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Meta-Analysis and the Integration of Terrorism Event Databases

Timothy Lee Jones, University of Michigan, USA*
https://orcid.org/0000-0002-9289-0121

ABSTRACT

Why do terrorist attacks occur in certain places and times but not others? Despite advances in collection and empirical methods, the literature has produced divergent results and reached little consensus for common hypotheses about the economic, political, and social causes of terrorism. It is hard to know what to make disagreements as studies adopt disparate research designs using different datasets covering different locations and times. This article applies the xSub data protocol to conduct a meta-analysis of terrorism event datasets and isolate explanations for variations in findings. Although the datasets are constructed for different purposes by different research teams, with different inclusion standards, processing data onto a common event typology, and conducting analysis across common coverage reduces heterogeneity in findings. This protocol also facilitates comparisons with general conflict event datasets, providing researchers, policymakers, and practitioners with a broader context for understanding terrorism in relation to other forms of violence.

KEYWORDS

Data Integration, Event Data, Meta-Analysis, Political Violence, Subnational, Terrorism

INTRODUCTION

One of the most widely studied questions in contemporary political science is why terrorism occurs in certain places and times but not others. Since the year 2000, an article on this topic has appeared in, on average, every fourth issue of the *American Political Science Review*, every fifth issue of *International Organization*, and every third issue of *The Journal of Conflict Resolution*. There are currently at least nine peer-reviewed journals dedicated exclusively to the study of this phenomenon and dozens of terrorism databases and datasets have been constructed for associated analysis (SCImago, 2022; Bowie, 2021; Chenoweth, 2019). Despite the scale of this combined research effort, scholars have reached little consensus on the empirical determinants of terrorism. In the analysis of political, economic, and social factors, studies have recorded contradictory findings in signs, size, and significance in their findings. Why do studies on the same topic report such divergent results? Are these differences driven by some underlying heterogeneities and causal complexities or by differences in scope conditions, the usage of disparate datasets, or other some other elements of research design?

This article outlines a systematic approach for researchers to conduct cross-dataset comparisons, isolate sources of variation in empirical findings, and determine the robustness or uniqueness of

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*Corresponding Author

determinants in the context of terrorism and other forms of political violence. To demonstrate the utility of this process, the author assembles three of the largest and most widely used terrorism datasets and applies the Cross-National Data on Sub-National Violence (xSub) data integration protocols to process event data into a common event typology with consistent categories and units by space (country, province, district, grid cell), time (year, month, week, day), and target (Zhukov et al., 2019). After processing the events onto a common typology, these standardized measures are combined with data for economic conditions, regime type, demographics, and weather and fit empirical models across a common set of spatial-temporal coverage and scales. Once these data are harmonized onto a standardized event typology with consistent categories and the analysis is confined to shared spatio-temporal dimensions, the findings exhibit greater consistency. Past divergences observed in cross-national studies may, in part, reflect that relationships between common correlates of terrorism are context-specific, and vary across different time periods and geographical locations examined in individual studies.

Terrorism research would also benefit from a process by which scholars can more confidently compare findings between terrorism datasets and general conflict event datasets that capture other forms of political violence, often perpetrated by the same actors. Our understanding of terrorism remains incomplete when studied in isolation as, “most uses of terror actually occur as complements or as byproducts of struggles in which participants…are engaging simultaneously or successively in other more routine varieties of political claim making” (Tilly, 2004). In fact, many hypothesized determinants of terrorism are shared with other forms of violent contention. Therefore, a framework, such as that presented in this article, which facilitates such a comparison, has the potential to provide additional insight into whether certain correlates explain the occurrence of terrorism or simply rebellion in general (Beuno De Mesquita, 2005).

Consider recent events in Afghanistan. The Taliban, an entity that has oscillated between status of an incumbent government and an insurgent organization, has employed a spectrum of political violence. Some of these actions, particularly indiscriminate attacks on civilians, align with most scholarly definitions of terrorism. Consequently, these events are likely to be reflected in terrorism event databases. However, what about other forms of violence in which the Taliban is engaged, such as skirmishes with Pakistani border guards or the former Afghan Army? What about the violence they pursue now that they have regained control in Afghanistan? Most terrorism databases exclude acts carried out by state forces. Therefore, if we exclusively consider events involving the Taliban using only terrorism event databases, we are likely to obtain an incomplete picture regarding the determinants of when they use terrorism or other forms of violence.

