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Terrorism in armed conflict: new data attributing terrorism to rebel organizations

Virginia Page Fortna
Columbia University, USA

Nicholas J. Lotito
Yale University, USA

Michael A. Rubin
University of Connecticut, Human Rights Institute, USA

Abstract

The Terrorism in Armed Conflict project integrates the Uppsala Conflict Data Project sample of rebel organizations with START's Global Terrorism Database, covering 409 organizations for 1970–2013. For many Global Terrorism Database incidents, perpetrator information is missing, or ambiguous. Because the accuracy of perpetrator information likely varies systematically, simply dropping these incidents from analyses may bias results. Terrorism in Armed Conflict provides possible attribution to specific rebel groups with coding for uncertainty, enabling researchers to (1) address "description bias" in media-based terrorism data, (2) model uncertainty regarding perpetrator attribution and (3) vary the way terrorism is counted. The Terrorism in Armed Conflict dataset further provides a measure of *deliberately indiscriminate terrorism* that allows for more nuanced testing of arguments about the strategic logic of terrorism.

Keywords

Civil conflict, civil war, political violence, terrorism

Why do some rebel organizations employ terrorism while others eschew the tactic? What are the consequences for conflict when rebels use terrorism? Understanding the causes of terrorism requires explaining why some political organizations adopt terrorism in their repertoire of tactics while others do not. The Terrorism in Armed Conflict (TAC) dataset contributes to the study of terrorism by providing a flexible tool for measuring terrorism in civil conflicts,

Corresponding author:
Nicholas J. Lotito, Yale University, 115 Prospect Street, New Haven, CT 06520, USA.
Email: nicholas.lotito@yale.edu

by systematically matching information in the two most comprehensive and commonly used data sources from both research communities: the Uppsala Conflict Data Project (UCDP) Dyadic Dataset (version 1-2014) (Harbom et al., 2008; Themnér and Wallensteen, 2014)[1] and START's Global Terrorism Database (GTD) (LaFree and Dugan, 2007). Importantly, TAC facilitates the inclusion of incidents for which attribution to any particular rebel organization is ambiguous or uncertain, whereas previous efforts to link the UCDP and GTD datasets discard these incidents from analysis. TAC provides new "off the shelf" measures of terrorism by rebel organizations and also allows users to generate additional measures based on alternative definitions. The data currently cover 409 rebel organizations included in the UCDP Dyadic Dataset, spanning 166 intrastate conflicts in 96 countries from 1970 to 2013.[2]

A robust, largely quantitative, literature has investigated variation in terrorism across countries, exploring why some countries suffer exposure to terrorism at certain times and with varying levels of intesity. While scholars have also long investigated organization-level variation in the use of terrorism, empirical work at this level has only recently begun to draw upon the tools of large-N quantitative analysis. Limitations in the available data measuring terrorism have constrained the use of quantitative methods to understand variation among organizations' use of terrorism because leading data collection efforts have focused on recording information about terrorism incidents. Such data are appropriate for addressing questions that require examination of variation across countries and *among groups that use terrorism*. However, they cannot be used to test explanations for why political organizations use terrorism in the first place or the conditions under which they do so. Because existing data include only organizations that use terrorism, they lack a comparison with similar organizations that could have chosen to employ terrorism but did not. Therefore, a study using only conventional datasets of terrorism incidents or perpetrators to explain the conditions under which organizations use terrorism would be "selecting on the dependent variable."[3]

Identifying the universe of political organizations that *may* use terrorism is a difficult task, though one that is essential to advance our understanding of modern terrorism. As a first step, scholars have recently begun to focus on specific types of political organizations, most notably rebel organizations engaged in civil conflicts.[4] All civil conflicts include, by definition, at least one rebel organization willing to use violence. Some, but not all, rebel organizations use terrorism, and not all that use terrorism do so all of the time. Thus, rebels constitute a population of otherwise similar actors who vary in their use of terrorism, enabling an informative comparison. Furthermore, explaining variation in political violence within civil conflicts is of clear substantive importance. Increasingly, scholars are bridging the long-standing divide between scholarship on terrorism and on civil war (Asal et al., 2019; Belgioioso, 2018; Findley and Young, 2012, 2015; Fortna, 2015; Fortna et al., 2018; Keels and Kinney, 2019; Polo and Gleditsch, 2016; Stanton, 2013; Thomas, 2014).

TAC is not the first project to combine the UCDP and GTD datasets, but it builds in important ways upon previous efforts (e.g., Asal et al., 2015, 2019; Cousins, 2014; Findley and Young, 2012; Polo and Gleditsch, 2016) by providing a more thorough and flexible system for attributing terrorism incidents to rebel organizations. Because many terrorism incidents in GTD are not clearly attributed to specifc perpetrators, and linking perpetrators in GTD with rebel organizations in UCDP is complicated (for reasons discussed in detail below), much of the information in GTD has been lost in previous efforts to integrate these datasets. TAC provides a structured resource for researchers to assign incidents of terrorism recorded in GTD to rebel organizations included in UCDP, with flexibility to account for sources of uncertainty inherent in assigning responsibility for unattributed or ambiguously attributed attacks.

TAC grapples with a persistent, but largely unaddressed,[5] problem of systematic measurement error in attributing attacks to specific perpetrators when relying on open-source media. To date, scholars have paid attention to a specific source of systematic measurement error in terrorism data: media sources under-report terrorism events based on factors that are correlated with predictors of interest. For example, incidents that occur in countries with weaker press freedoms, in more remote and less densely populated areas, and incidents that are less bloody are less likely to be reported and therefore observed in existing terrorism databases (e.g., Drakos and Gofas, 2006, 2007; Dugan and Distler, 2016; Weidmann, 2016, among others). This is a critical issue for the inferences we, as researchers, may draw from analyses using events data relying upon media sources but is not the focus of TAC's contribution.

Instead, TAC addresses a second source of measurement error associated with media-based terrorism data: *description bias*. Among those events that are reported in the press, some are described with greater accuracy and in more detail than others, and some events may be prone to interpretations that distort the facts. Davenport (2010), for example, finds that newspapers with different partisan affiliations portrayed the same events involving the Black Panther party in considerably different ways. Analyzing GTD data, Nemeth and Mauslein (2019) find that researchers coded information on a greater number of variables and with greater confidence for events closer to areas with higher population density, and those involving particular tactics, compared with otherwise similar events.

TAC addresses a specific source of description bias central to research questions regarding organization-level variation in terrorism: the problem that terrorism events vary systematically in their inclusion of (accurate) information on the *perpetrator* of terrorism. Crenshaw and LaFree (2016), for example, show that the percentage of terrorism incidents that include perpetrator information varies substantially across world regions. Reporters may not find information on attack perpetrators credible or relevant to certain types of stories, and information on whether attacks are claimed by an organization or alleged by others is uneven. Systematic patterns underlying missing or vague perpetrator information yield an additional complication which, although critical to organization-level empirical investigations, scholars of terrorism drawing upon media-based data sources have yet to address seriously. While TAC cannot improve the underlying source data in this regard, it provides a way for researchers to include a much larger set of incidents in analysis, and to vary what is included in measures of terrorism based on the level of certainty with which particular incidents can be attributed to particular groups.

Because the scholarly community has yet to settle on a consensus definition of terrorism,[6] we do not impose a universal definition. Instead, TAC allows researchers to implement their own definitions and to examine how differences in definition and measurement affect their findings. We provide code (for both R and STATA) as well as an interactive web application to make it easy for scholars to use the data in the ways that best fit their research purposes.[7] At the same time, TAC structures the process of extracting events that fit a given definition of terrorism in a way that ensures transparency and replicability.

