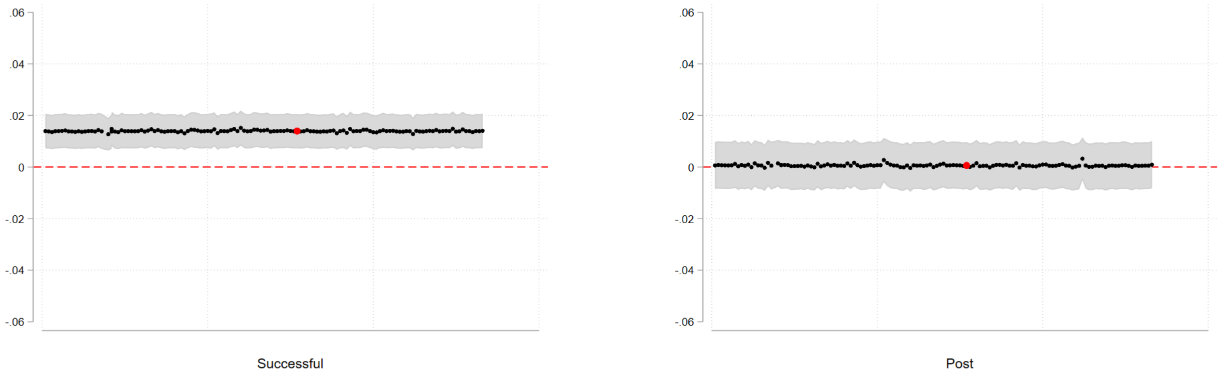
Note: Figure shows estimates as per Equation 5, but defines the success of an attack based on the number of fatalities. The dependent variable is DT_{iym}. $Successful$ is a binary variable =1 for all country-months where a successful terror attack (leading to 0,1,5,10 fatalities, respectively) occurred 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. Dots and vertical lines of similar colour represent a single regression estimate. The unit of measurement is a country-month. All specifications include country×year fixed effects and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure B.3: Alternative fixed effects



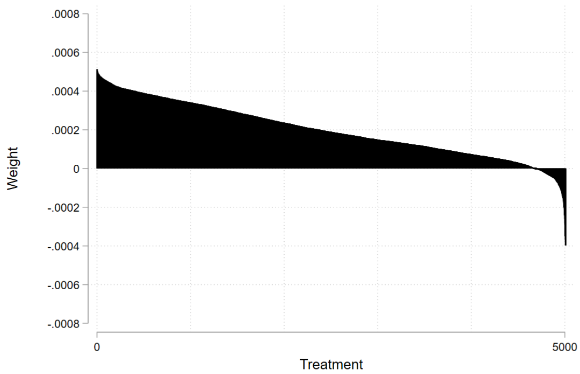
Note: Figure shows estimates as per Equation 5, but uses alternative sets of fixed effects. $Successful$ is a binary variable =1 for all country-months where a successful terror attack occurred and for up to 11 monthly lags. $Post$ is a binary variable =1 for all country-months where a terror attack 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. Dots and vertical lines of similar colour represent a single regression estimate. The unit of measurement is a country-month. All specifications include country×year fixed effects and month fixed effects. Standard errors are clustered at the country level. Vertical lines indicate 90% confidence intervals.

Figure B.4: Dropping one country at a time

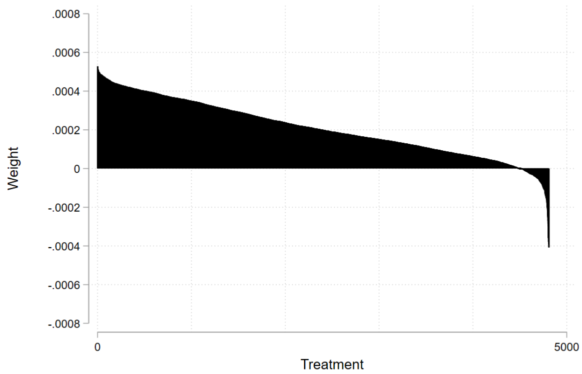


Note: Figure shows second stage estimates as per Equation 5, when excluding one country at a time from the sample. Each dot represents a separate regression estimate. The red dot in each panel indicates the baseline estimate for the full sample. All specifications include country×year fixed effects and month fixed effects. The unit of measurement is a country-month. Standard errors are clustered at the country level. Shaded area indicates the 90% confidence interval.