As such, this article compares findings from the terrorism event databases with some of the general conflict datasets already available in the xSub repository.[1] Additionally, the author demonstrates how this protocol facilitates the integration of the databases using the Merging Event Data by Location, Time, and Type (MELTT) software package, which can help account for missingness and provide more comprehensive coverage of violence for researchers (Donnay et al., 2018).

The contributions of this exercise are threefold. First, this type of meta-analysis helps identify factors driving the heterogeneity of results. Adopting a consistent set of data aggregation standards allows us to isolate the role of specific research design decisions, such as sampling variation across datasets or differences driven by model specification. Second, by carrying out hypotheses testing in the broadest of empirical settings, at different levels of analysis, it allows scholars to systematically assess whether their geographic and temporal scope conditions are valid and whether the types of empirical phenomena to which a given theory applies are narrower (or more general) than initially specified. Finally, this process can reduce barriers to conducting comparative research of different forms of political violence, facilitating discovery of previously unknown heterogeneities or phenomenon while opening new lines of inquiry. While the xSub protocol has been applied to 22 different conflict databases, this is the first time it has been applied to terrorism event datasets. Scholars can find replication code online, which can be customized to align with variation in researchers’ definitions of terrorism or to account for specific research questions.[2]

BACKGROUND

Terrorism event databases were constructed for different purposes by distinct organizations and research teams with diverse definitions and original sources of varying consistency and quality over time and inherently face biases due to their reliance on news sources (Weidmann, 2015; Chenoweth, 2019). These descriptive differences and limitations of terrorism event databases are well documented (Dugan et al., 2008; Enders et al., 2011; Young, 2019; Bowie, 2021), but an understanding of how these differences affect empirical findings remains incomplete due to challenges in conducting a systematic comparison across datasets with variation in scope and coverage (Chenoweth, 2019).

Such an undertaking requires classifying events into a common typology and geo-locating events to assign them to appropriate levels of spatial and temporal specification. Previous efforts aggregated events to country-year level in search of robust correlates across datasets (Gassebner & Luechinger, 2011); however, without consistent units and common coverage across time and space, it remains unclear whether the convergence and divergence in findings was due to some peculiarity of a dataset, the research design, or a reflection of how the relationship of determinants are unique in different time periods and locations with the occurrence of terrorism. Absent from the terrorism literature is a meta-analysis that evaluates why there is heterogeneity in findings across and within datasets, not just which correlates appear robust.

Determinants of Terrorism

Economic, political, and societal characteristics and grievances encompass the most explored structural explanations of terrorism in extant research (Gassebner & Luechinger, 2011). However, this literature has produced wildly divergent results and yielded little consensus on the nature of their relationships with terrorism.

For example, consider the literature that analyzes the relationship between economic wealth and the occurrence of terrorism. One prominent argument revealed in this body of research is that economic hardships and underdevelopment aggravate grievances, create sanctuaries for terrorists, alter opportunity costs that affect recruitment, influence the quality of terrorism, and are accompanied by a general instability that promotes the likelihood of violence (Berman & Laitin, 2008; Freytag et al., 2011; Choi & Luo, 2013).

Alternatively, other scholars have posited that more economically endowed countries should experience a greater number of terrorist events by posing as a more attractive target in which to garner press coverage and attention to causes (Abadie, 2006; Blomberg & Hess, 2008). Wealthy countries are expected to have a higher power ratio relative to any would-be challenger, making terrorism a potentially lucrative violent strategy for disadvantaged militants (Crenshaw, 1981).

Finally, others contend that once accounting for other factors like political grievances, liberties, or population, there is no direct relationship between levels of national wealth or income inequality and the likelihood of terrorism (Krueger & Maleckova, 2003; Goldstein, 2005; Piazza, 2006).

Competing theories on the causes of terrorism are not unique to measures of economic wealth. Terrorism research concerning political and social determinants suffers from a similar divergence in theory and findings, failing to reach a consensus and advance our understanding of why terrorism occurs in certain places and times but not others.

A survey of 24 influential articles, presented in Table 1, offers some insight on this discontinuity. Each study adopts a slightly different research design, using disparate datasets, while focused on different types of terrorism, using various empirical methods, covering different countries, levels of analysis, or historical periods.[3] As such, it is not surprising that this work has failed to converge in some sort of consensus.