In addition to the data contribution, we introduce a set of measures of deliberately *indiscriminate terrorism*, as distinct from more selective forms of civilian targeting. Part of the reason the research community has proven unable to settle on a consensus definition of terrorism is that it encompasses such diverse forms of politically motivated, civilian-targeting violence. Identifying distinct types of terrorism and theorizing the distinct logic by which actors may adopt each type will further our understanding of terrorism and its consequences. For example, while most scholars consider attacks on civilian government targets as terrorism, the strategic logic underlying decisions to target government officials or buildings, and the political conequences thereof, may differ dramatically from the logic and consequences of targeting a public square. Along these lines, Polo and Gleditsch (2016) push scholars to consider the different causes and effects of *hard* vs. *soft* civilian targets of terrorism.

The concept of *indiscriminate terrorism*, defined in greater detail below, focuses on what makes terrorism so terrifying: the fact that anyone can be targeted in public spaces far from the battlefield, regardless of their actions. The logic underlying violent political organizations' decision to employ indiscriminate targeting of non-government, non-combatant civilian populations and public spaces is likely distinct from other forms of civilian targeting included under the broad definition of terrorism, and therefore warrants study as a distinct phenomenon.

The article proceeds as follows. We first describe the procedures used to link perpetrators in GTD to rebel organizations in UCDP, including the ways TAC grapples with the inherent uncertainty in assigning many incidents to particular actors. We then introduce the concept of *indiscriminate terrorism*, using it to illustrate how to generate custom measures of terrorism using TAC. We discuss caveats and cautions for the data's use and, finally, briefly re-examine a recent study (Asal et al., 2019) with the new data.

Linking rebel organizations to incidents of terrorism

The UCDP Armed Conflict Data project defines armed conflict as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in a year" (Themnér, 2014: 2). We focus on civil or "intrastate" conflicts here. Intrastate conflicts are those between a state government (*SideA*) and a non-state rebel organization (*SideB*). Rebel organizations included in the dyadic version of UCDP form our basic unit of analysis. The Global Terrorism Database is made up of specific incidents of terrorism, very broadly defined. Where possible, GTD identifies the perpetrator of each incident, recorded under *gname*.

The first step in merging information from these two databases is to identify which perpetrators in GTD (*gname*) refer to which actors in UCDP (*SideB*).[8] This exercise is straightforward for some events: when *gname* is the same as a *SideB* group in UCDP. However, even here variations in spelling, acronyms, and translations mean that the matching cannot easily be automated. In many cases, even a human coder needs case-specific knowledge to determine whether two very similar names refer to the same group. Factions in civil conflicts regularly evoke Monty Python's spoof of the distinction between the Judean People's Front and the People's Front of Judea (Jones, 1979). Conversely, groups whose names betray no apparent connection may in fact be the same or closely related. For example, that "Barzani Guerillas" is a reference to the KDP in Iraq is not obvious unless you know that Mustafa Barzani was the founder of the KDP. The armed wing of a rebel organization may be listed under a different name, or GTD and UCDP may alternately refer to factions, subsets, umbrella organizations, or collective identities in ways that confound an automated or even uninformed human matching procedure. Rebel organizations also join, split apart, change names, and otherwise behave in ways that make deciding which perpetrator names to count, and during which time periods, difficult.

Furthermore, GTD perpetrator names also include a vast array of generic descriptors. In many cases, a descriptor like "Kurdish separatists" may (although not necessarily) be journalistic shorthand for a specific organization, such as the Kurdistan Workers' Party (PKK).[9] More general descriptors (e.g., "guerrillas" or "terrorists") may, likewise, represent possible matches for some UCDP organizations. The most generic ("gunmen," "armed people," or the most common perpetrator in GTD by far, "unknown") leave no possibility of identification, but should not necessarily be ignored altogether. Because relying on open-source media to record incidents of terrorism may introduce reporting biases, which is compounded by differences in the propensity and accuracy of naming attack perpetrators, treating these events unequivocally as non-events or as events not attributable to the relevant rebel organizations may introduce systematic measurement error.

In the context of civil conflict, it is quite possible that many unattributed or vaguely attributed attacks are the work of rebel organizations. Reporters may fail to attribute attacks to a specific rebel organization because general terms are sometimes used as shorthand, because they consult sources that do not reveal the perpetrators, or because they (wisely) have strict journalistic standards requiring verifiability of the information in order to print, which may be difficult to meet in the context of armed conflict. Furthermore, rebel organizations may not always claim responsibility for their attacks, which exacerbates these perpetrator-specific reporting patterns. Claiming attacks is a strategic decision, based on the expected political returns (or fallout) associated with the attack and its consequences, such that unclaimed attacks are unlikely to be evenly or randomly distributed (Abrahms and Conrad, 2017). Moreover, because of the media sources it relies upon, GTD sometimes misses claims made later, or on an organization's website. For example, as Miles (2014: 24) notes, Hamas' armed wing, the al-Qassam Brigades, did not claim attacks during Israel's Operation Cast Lead (i.e., Gaza War) until after the fighting stopped, when they posted a detailed communique of their attacks in neat tables.[10] GTD attributes none of these attacks to Hamas, listing most as perpetrator "unknown."

Omitting unknown perpetrator attacks from analysis altogether, as most group-level analyses of GTD data appear to do, may therefore bias results by under-counting incidents. However, including these incidents risks over-counting by including events not perpetrated by the group. We designed TAC to allow researchers maximum flexibility to include or exclude partial or uncertain matches and generic perpetrator events in robustness checks to address this problem.

Procedure

We started by casting a wide net to identify all possible matches between UCDP actors (*SideB*) with GTD perpetrators (*gname*). We examined any GTD perpetrators responsible for incidents that occurred in the country experiencing civil conflict, or targeting its citizens abroad, in an expanded time frame that begins before and continues after the years of active conflict included in UCDP.[11] This process yielded over 9000 possible matches.

With the help of a large team of research assistants, we hand-coded the relationship between the UCDP and GTD groups in each of these over 9000 pairs, using existing compendia of civil conflicts, terrorist organizations,[12] and other case-specific research, as necessary. We assigned matching codes to each *SideB–gname* pair to characterize various levels of affiliation and certainty, from perfect matches, factions, and umbrellas, to applicable generic descriptors and unknown links.[13]

It is important to note that for some multiparty conflicts, generic descriptors may apply to more than one rebel organization. Therefore, some incidents will be duplicated (or more) in TAC's underlying data linking UCDP to GTD. Researchers should be aware of this when measuring rebels' use of terrorism using incidents for which the perpetrator listed includes generic descriptors. Because the best method of addressing this duplication issue may depend on the research question and how these versions of the data are used, we leave the choice of how to do this up to the researcher. One relatively easy, if somewhat crude, approach is to divide the number of generic descriptor incidents (or fatalities, depending on what is being counted) by the number of UCDP groups to which that descriptor applies.[14]

TAC provides six different versions of each terrorism count, according to each GTD–UCDP match type. The most conservative estimate, version A, includes only direct matches and armed wings.[15] Version B includes these incidents, plus those involving factions or subsets and umbrella groups. Version C adds groups from the same movement or conflict who fight together, coordinate, or share membership, but who are not otherwise listed in UCDP as distinct rebel organizations.[16] Version D includes all of the above plus groups that are connected but there is uncertainty, or change over time in the relationship. Version E adds applicable generic descriptors (e.g., "Kurdish separatists"). Finally, the least conservative, Version F, also includes all incidents for which the perpetrator is unknown or identified in a way that is too vague or general to pin to a particular organization, provided that it took place in or targeted the country in question during the relevant time period. For most rebel organizations, the difference made by adding the matches from levels B, C, and D to the overall counts of terrorism is relatively small, while the additions for E and F are much more substantial.