Figure B.5: Diagnostic tests - Weights attached to each treatment as per De Chaisemartin and D'Haultfœuille (2020)



(a) Treatment: Any terror attack



(b) Treatment: Successful terror attack

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

Table B.1: Predicting terror attacks - "Attacks vs no attacks" strategy

	(1)	(2)	(3)
Panel A: Two sided t-tests	*Attack*	*No Attack*	*Difference*
$Public\ Discontent_{iym-1}$	0.0007	-0.0001	-0.0008
	(0.0951)	(0.1219)	(0.0018)
$Attack\ Count_{iym-1}$	0.1353	-0.0296	-0.1649*
	(13.3731)	(0.9152)	(0.0893)
Observations	5,009	22,891	
Panel B: Predicting attack	*Attack*	*Attack*	*Attack*
$Public\ Discontent_{iym-1}$	0.0086	0.0084	0.0080
	(0.0106)	(0.0106)	(0.0107)
$Attack\ Count_{iym-1}$		0.0013**	0.0013**
		(0.0005)	(0.0005)
Observations	27,900	27,900	27,900
Country-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. Estimates are for the full sample, and the comparison is between country-months with any terror attack and country-months without a terror attack. Panel A provides the means of the observable variables for country-months with terror attacks (Column (1)) and country-months without terror attacks (Column (2). Column (3) in Panel A provides the differences in the means. Country×year fixed effects and month fixed effects are included, Parenthesis refer to standard deviations (for Columns (1) and (2)) and standard errors (in Column (3)). Panel B provides the results of the estimation exercise that attempts to predict the occurrence of a terror attack using the key explanatory variables. Standard errors, clustered at the country level, are in parenthesis. Columns (1) and (2) include country×year fixed effects and month fixed effects, while Column (3) additionally includes weapon and attack type fixed effects. *Public Discontent* 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. *Attack* is a variable representing the number of terror attacks. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.2: Predicting terror attacks - "Successful vs failed attacks" strategy

	(1)	(2)	(3)
Panel A: Two sided t-tests	*Successful*	*Failed*	*Difference*
$Public\ Discontent_{iym-1}$	0.0008	-0.0042	-0.0051
	(0.0958)	(0.0710)	(0.0069)
$Attack\ Count_{iym-1}$	0.0549	0.2411	0.1862
	(7.0783)	(3.0483)	(0.5037)
Observations	4,810	199	
Panel B: Predicting success	*Successful*	*Successful*	*Successful*
$Public\ Discontent_{iym-1}$	0.0157	0.0159	0.0131
	(0.0199)	(0.0199)	(0.0195)
$Attack\ Count_{iym-1}$		-0.0002	-0.0001
		(0.0002)	(0.0002)
Observations	5,009	5,009	5,009
Country-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 is restricted to country-months with terror attacks, and the comparison is between country-months with a *successful* terror attack and country-months with a *failed* terror attack. Panel A provides the means of the observable variables for country-months with successful terror attacks (Column (1)) and country-months with failed terror attacks (Column (2). Column (3) in Panel A provides the differences in the means. Country×year fixed effects and month fixed effects are included, Parenthesis refer to standard deviations (for Columns (1) and (2)) and standard errors (in Column (3)). Panel B provides the results of the estimation exercise that attempts to predict the success of a terror attack using the key explanatory variables. Standard errors, clustered at the country level, are in parenthesis. Columns (1) and (2) include country×year fixed effects and month fixed effects, while Column (3) additionally includes weapon and attack type fixed effects. *Public Discontent* 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. *Attack* is a variable representing the number of terror attacks. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table B.3: Alternative outcome variable: Effect of terror attacks on public protests