This effort to uncover a relationship between terrorism economic and political determinants remains ongoing in terrorism research. For example, in a 2023 study, Biglaiser et al. employed a cross-national analysis encompassing 114 countries spanning from 1991 to 2017 to assess the impact

Table 1. Influential empirical studies testing economic determinants of terrorism

Study	Period	N	Type	Level	Dataset	IV	DV	Method	Finding
Abadie (2006)	2003-2004	186	all	country-year	ITERATE	GDPpc	risk*	OLS	-
Basuchoudhary & Shughart (2010)	1982-1997	2630	transnational	country-year	ITERATE	GDPpc	counts	Neg. Bin.	∅
Campos & Gassebner (2013)	1973-2003	3274	transnational	country-year	ITERATE	GDPpc	counts	Neg. Bin.	∅
Choi (2010)	1984-2004	2213	all	country-year	GTD	GDPpc	counts	Neg. Bin.	+
Choi (2010)	1984-2004	2213	transnational	country-year	ITERATE	GDPpc	counts	Neg. Bin.	+
Dreher and Fischer (2011)	1998-2004	233	domestic	country-year	MIPT	GDPpc	counts	Neg. Bin.	∅
Dreher & Gassebner (2008)	1975-2001	2263	transnational	country-year	MIPT	GDPpc	counts	Neg. Bin.	∅
Eyerman (1998)	1968-1986	2038	transnational	country-year	ITERATE	GDPpc	counts	Neg. Bin.	+
Freytag et al. (2011)	1971-2007	3956	all	country-year	GTD	GDPpc	counts	Neg. Bin.	∩
Kis-Katos et al. (2011)	1970-2007	5166	all	country-year	GTD	GDPpc	counts	Neg. Bin.	+
Krueger and Laitin (2011)	1997-2002	150	transnational	country-year	Dept. of State	GDPpc	counts	Neg. Bin.	+
Krueger and Maleckova (2003)	1997-2002	148	transnational	country-year	Author	GDPpc	counts	Neg. Bin.	∅
Kurrild-Klitgaard et al. (2006)	1996-2002	319	transnational	country-year	ITERATE	GDPpc	counts	Logit	+
Lai (2007)	1968-1998	3072	transnational	country-year	ITERATE	GDPpc	counts	Neg. Bin.	∩
Li (2005)	1975-1997	2232	transnational	country-year	ITERATE	GDPpc	counts	Neg. Bin.	-
Li and Schaub (2004)	1975-1997	1996	transnational	country-year	ITERATE	GDPpc	counts	Neg. Bin.	-
Marineau et al. (2020)	1968-2013	1,894,453	transnational	grid-year	ITERATE	GCP	counts	Neg. Bin.	+
Nemeth et al. (2014)	1990-2008	55682	domestic	grid-cell	GTD	GCP	counts	Hot Spot	-
Neumayer & Plümper (2009)	1969-2005	575,876	transnational	dyad-year	ITERATE	GDPpc	counts	Neg. Bin.	+
Piazza (2006)	1986-2002	95	transnational	country-year	Dept. of State	GDP	counts	OLS	∅
Plümper & Neumayer (2010)	1968-2003	484,729	transnational	dyad-year	ITERATE	GDPpc	counts	Neg. Bin.	+
Savun & Philips (2009)	1998-2004	777	domestic	country-year	MIPT	GDPpc	counts	Neg. Bin.	+
Tavares (2004)	1987-2001	964	all	country-year	IPICT	GDPpc	counts	OLS	+
Walsh & Piazza (2010)	1998-2004	774	all	country-year	MIPT	GDPpc	counts	Neg. Bin.	∅
Walsh & Piazza (2010)	1981-2003	2547	all	country-year	ITERATE	GDPpc	counts	Neg. Bin.	+

Note: IV – Independent Variable; DV – Dependent Variable. ∅ - No relationship identified. ∩ - Inverted-U shape relationship. OLS – ordinary least squares. *Abadie (2006) uses the World Market Research Center's Global Terrorism Index (WRMC-GTI) for terrorism risk in 2003-2004 as the dependent variable. Global Terrorism Database (GTD), International Terrorism: Attributes of Terrorist Events (ITERATE), Memorial Institute for the Prevention of Terrorism (MIPT), and the RAND Database of Worldwide Terrorism Incidents (RDWTI).

of foreign direct investment (FDI) on terrorism. Additionally, Jetter et al. (2023), conducted a sub-national examination in 75 countries from 1970 to 2014 of the relationship between GDP and the onset of terrorism. In a separate investigation conducted by Hand and Saiya (2023), spanning data from 1972 to 2016 across 200 countries, the authors explored the impact of democracy on the incidence of terrorism while accounting for the goals of different terrorist organizations.