These six versions are not distinct measures of terrorism; instead, they allow researchers to explore patterns in rebel organizations' use of terrorism across levels of uncertainty in the assignment of responsibility for specific attacks. Figure 1 illustrates the cumulative match patterns for versions A–F. As an example, Table 1 shows the specific GTD perpetrator names ("gname") that are assigned to two groups: the Communist Party of Nepal—Maoist (CPN-M) and the Kurdistan Workers' Party (PKK) in Turkey, at each matching level.

Figure 2 shows the number of attacks counted for CPN-M over time across the six matching levels.[17] As Figure 2 illustrates, there are circumstances in which including factions within the organization makes a difference in the observed use of terrorism. In this case, a huge divergence occurred after the war ended with a peace settlement in 2006, suggesting that elements of the CPN-M may have continued violence. In general, this type of divergence could represent the work of splinter groups unhappy with a settlement and willing to turn on the central leadership or continue violence with the central leadership's blessing, the agreement notwithstanding. Addressing such gray areas is precisely the utility of using TAC to explore robustness to alternate coding decisions.

The discrepancy between more exclusive versions (closer to A) and more inclusive ones (closer to F) is largest in: (1) less well-known or reported on conflicts for which GTD's sources may not have provided specific information about the perpetrator (only identified by a generic descriptor), (2) more complicated and fractionalized conflicts in which factions and umbrella groups proliferate, (3) conflicts in which multiple rebel organizations are fighting, for whom the same generic descriptors apply, and (4) conflicts in which the perpetrating organizations are least likely to claim their attacks. Accordingly, the six match levels enable

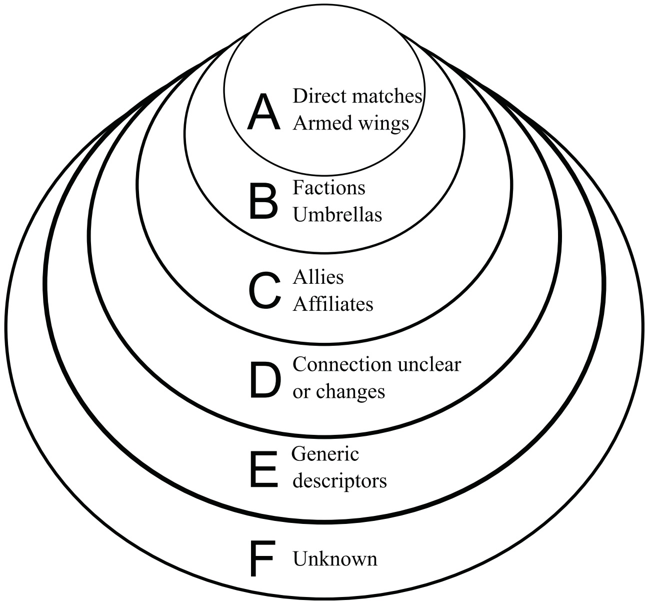


Figure 1. Matching UCDP groups with GTD perpetrators.

Table 1. GTD group names at each matching level (two examples).

	Communist Party of Nepal—Maoist (CPN-M)	Kurdistan Workers' Party (PKK)
A	Communist Party of Nepal—Maoist (CPN-M)	Kurdistan Workers' Party (PKK)
B adds	Communist Party of Nepal—Unified Marxist-Leninist (CPN-UML); All Nepal National Free Student Union—Revolutionary; Janatantrik Terai Mukti Morcha—Goit (JTMM-G); Janatantrik Terai Mukti Morcha—Jwala Singh (JTMM-J); Janatantrik Terai Mukti Morcha (JTMM)	Kurdistan Freedom Hawks (TAK)
C adds		Support of Ocalan—The Hawks of Thrace
D adds		Kurdish Islamic Unity Party; Union of Revolutionary Communists in Turkey (TIKB)
E adds	Anti-Government Guerrillas; Maoists	Kurdish Rebels; Kurdish Militants; Kurdish Guerrillas; Kurdish Separatists; Kurdish Dissidents; Kurdish Sympathizers; Kurds; Separatists; Turkish Separatists (probably Kurds)
F adds	Other; Unknown	Gunmen; Individual; Turks; Other; Unknown

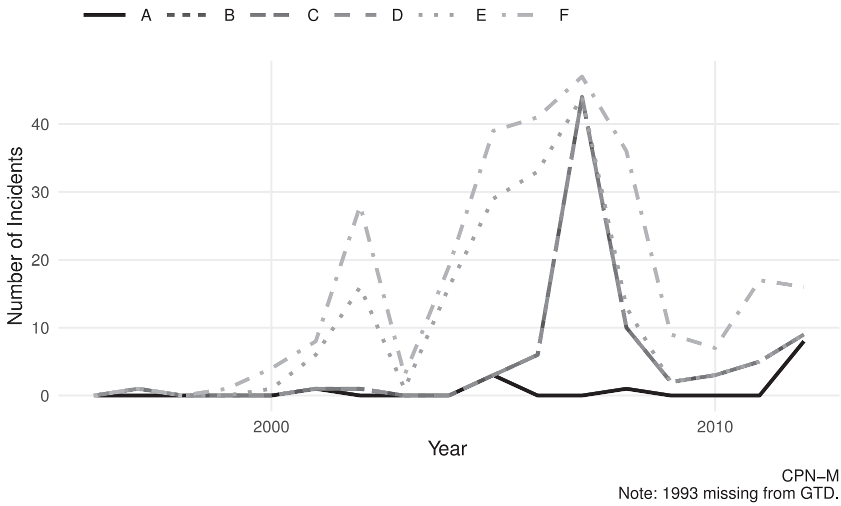


Figure 2. Incident counts by UCDP–GTD matching level, Communist Party of Nepal–Maoist (CPN-M).

researchers to consider how matching procedures may affect their findings and perform corresponding robustness checks.

Existing UCDP–GTD merges and TAC's contribution

TAC expands and improves significantly on earlier efforts to combine information from UCDP and GTD: the TORG "Crosswalk" (Asal et al., 2015, 2019); Cousins (2014); Polo and Gleditsch (2016); and Thomas (2014). These data also link UCDP actors with GTD terrorism incidents, but only include direct matches; therefore, they cannot be used to explore robustness to the systematic description bias associated with unattributed attacks in the underlying source data. In contrast, TAC allows researchers the flexibility to examine terrorism committed by groups that are factions, umbrellas, or affiliates of the UCDP rebel organization, and to consider attacks perpetrated by actors identified by generic descriptors.

Moreover, civil conflict researchers are likely to know, for example, that the term "Naxalites" refers to Maoist insurgents in India and thus to link incidents to CPI-Maoist in UCDP. However, more obscure connections (for example, that the Suriname Liberation Army is also referred to as "the Jungle Commando" and was led by Ronnie Brunswijk, such that "Brunswijk Jungle Commando" is a direct match for the SLA) are more likely to be missed. Thus, undercounting of terrorism owing to description bias is more likely in conflicts with lower visibility or legibility to Western researchers.[18] Because these existing attempts to link UCDP actors to GTD incidents provide little information on the matching procedure used, it is also unclear which of the less-obvious perpetrator names in GTD, if any, are linked to each rebel organization, what the general criteria are for these choices, and how systematically the procedure has been implemented across conflicts. Furthermore, without the underlying UCDP SideB-to-GTD gname matches, it is impossible for other researchers to scrutinize the coding of matches for their own work or to implement robustness checks across multiple decisions for how to assign attack responsibility.