	(1) *Public* $Protests_{iym}$	(2) *Public* $Protests_{iym}$	(3) *Public* $Protests_{iym}$	(4) *Public* $Protests_{iym}$
$Successful_{iym}$		0.1134*	0.1173**	0.1212**
		(0.0585)	(0.0585)	(0.0593)
$Post_{iym}$	0.0514	-0.0497	-0.0504	-0.0524
	(0.0390)	(0.0663)	(0.0662)	(0.0662)
Observations	13,568	13,568	13,568	13,568
No. of Countries	125	125	125	125
Month FE	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes
Attack Count	No	No	Yes	Yes
Weapon/Attack FE	No	No	No	Yes
Mean *Public Protest*	0.4082	0.4082	0.4082	0.4082

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: Excluding the month of the attack: Effect of successful vs failed terror attacks on *Public Discontent*

	(1) *Public* $Discontent_{iym}$	(2) *Public* $Discontent_{iym}$	(3) *Public* $Discontent_{iym}$	(4) *Public* $Discontent_{iym}$
$Successful_{iym}$		0.0126***	0.0127***	0.0128***
		(0.0043)	(0.0043)	(0.0044)
$Post_{iym}$	0.0115**	0.0007	0.0007	0.0010
	(0.0055)	(0.0055)	(0.0055)	(0.0055)
Observations	14,377	14,377	14,377	14,377
No. of Countries	132	132	132	132
Month FE	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes
Attack Count	No	No	Yes	Yes
Weapon/Attack FE	No	No	No	Yes
Indicator for month of attack	Yes	Yes	Yes	Yes
Mean *Public Discontent*	0.0997	0.0997	0.0997	0.0997

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.5: Alternative time horizons

	(1) Public $Discontent_{iym}$	(2) Public $Discontent_{iym}$	(3) Public $Discontent_{iym}$	(4) Public $Protests_{iym}$
Panel A: Time horizon – 9 months before and after the attack				
$Successful_{iym}$		0.0147***	0.0145***	0 .0147***
		(0.0040)	(0.0040)	(0.0041)
$Post_{iym}$	0.0119**	-0.0009	-0.0009	-0.0007
	(0.0052)	(0.0053)	(0.0053)	(0.0053)
Observations	13,412	13,412	13,412	13,412
Mean *Public Discontent*	0.1012	0.1012	0.1012	0.1012
Panel B: Time horizon – 6 months before and after the attack				
$Successful_{iym}$		0.0168***	0.0166***	0 .0167***
		(0.0045)	(0.0045)	(0.0046)
$Post_{iym}$	0.0129**	-0.0012	-0.0012	-0.0012
	(0.0052)	(0.0052)	(0.0053)	(0.0054)
Observations	11,673	11,673	11,673	11,673
Mean *Public Discontent*	0.1047	0.1047	0.1047	0.1047
Panel C: Time horizon – 3 months before and after the attack				
$Successful_{iym}$		0.0153***	0.0152***	0.0151***
		(0.0048)	(0.0049)	(0.0051)
$Post_{iym}$	0.0127**	-0.0002	-0.0002	-0.0004
	(0.0050)	(0.0056)	(0.0056)	(0.0056)
Observations	9,259	9,259	9,259	9,259
Mean *Public Discontent*	0.1103	0.1103	0.1103	0.1103
Month FE	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes
Attack Count	No	No	Yes	Yes
Weapon/Attack FE	No	No	No	Yes
No. of Countries	132	132	132	132

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 9,6,and 3 temporal lags and leads, in Panels A, B and C, respectively. 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 9,6,and 3 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 9,6,and 3 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.