As terrorism scholars continue to seek to identify important determinants of terrorism across and within nations, a process by which to consider how dataset selection and variation in temporal and spatial coverage may be driving findings could enhance and contribute to this effort placed on uncovering a relationship between terrorism economic and political determinants.

DATA MANAGEMENT AND PROCESSING

To investigate potential drivers of discontinuity, event data is assembled from the largest and most widely utilized datasets in the empirical study of terrorism: the National Consortium for the Study of Terrorism Responses to Terrorism (START)'s 2019 Global Terrorism Database (GTD), the 2009

Memorial Institute for the Prevention of Terrorism (MIPT)'s RAND Database of Worldwide Terrorism Incidents (RDWTI), and International Terrorism: Attributes of Terrorist Events (ITERATE) (Mickolus et al., 2021). Then, to consider the generalizability of findings, results are compared with data from two of the largest general conflict event databases already available in xSub: the Uppsala Conflict Data Program (UCDP)'s Georeferenced Event Dataset (GED) and the Armed Conflict Location & Event Data Project (ACLED) (Sundberg & Melander, 2013; Raleigh et al., 2010).

Types of Terrorism

Importantly, variation exists in the types of terrorism each dataset catalogs. ITERATE only records international/transnational terrorism events, MIPT limits collection to transnational incidents for the first 30 years over coverage but started cataloging domestic incidents beginning in 1998, and GTD records both international/transnational and domestic terrorism incidents for the entirety of its holdings.[4]

Given this variation, events are first organized by type. International terrorism and/or events that are state sponsored (confirmed or suspected) are omitted in the empirical models in this article. Events coded in GTD as "doubt terrorism" are similarly omitted. Table 2 details the number of events and years of coverage available at the time of analysis.[5]

Next, events are categorized into common perpetrator-target dyads using the xSub actor types: government, opposition, civilian, and unaffiliated. Given that each dataset has a unique typology, individual actor dictionaries are generated to map events onto the common classification depicted in Table 3. Actor and event type dictionaries for each dataset are available through online replication material.[3]

An example of how the target/victim coding is used to map GTD events onto this typology is depicted in Table 4. As terrorism definitions often differ by dataset and scholar, the researcher can match targets to the definition being operationalized in respective studies and evaluate whether certain determinants uniquely effect attacks against different target types. For example, the researcher could omit attacks against other terrorist groups if it did not match with their definition of terrorism.

Table 2. Terrorism dataset descriptive statistics

Dataset	Domestic + Transnational	Transnational	Domestic	Period
GTD	181,691	37,525	144,166	1970-2017
MIPT	40,129	10,531	29,598	1968-2009
ITERATE	N/A	14,898	N/A	1968-2018

Table 3. Actor typology

Actor	Examples
Government	Incumbent government, pro-government militia, third party acting on incumbent's behalf
Challenger	Rebels, anti-government militia, third party acting on challenger's behalf, other armed groups directly challenging the government
Civilian	Civilians
Unaffiliated	Local militia, tribe, other armed actor *not* directly challenging the government (e.g., self-defense force), peacekeeping forces

Table 4. Categorization of GTD events by target

GTD Target/Victim Code	xSub Target
1 – Business	Civilian
2 – Government (General)	Government
3 – Police	Government
4 – Military	Government
5 – Abortion Related	Civilian
6 – Airports & Aircraft	Civilian
7 – Government (Diplomatic)	Government
8 – Education Institution	Civilian
9 – Food or Water Supply	Civilian
10 – Journalists & Media	Civilian
11 – Maritime	Civilian
12 – NGO	Civilian
13 – Other (e.g., ambulance, firefighter)	Civilian
14 – Private Citizens & Property	Civilian
15 – Religious Figures/Institutions	Civilian
16 – Telecommunication	Civilian
17 – Terrorists/Non-State Militias	Rebel
18 – Tourists	Civilian
19 – Transportation (other than aviation)	Civilian
21 – Utilities	Civilian
22 – Violent Political Parties	Government

Spatial and Temporal Levels of Analysis

Drawing from the respective geographic precision codes for each event in each terrorism dataset, aggregates are constructed at the appropriate units across space, see Table 5. I then generate event counts within each spatial unit at different time intervals (year, month, week, and day).[4]

Common Support

To explore whether variation in geographic and historical coverage drives heterogeneity of results, common support datasets are generated, which are limited to overlapping spatial and temporal units

Table 5. Spatial levels

Geo-Precision	Description
ADM0	country
ADM1	1st order administrative division (e.g., province or state)
ADM2	2nd order administrative division (e.g., district or county)
PRIO-GRID	grid cell (0.5 x 0.5 decimal degree grid)

of analysis across all three terrorism datasets. In models that compare findings from the terrorism datasets to those from ACLED and GED, this process is repeated to generate common support across all five datasets. Specifically, as MIPT ceased collection in 2009, common support datasets in this article also end in 2009. Similarly, when ACLED is included in the common support, analysis datasets only start in 1997. This is repeated at each level of spatio-temporal specification (e.g., only matching grids-months).