Furthermore, TAC includes connections between 66 UCDP groups and GTD actors missing from the TORG "Crosswalk," including some prominent cases for which TAC records an unambiguous match. While some of these UCDP organizations missing from TORG commit very few acts of terrorism, a few are responsible for a significant amount of damage from terrorism attacks.[19] For example, TORG includes no matches to GTD for the FMLN in El Salvador, which TAC links to 1665 attacks and 1794 fatalities over 19 years.[20] Other prominent groups with no terrorism connections reported in TORG include the Provisional Irish Republican Army in the UK (636 attacks and 288 fatalities over 42 years), the Communist Party of the Philippines (383 attacks and 666 fatalities over 44 years), Renamo in Mozambique (160 attacks and 1797 fatalities over 37 years), the Palestine Liberation Organization (37 attacks and 102 fatalities over 26 years), Hizb-i-Islami in Afghanistan (16 attacks and 39 fatalities over 34 years) and Sinhalese Janatha Vimukthi Peramuna in Sri Lanka (74 attacks and 231 fatalities over 25 years), among others (see TAC Codebook). We identified 21 direct connections included in TORG but not in TAC. In our attempt to verify these TORG links, we were unable to confirm any GTD *gnames* that represent direct matches to their respective UCDP groups.

Taking a different approach, the Matching Event Data by Location, Time and Type (MELTT) project (Donnay et al., 2019) provides a framework for identifying violent incidents that show up in multiple datasets, in order to avoid duplicating events when drawing upon data sources that may overlap. MELTT's event-level matching procedure thus allows researchers to link UCDP actors to GTD incidents, but only for the limited subset of events that overlap the two datasets. In the case of UCDP–GTD, this overlap consists of the civilian-targeting in UCDP that may count as terrorism and the civilian-targeting in GTD that does not fit the definition of terrorism but is included in GTD's broad criteria. TAC's contribution is to link UCDP rebel organizations to the full sample of terrorism incidents, not only to those that also show up in UCDP's own event data.

Indiscriminate terrorism: definition and measurement

Next, we introduce a set of measures of deliberately indiscriminate terrorism. We argue that a focus on the indiscriminate nature of attacks may be important for substantive reasons,[21] and TAC provides "off the shelf" measures that proxy for indiscriminate terrorism. However, we also acknowledge that many researchers may wish to work with broader definitions and measures of terrorism. TAC is flexible in this regard. The procedures outlined here operationalize our own working definition of indiscriminate terrorism by filtering the wide selection of GTD incidents based on characteristics like target and mode of attack. We view this procedure as an example of how others can use TAC to create measures that fit their own definitions of terrorism. To begin, we define indiscriminate terrorism as *intentionally indiscriminate political violence against public civilian targets to influence a wider audience*.[22] Like many definitions of terrorism, ours involves the deliberate targeting of civilians, as opposed to attacks on military targets that occur, by definition, in all armed conflicts. Because research shows that virtually all civil war combatants engage in deliberate attacks on civilians suspected of collaborating with the government (Stanton, 2016: 30), and these incidents follow a strategic logic that likely differs from indiscriminate civilian-targeted violence designed to sow fear in society, we narrow our focus further to exclude targeted or discriminate attacks on civilians. We thus examine only indiscriminate attacks, such as bombs on buses or attacks on markets, in which the intent is to kill individuals arbitrarily, as opposed to the ubiquitous practice of targeting specific civilians found to collaborate with the government.[23] That civilians are targeted indiscriminately exemplifies the "terror" in terrorism—anyone could be hit at any time.

Note that we include in the notion of "indiscriminate" the targeting of members of certain identity groups: what Goodwin (2006) refers to as "categorical terrorism." The distinction is between targeting people as specific individuals and targeting people at random, even if it is at random within a segment of the population. Here we follow Walzer (1977), who distinguishes between targeting people for who they are as opposed to what they do.[24]

The GTD's criteria for including events in the database are intentionally broad to capture the phenomenon very broadly defined. GTD requires each of three core criteria to be met for inclusion in the database: that incidents are (1) intentional, (2) acts or threats of violence, and (3) carried out by non-state actors. These criteria are consistent with but broader than our definition and many others adopted in the literature. To create measures of deliberately indiscriminate terrorism, we use three sets of variables in GTD to isolate incidents that fit our narrower definition. While the term "deliberately indiscriminate" implies intent, we acknowledge that it is not feasible to observe actors' intentions directly. Doing so would require getting inside the heads of decision-makers in rebel organizations at specific moments in time. Instead, These three sets of variables are used to create proxies for the incidents most likely to be the result of intentionally indiscriminate attacks.

(1) "Filtering" criteria

GTD records three "filtering" criteria (at least two of which must be met for inclusion): the incident must have been (a) perpetrated in service of a political, economic, religious, or social goal; (b) intended to reach a broader audience; and (c) outside the context of legitimate warfare, i.e., targeting non-combatants (START, 2013: 7–8). We include in our measures only incidents that fulfill all three criteria.

(2) Attack and target type

GTD includes a variety of attacks that do not fit our definition, either because they target actors other than civilian non-combatants (e.g., attacks on government or military personnel) or are unlikely to be indiscriminate (e.g., assassinations). Unfortunately, GTD does not include any direct measure of whether the attack was discriminate or indiscriminate. We thus use GTD information on attack and target type, aspects of terrorist incidents that are chosen intentionally by perpetrators, to identify incidents that are most likely to be deliberately indiscriminate attacks on civilians. Because these are imperfect proxies, we create two versions:

The *Less Restrictive Measure of Indiscriminate Terrorism* includes the following *attack types*: hijacking, hostage taking (kidnapping), hostage taking (barricade incident), bombing/explosion, armed assault, and unknown. It excludes assassination, unarmed attack, and facility/infrastructure attack.[25]

It includes the following *target types*: business, airports & aircraft, educational institutions, food or water supply, maritime, private citizens/property, religious figures/institutions, telecommunications, tourists, transportation (other than aviation), utilities, and unknown. It excludes: government (general), police, military, abortion related, government (diplomatic), journalists & media, NGO, other, terrorists/non-state militias, and violent political parties.

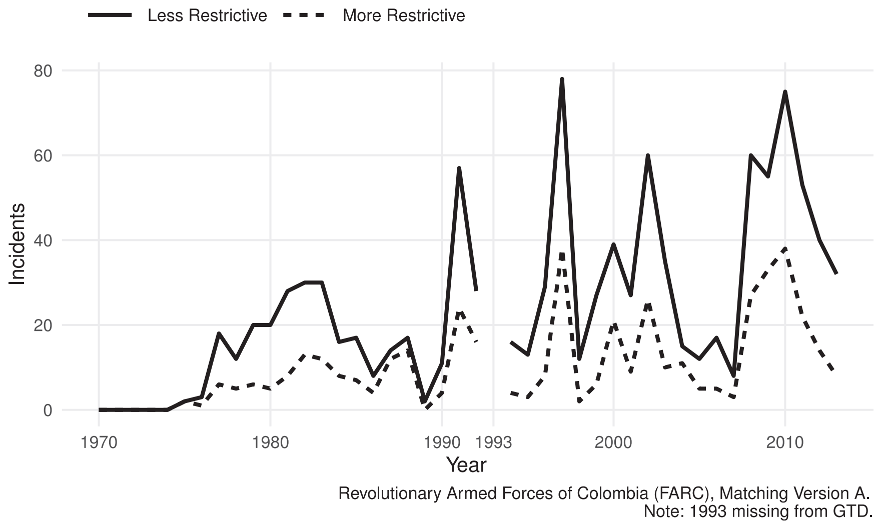


Figure 3. More and less restrictive measures of indiscriminate terrorism (FARC).

The *More Restrictive Measure of Indiscriminate Terrorism* includes only the two *attack types* that are most likely to involve indiscriminate attacks: armed assaults and bombings/explosions, excluding all others.

It also uses not just target type, but also *target subtype* to hone in on the attacks most likely to be targeting civilians in an indiscriminate manner as they congregate in public. For example, among the attacks targeting businesses, it includes only those for which the target is likely members of the public, such as a restaurant/bar/café, while it excludes business targets such as gas/oil and private security companies.[26]

Figure 3 shows the difference between the number of attacks counted under the less restrictive and the more restrictive ways that we use attack and target type to proxy for indiscriminate terrorism, using the Revolutionary Armed Forces of Colombia (FARC) as an example.[27]

Figure 4 shows the annual number of all terrorism incidents included in GTD attributed to rebel organizations in UCDP, along with TAC's counts for the more and less restrictive measures of deliberately indiscriminate attacks. Note that many attacks that generate the large spike recorded in GTD since the mid-2000s, and especially after 2011, and much of the peak around the end of the Cold War, consist of attacks that do not fit our definition, and would not fit many common definitions of terrorism. Approximately 47% of attacks attributed directly to UCDP rebel organizations target military and government targets (government, military, police, and diplomatic target types).[28] This illustrates the importance of careful consideration to ensure one's measure of terrorism from off-the-shelf data conforms to one's own definition.

(3) Fatalities

As Young (2019) notes, the quantitative literature has tended to focus on incident counts, but this approach treats each incident as equally important, whether hundreds or even thousands were killed (as on 9/11) or whether no one or very few were killed. We use information

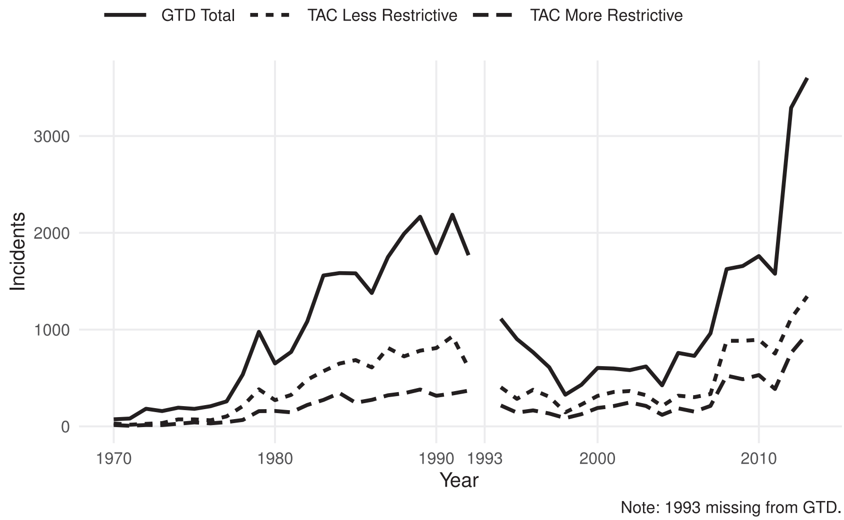


Figure 4. Annual terrorism incidents by UCDP rebel organizations in GTD and in TAC's more and less restrictive measures of indiscriminate terrorism.

in GTD on fatalities to create three sets of incident counts and one count of total fatalities per annum.

- *Total incidents*: number of incidents, including fatal and non-fatal attacks.
- *Fatal incidents*: number of incidents with at least one fatality.
- *Mass violence incidents*: number of incidents in which five or more people are killed.
- *Fatalities*: total number killed.[29]

These four measures often provide strikingly different pictures of a group's use of terrorism.[30] Counting only fatal attacks screens out many attacks in GTD (over half of the total) which may be irrelevant to some theories of terrorism. Counting mass attacks helps filter out attacks that may, in fact, be selective targeting of a particular individual, rather than indiscriminate targeting of civilians.[31]

Between multiple matching levels, more and less restrictive proxies for indiscriminateness, and these different ways of counting terrorism, TAC provides a plethora of measures (detailed in the codebook), allowing researchers great flexibility, and the ability to examine the robustness of findings to multiple measurement strategies.

Figure 5 shows the distribution of group-year measures of total incidents and fatalities in TAC. Note the log-transformed scale of the y-axis.[32] Figure 5 illustrates that most rebel organizations refrain from carrying out terrorism most of the time, while the tail of the distribution is quite long, with some groups carrying out a large number of attacks, and killing a large number of people, in some years.

It bears reiterating that researchers with definitions of terrorism that do not accord with our narrow definition focusing on indiscriminate terrorism can use TAC's incident-level mapping of GTD and UCDP rebel organizations to create their own measures in ways that

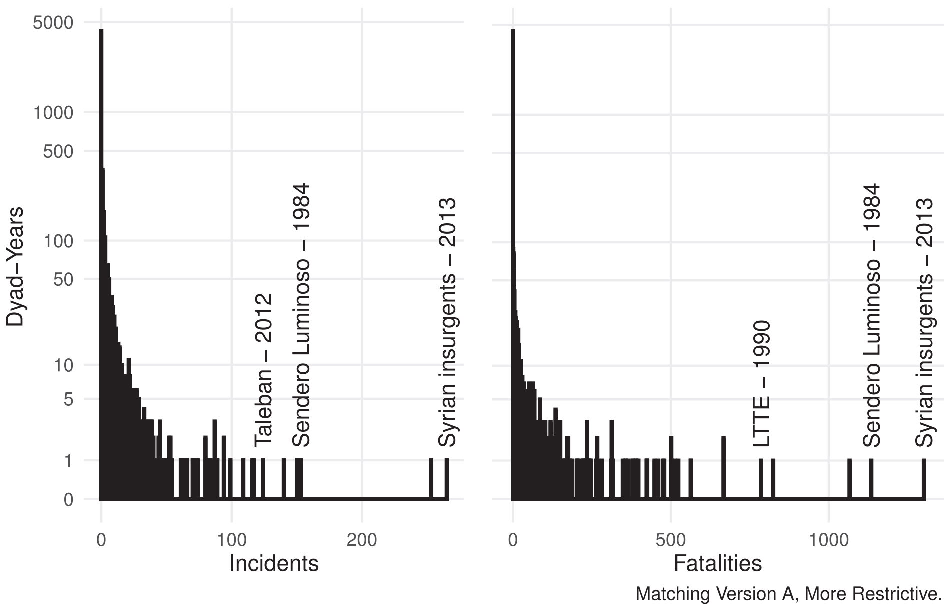


Figure 5. TAC indiscriminate terrorism incidents and fatalities.

are flexible, amenable to robustness checks, transparent, and replicable. This will also allow scholars working with different definitions of terrorism to examine whether differences in findings across studies are driven by differences in definition and measurement.

Limitations

Like all cross-national conflict data, TAC is limited by the quality of the underlying sources used to construct it. First, TAC inherits a degree of measurement error from GTD. Because GTD relies on media reports, it undoubtedly captures more events in countries, and areas within countries, with better press coverage. Much of the increase in the measures of terrorism over time may reflect the increasingly free flow of information in a globalizing world, as well as increased attention to the phenomenon of terrorism worldwide. In the early years, data collection may have missed many events that were not then labeled as "terrorism" as opposed to insurgency, that arguably nevertheless fit the GTD's definition and inclusion criteria. GTD's coding protocols have also evolved over time, as the project moved institutional homes in 1998, 2008, and again in 2011.

Nevertheless, TAC helps ameliorate the measurement error inherent in GTD. Specifically, TAC addresses the additional source of "description bias" associated with systematic patterns in (non-)attribution of violent incidents to particular actors in media sources. Conflicts with less dense media coverage may be more likely to see incidents attributed to generic descriptors or unknown perpetrators. By including such incidents in some measures of terrorism, TAC allows investigators to probe the sensitivity of their results to this reporting bias in a systematic way.