Dependent Variable

The dependent variable used in this article is counts of terrorist attacks. For this analysis, attacks against any targets are included. Again, if a scholar has a more restricted definition for their respective theory or research question, they could limit events to match those requirements (e.g., civilian targets only).

META-ANALYSIS OF DETERMINANTS OF TERROR

For illustrative purposes, this article considers the sensitivity of some of the common explanatory variables found in terrorism and conflict literature. Models are initially fit without common support to consider the relationships one might observe if relying on a single dataset for their analysis. Subsequently, models are fit only where there is overlapping geographic and temporal coverage across all datasets. This step-by-step method can help determine whether divergence in results is driven, in part, by any peculiarities of the datasets or the result of variation in the relationship with predictors over time and in different geographic contexts. The models here cannot, nor are they intended to, identify causal effects. Researchers applying this protocol and seeking to make causal claims will still need to account for any issues of endogeneity and sources of bias in their research design.

As this meta-analysis is intended to help researchers isolate and understand drivers in the variation in findings, the author first fits the following core linear fixed-effects model: $Terrorism_{it} = z_{it} + \alpha_i + \gamma_t + u_{it}$, where $Terrorism_{it}$ is the number of terrorism events in locality I at time t, and z_{it} represents a vector of the determinants of interest. Locality fixed effects, α_i, are used to help account for unobserved, time-constant factors that affect $Terrorism_{it}$ and γ_t to account for shocks over time. The fixed-effects model helps us consider how the variables of interest perform across datasets, while reducing some concern of omitted variable bias. Subsequently, models are repeated with a negative binomial regression model common for terrorism analysis given over-dispersion in the data.

Cross-National Analysis and Common Support

To consider why previous studies have yielded little consensus, this article uses measures of economic productivity ubiquitous in extant research—gross domestic product per capita (GDPpc) from the World Bank (2022). The author begins at the most prevalent level of analysis in terrorism research (country-year) before conducting subnational analysis. The models also show control for population density, regime type using polity scores from Marshall and Jaggers (2020), and standard deviations in temperature and precipitation. All covariates are lagged one unit of time.

Results from the base fixed-effects model (Table 6) mirror the discord in the literature. Estimates vary in sign, size, and significance by dataset. Even when analysis is limited to common support, overlapping country-years, results still vary across datasets (see Table 7).

Variation in Model Specification

Some scholars have posited an inverted-U relationship exists between economic wealth and polity scores with terrorism (Lai, 2007; Freytag et al., 2011; Gaibulloev, et al., 2017). To assess whether disparate findings might be a function of forced linearity, quadratic terms

Table 6. Fixed effects model (AMD0-year) without common support

	Dependent Variable: Any Target						
	GTD	**MIPT**	**GTD**	**MIPT**	**ITERATE**	**GTD**	**MIPT**
	All	**All**	**Tran'l**	**Tran'l**	**Tran'l**	**Domestic**	**Domestic**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
GDPpc (log)	18.06	42.63*	-2.32	3.32	-2.5**	21.77	-13.93
	(13.04)	(17.89)	(3.27)	(2.03)	(0.77)	(13.3)	(23.61)
Polity IV	0.98	-1.26	0.36	0.12	0.03	1.18	-8.06
	(1.16)	(0.74)	(0.28)	(0.09)	(0.05)	(1.26)	(4.94)
Pop. Density (log)	49.43	51.49**	7.1	4.47	-0.78	47.77	15.43
	(26.86)	(18.71)	(3.84)	(2.71)	(0.72)	(27.44)	(86.22)
Temp. SD	-0.20	2.54*	0.3	0.5	-0.21	-0.23	1.94
	(1.69)	(1.1)	(0.45)	(0.33)	(0.13)	(1.55)	(4.68)
Precipitation. SD	-0.89	1.46	-0.52	-0.06	-0.07	-0.48	4.95
	(2.43)	(1.57)	(0.55)	(0.29)	(0.13)	(2.19)	(3.72)
Constant	-324.2	-537.7**	-4.33	-40.72	26.23***	-353.1	106.9
	(186.1)	(187.5)	(35.53)	(22.10)	(6.96)	(189.1)	(374.5)
Observations	4340	2551	3253	2013	3871	3927	495

Tran'l- Transnational
Standard errors in parentheses
* p<-0.05, ** p<0.01, *** p<0.001

for GDP and polity scores are incorporated (Table 8). There is general agreement of an inverted-U relationship for GDP across datasets, although there remains variation in whether this relationship is statistically significant.