Second, we rely on UCDP to identify and differentiate rebel organizations. In several conflicts with many factions, UCDP simply lumped all factions together as a single "actor" (for example, "Syrian insurgents" in the Syrian civil war or "Kashmir insurgents" fighting to secede from India). Researchers investigating questions for which the number of groups in a conflict is a relevant variable should keep this in mind. In addition, UCDP sometimes identifies splits or merges between groups during a conflict. This makes the matching of groups that incorporate umbrellas and factions tricky, as incidents may be connected to a group that does not yet or has ceased to exist. We retain this flexibility to allow researchers to make their own decisions regarding actor genealogy.

Third, in UCDP, there are often multiple groups fighting a single government. Researchers are thus cautioned to consider the independence, or lack thereof, among rebel organizations (Cranmer and Desmarais, 2016). TAC retains information on both the conflict in which the rebel organization fought, and the government against which it fought so that these dependencies can be modeled appropriately.

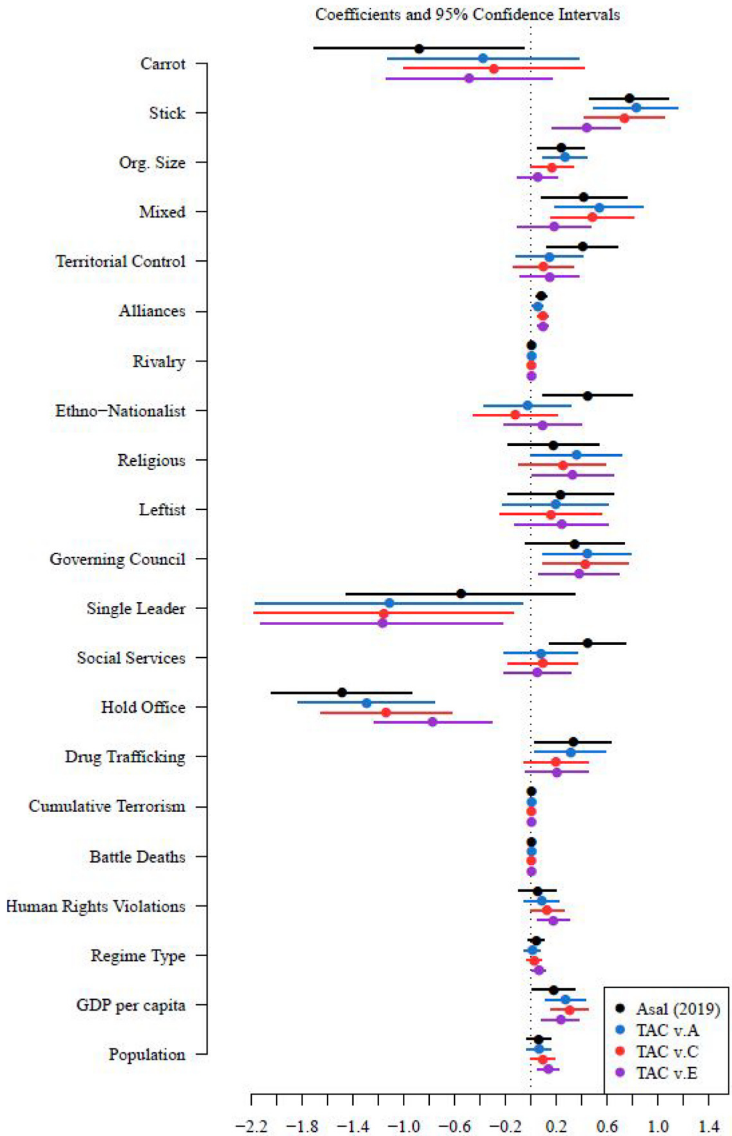
Re-evaluating existing findings using TAC

To illustrate TAC's implications for empirical research, we replicate the core findings of Asal et al. (2019), which examines variation in violent organizations' use of terrorism. The groups included in their sample are also based on the UCDP data, although three of these groups never meet the threshold of "armed conflict" (25 + battle deaths in conflict with the government), and so are not included in TAC. Their analysis is conducted at the group-year level, covering 134 groups between 1998 and 2012 (133 of which are included in TAC). Although TAC covers the 1970–2013 range, we restrict the analysis in the replication to the 1998–2012 period for a direct comparison with the findings of Asal et al. In the main replication, we draw upon the same broad definition of terrorism used in the original study, again for the purposes of comparing the results. We subsequently conduct analyses using our narrower measures of indiscriminate terrorism. Because the replication requires auxiliary variables from Asal et al.'s data (e.g., on organizational size, connections to other groups, social services provision), we are forced to drop groups included in TAC but not in their matching of UCDP and GTD groups (see above).

Asal et al. focus on the results from models fit with a binary indicator for whether a group uses terrorism at all in a given year, rather than the models using the count measure of terrorism. Nevertheless, the results are consistent using the count variable measure, and they draw similar inferences from those results. Because our goal here is to illustrate the implications for TAC's count measures, we replicate the analysis using the count dependent variable, using their same negative binomial specification with group-level random effects and year fixed effects.

Figure 6 reports the results of the replication in a coefficient plot that compares the estimated coefficients on each predictor across models in which we substitute TAC measures using various criteria for assigning attacks to rebel organizations (matching levels), for the measure of terrorism used by Asal et al.

A few interesting differences in the results emerge from this re-analysis. First and foremost, one of the main conclusions of Asal et al. is not supported when using TAC to measure rebel terrorism. We find no support for Hypothesis 1, which states that "rebel groups targeted with conciliatory actions (carrots) by governments should be less likely than other groups to target civilians" (Asal et al., 2019: 1715). Although the direction of the coefficient



	Asal (2019)	TAC v.A	TAC v.C	TAC v.E
Sample Size	1240 (134 groups)	1145 (133 groups)	1145 (133 groups)	1145 (133 groups)
Log Likelihood	-2118.82	-2295.36	-2398.93	-270.26

Figure 6. Replicating Asal et al. (2019) Model 3, count dependent variable.

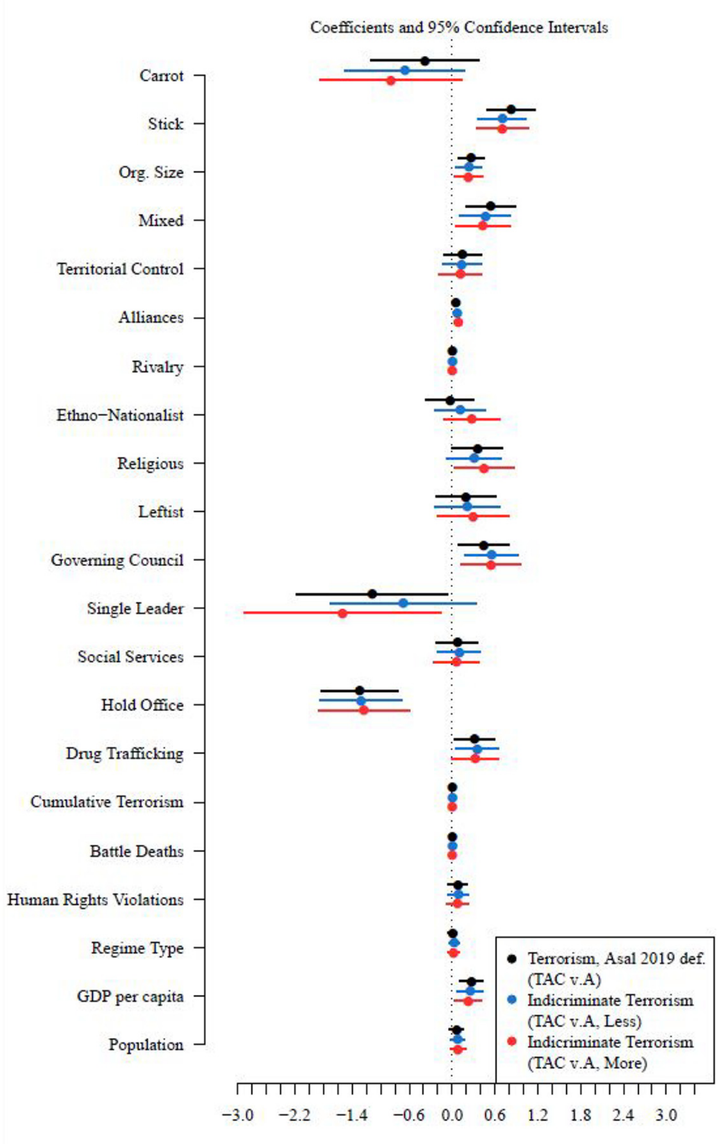
estimates in the analysis using TAC is also negative, it is not statistically distinguishable from zero, even when using the count variable based only on "direct" matches to the group (v. A). In contrast, Hypothesis 2, which predicts that rebel groups targeted with coercion (sticks) will engage in more terrorism, is supported using TAC, also regardless of the criteria for assigning attacks to rebels.

The coefficient estimate on organization size, another predictor, when using the count of attacks including only "direct" matches (v. A), is nearly identical to that in the original study. However, if we consider the possibility that factions and affiliates (v. C) and also generic descriptors of the group (v. E) may reflect the group's activity, the finding that organization size increases terrorism no longer holds. This could be because larger organizations are generally less obscure. If so, smaller ones may have, on average, many more unattributed or vaguely attributed incidents. Once these incidents are taken into account, the relationship between organization size and terrorism falls away. Since this variable is taken to proxy group strength, it has implications for the broad debates surrounding the relationship between (relative) group strength and use of terrorism, including the conventional wisdom in the "weapon of the weak" argument. Robustness to systematic measurement error in the outcome is thus especially important.

In general, it is dubious to draw conclusions from the coefficients on control variables without a defensible causal model that suggests they are not susceptible to collider bias. This is especially problematic in this case, because the model specification of Asal et al. includes so many predictors. Nevertheless, the original study does offer some implications from the control variables. To the extent that these correlations may be informative of causal relationships, there are a few other interesting differences in the results when using TAC. The reanalysis suggests no support for the claims that rebels' territorial control and social service provision, respectively, increase rebel terrorism. Analysis using TAC also suggests that there is no support for the claim that ethno-nationalist groups use more terrorism than others.

Next, we turn to the issue of distinguishing deliberately indiscriminate terrorism from deliberate civilan targeting more broadly as a way to investigate causal mechanisms. Asal et al. define terrorism as intentional civilian victimization by rebels, putting their study in line with the broader literature on civilian targeting (e.g., Kalyvas, 2006) and "one-sided violence" in civil conflicts (e.g., Eck and Hultman, 2007). They emphasize that terrorism is a form of communication or signaling (cf. Kydd and Walter, 2006), and focus on terrorism used to "coerce the compliance or win support of civilians" as they put it (Asal et al., 2019: 1714), that is, a strategy of "intimidation" (Kydd and Walter, 2006) and "control" (Stanton, 2016), to induce the population to collaborate with one's own side and deter such collaboration with the government. Terrorism is thus used to signal both to the government and to the civilian population.

Asal et al. argue that when the government offers carrots (negotiations and concessions), rebels should respond by reducing their use of terrorist attacks to demonstrate to the government that they can control the violence. This logic, we argue, should apply to both selective and indiscriminate types of violence. They argue that the government's use of sticks (counterterrorism violence) likely increases rebels' use of terrorism. Because effective sticks rely on civilian collaboration, rebels may respond by targeting civilians. Although not as militarily effective as damaging military targets, "soft" civilian targets are easier and reflect a strategic logic of undermining government intelligence. Unlike the logic behind carrots and restraint, this part of Asal et al.'s theory implies that sticks should increase *only* selective and *not* indiscriminate civilian targeting. Indiscriminate attacks are not useful, and may in fact be



	Terrorism (Asal def.)	Indiscriminate Terrorism (Less)	Indiscriminate Terrorism (More)
Sample Size	1145 (133 groups)	1178 (133 groups)	1178 (133 groups)
Log Likelihood	-2295.36	-2073.28	-1694.9

Figure 7. Asal et al. (2019) Model 3, terrorism vs. indiscriminate terrorism.

counter-productive, for inducing cooperation with one's own side and deterring collaboration with the other (Kalyvas, 2006). Moreover, it is not clear that indiscriminate targeting serves as a credible signal of strength or resolve (Fortna, 2015). Selective attacks, in contrast, signal the capacity to discriminate.

An alternative argument suggests a *backlash effect* of government repression, in which sticks would increase both selective and indiscriminate civilian-targeting (Walsh and Piazza, 2010). In this dynamic, government violence leads rebels to seek (and their constituents to support) revenge. Rebels thus have an incentive to attack perceived collaborators and civilian representatives of the government with selective attacks. And they also face lower legitimacy costs among their own potential supporters for targeting the general citizenry with indiscriminate ones, particularly if the government perpetrated indiscriminate violence against civilians in its harsh counter-terror response (Fortna et al., 2018). Both types of attack may thus increase.

To investigate these alternatives, we fit the same model from Asal et al., substituting the measures of deliberately indiscriminate terrorism proposed above for the broader category of terrorism used by Asal et al. Figure 7 reports the results alongside the results using their definition of terrorism (reported in the replication in Figure 6). We use the total number of attacks that fit our definition of indiscriminate terrorism, rather than restricting to fatal attacks, for comparison. We include the results using both the more and less restrictive measures of indiscriminate terrorism.

Unsurprisingly, there are a lot of parallels in the results between the broader definition of terrorism and the specific subset of indiscriminate terrorism. After all, the broader definition includes incidents of indiscriminate terrorism in its measure(s), and we would therefore expect a correlation between the measures and at least some similarities across the data generating processes. Thus, the analysis here provides additional evidence that, focusing on indiscriminate terrorism specifically, the empirical associations highlighed in the original article largely hold.

However, as noted above, extending the logic of Asal et al. suggests the effect of sticks should fall away once we hone in on indiscriminate targeting, as only discriminate attacks send credible signals to both the government (of capacity) and the population (that collaboration with the government will be punished and cooperation with rebels will not be). The coefficients are slightly smaller for the measures of indiscriminate terrorism, but only marginally so, and they remain statistically significant. This suggests greater support for alternative arguments, like the backlash effect, that expect similar results whether we look at discriminate or indiscriminate targeting of civilians. While this replication exercise is by no means a full test of alternative mechanisms, and space constraints preclude further tests to probe these issues more deeply, these results suggest that distinguishing deliberately indiscriminate terrorism from the broader category of civilian targeting may be fruitful for elucidating and testing the causal logics that drive rebel organizations to choose terrorism or to refrain from such attacks.

Conclusion

A burgeoning literature has contributed a great deal to understanding the causes and consequences of terrorism, but has long been stymied by crucial shortcomings in data comparing groups using terrorism with similar groups that do not. A growing number of researchers have turned to analyzing terrorism in the context of civil conflict to address this issue, comparing variation in the use of terrorism across rebel organizations. However, linking data on civil conflicts with existing data on terrorism is not as straightforward as recent efforts might imply.

TAC provides a new resource for terrorism researchers, improving upon existing efforts to link the UCDP intrastate conflict data to the GTD data. The matching of groups across the two datasets is informed by extensive qualitative research into armed group histories and identities, and goes beyond including only those incidents in GTD with direct attribution to UCDP groups. Existing datasets do not provide options for scholars to address the measurement error associated with the many unattributed or vaguely attributed incidents of terrorism present in GTD, nor the often complicated or non-obvious relationships between actors in UCDP and perpetrators listed in GTD. By providing a flexible system of assigning responsibility for incidents when only partial perpetrator information is available, TAC represents the first opportunity to systematically explore the sensitivity of one's conclusions to this form of measurement error. TAC also provides a novel way to use information in GTD to proxy for deliberately indiscriminate terrorism, which we argue may follow a different strategic logic than other types of civilian targeting or more selective attacks such as assassinations.

While only suggestive, the brief replication exercise indicates that findings in terrorism research may be sensitive to decisions about how to handle the inherent uncertainty about how to attribute attacks to specific groups. It also suggests that distinguishing among types of civilian targeting, particularly indiscriminate attacks rather than more discriminate forms of intimidation, will allow researchers to develop and test theories about the strategic and causal logics of terrorism in more nuanced ways.

TAC provides the flexibility for researchers to measure terrorism as best befits their research question and to examine the implications for their findings of alternative definitions and measurement of terrorism. Our hope is that, by integrating data on terrorism and armed conflict in a more systematic and flexible way than has been done in the past, TAC will contribute to a greater understanding of violence in civil conflicts and of the causes and effects of terrorism more generally.

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ORCID iDs

Nicholas J. Lotito https://orcid.org/0000-0002-1203-5353
Michael A. Rubin https://orcid.org/0000-0002-5623-4397

Supplemental material

Supplemental material for this article is available online.

Notes

1. These data build on the Armed Conflict Dataset originally compiled in collaboration with the Peace Research Institute Oslo (Gleditsch et al., 2002) and the work of Cunningham et al. (2013).
2. We intend to update the data through 2020 in coming releases. As GTD is missing all data from 1993, that year is missing in our data as well. Acosta and Ramos (2016) have coded data comparable with GTD for 1993, which we plan to incorporate in future releases of TAC.
3. That is, cases would be selected out of the analysis because the dependent variable (terrorism) is always zero. This is true even if terrorism counts are zero for particular observations (e.g., years) for organizations that sometimes use terrorism; the dependent variable would still be truncated by the omission of groups that never use terrorism.
4. Following conventions in the literature, we use the term *civil conflict* to include both minor (25–999 battle deaths) and major (1000 + battle deaths) conflicts as defined by UCDP (see below).
5. See, especially, Nemeth and Mauslein (2019) for an example addressing description bias in the GTD data.
6. See, most recently, Chenoweth and Gofas (2019: 3) and Saul (2019) in the *Oxford Handbook of Terrorism*. The lack of a consensus definition of terrorism is oft-noted; for example Crenshaw (2000: 406), Weinberg et al. (2004), Sánchez-Cuenca (2014: 591), among many others.
7. Code and web-app are available at: https://github.com/TACDataProject/TAC.
8. One could avoid the problems of matching actors by using UCDP's "One-Sided Violence" Data (OSV) which is compatible with the Armed Conflict Data. The OSV data also have the benefit of including violence committed by states. However, the OSV data cover a broad array of types of violence against civilians (Eck and Hultman, 2007), with no ability to distinguish "terrorism," however defined, from others.
9. GTD data managers explain, reasonably enough, that because they do not have sufficient information across all conflicts to do so accurately, they explicitly avoid making inferences when assigning incidents that are identified by more generic terms in news sources to a specific group. (Email correspondence with author 20 February 2014.) We cannot, therefore, assume that incidents with more generically named perpetrators are definitely *not* the work of a specific organization.
10. "Statements." *Al-Qassam Brigades Information Office*. Available at: http://www.qassam.ps/statements-page9.html.
11. For each conflict, the timeframe starts in the year of the first battle death (UCDP) or the first direct match in a manual search of GTD, whichever comes first. It ends in the year of the last direct match or 5 years past the last year of active conflict, whichever comes later. See codebook for details.
12. For example, UCDP Conflict Encyclopedia, available at: https://www.ucdp.uu.se/ and Non-State Actor database data notes (Cunningham et al., 2013), available at: http://ksgleditsch.com/eacd.html.
13. See the codebook for a detailed description of this procedure. Our coding of all possible pairs, along with coding notes is available at: https://github.com/TACDataProject/TAC
14. Note, however, that because incidents are only matched to a UCDP group if they take place in or target the country against which the rebel organization fights, generic descriptor incidents are not duplicated across borders. For example, an attack by "Kurds" would only be matched to the PKK if it took place in or targeted Turkey. If it took place in Iraq, it would be matched to both the PUK and the KDP, as these are both Kurdish rebel organizations in Iraq, but not to the PKK (unless it targeted a Turkish target within Iraq).
15. In the latter case, the GTD *gname* is an armed wing of the organization named in UCDP's *SideB*, or vice versa.
16. Alliances of convenience, where groups that are clearly distinct or fight as part of separate movements ally (usually temporarily), are not included here.

17. The counts use the less restrictive measure of our own definition of terrorism, described below, regardless of fatalities.
18. Various factors may reduce the visibility and legibility of conflicts to Western researchers, including conflict size, geographic remoteness, language barriers, and sparse or censored media coverage.
19. See codebook for a detailed comparison.
20. These figures, and those following, use TAC's less restrictive definition of terrorism and match version A.
21. See Arblaster (1977: 421) on why terrorism should be defined as "essentially indiscriminate."
22. For further discussion of this definition, see Fortna et al. (2018) and the TAC Codebook. Note that this definition, in principle, could apply to both states and non-state actors. We sidestep the contentious issue of whether "state terror" is "terrorism" because the data we use here are only available for non-state actors.
23. Much of the literature on violence against civilians in civil conflicts (prominently including Kalyvas, 2006) focuses on this more common phenomenon, in which rebels use deliberately discriminate violence to control (Stanton, 2016) or intimidate (Kydd and Walter, 2006) the civilian population. The use of indiscriminate terrorism, we argue, follows a very different logic. Our focus on indiscriminate terrorism also excludes assassinations, which other scholars might want to include. Researchers will find it straightforward to include these kinds of attacks using TAC if they wish to do so.
24. For a critique of this approach, see Gutiérrez-Sanín and Wood (2017).
25. Under GTD's hierarchy of attack type coding, the "facility/infrastructure" coding is only used when an attack is not already coded as a bombing or armed assault, and when attacks are on non-human targets in which any human deaths were incidental (START, 2013: 23). Note that attacks on *target types* that constitute infrastructure (airports, bridges, etc.) may be included in our measures if *attack type* is otherwise included.
26. See codebook for a complete list of included and excluded attack and target (sub)types for each measure.
27. Figures 3 and 4 show the total number of attacks, using matching version A.
28. Another 2% are attacks on "terrorists/non-state militias" or "violent political parties."
29. Perpetrators killed in an attack are not counted in any of the variables that use fatality information. See codebook for details of fatality calculations and the implications of non-lethal terrorism. See also Brown (2020).
30. In the codebook, we illustrate the differences between these different ways of counting terrorism in the case of the African National Congress.
31. In our vetting of randomly selected incidents to check our proxies, we found a number of "false positives" where assassinations were not coded as such by GTD (see codebook for examples).
32. The bars in Figure 5 represent the log-transformed value for the number of dyad-years that experienced the given number terrorism incidents. As the uneven scale of the ticks on the y-axis indicate, the labels reflect the raw number of dyad-years. We did this because the distribution is so skewed as to make the bars representing the raw count of dyad-years at each level of terrorism illegible. Figure 5 excludes US-al Qaida (see codebook for discussion).

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