Alternative Estimation Methods

The process is repeated with a negative binomial model to account for overdispersion when using terrorism count data. The findings at each stage follow the fixed-effects linear models. The base model without quadratic terms varies with sign, size, and significance across datasets, even when analysis is limited to common support. There is more congruency among findings with the inclusion of quadratic terms for both GDP and polity scores. Disparity in effect sizes is further reduced when analysis is limited to overlapping country-years. All tables are reported in the online appendix,[5] and Table 9 is included here for negative binomial model using quadradic covariates and common support. Again, there is general agreement of a tendency toward the inverted-U relationship for GDP, but this finding is significant only considering domestic terrorism events.

Table 7. Fixed effects model (AMD0-year) with common support

	Dependent Variable: Any Target						
	GTD	**MIPT**	**GTD**	**MIPT**	**ITERATE**	**GTD**	**MIPT**
	All	**All**	**Tran'l**	**Tran'l**	**Tran'l**	**Domestic**	**Domestic**
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
GDPpc (log)	1.26	54.0*	-3.03	5.02	-2.38	32.04	-8.52
	(8.90)	(20.82)	(2.71)	(2.72)	(1.88)	(19.65)	(23.63)
Polity IV	0.47	-1.6	0.23	0.11	0.11	1.86	-7.93
	(0.77)	(0.82)	(0.14)	(0.09)	(0.07)	(5.01)	(4.91)
Pop. Density (log)	13.2	58.56**	-0.16	5.23	-1.40	136.8	-13.93
	(17.15)	(20.32)	(2.7)	(3.15)	(2.01)	(107.3)	(74.56)
Temp. SD	-1.18	2.69*	-0.27	0.46	-0.23	-3.37	2.79
	(1.43)	(1.2)	(0.3)	(0.4)	(0.27)	(2.72)	(5.53)
Precipitation. SD	-0.23	1.52	0.22	0.04	-0.05	4.8	5.15
	(1.62)	(1.74)	(0.43)	(0.3)	(0.2)	(3.18)	(3.75)
Constant	-44.16	-660.6**	30.87	-57.36	29.28	-834.7	186.9
	(110.6)	(220.6)	(28.51)	(29.56)	(19.25)	(459.2)	(340.3)
Observations	2312	2312	1755	1755	1755	498	498

Tran'l - Transnational
Standard errors in parentheses
* $p<-0.05$, ** $p<0.01$, *** $p<0.001$

Reflections

These findings do not invalidate theories or previous findings not supported here, but this illustrative example demonstrates how processing data into consistent units and generating a common support dataset can help isolate some of the drivers of findings. The results for economic wealth and regime type are sensitive to dataset selection, differences in geographic and temporal coverage, and model specifications.

SUBNATIONAL ANALYSIS AND GENERAL CONFLICT EVENT DATASETS

Applying the xSub protocol to the terrorism event databases also leverages geo-precision and temporal-precision codes in datasets to aggregate events at different levels for subnational and sub-annual analysis. At times, terrorism research has underutilized the tremendous amount of geo-referenced data. Admittedly, this is due in part to scarcity of key explanatory variables at levels below the country-year. However, when determinants are available at more micro-levels of analysis, applying the xSub

Table 8. Fixed effects model (ADM0-year) without common support and quadratic terms

	Dependent Variable: Any Target						
	GTD	MIPT	GTD	MIPT	ITERATE	GTD	MIPT
	All	All	Tran'l	Tran'l	Tran'l	Domestic	Domestic
	(15)	(16)	(17)	(18)	(19)	(20)	(21)
GDPpc (log)	168.3*	116.7	36.96*	6.92	18.27*	111.0	117.8
	(79.6)	(101.9)	(17.48)	(10.92)	(5.9)	(75.04)	(197.3)
GDPpc^2 (log)	-8.67	-4.64	2.31*	-0.22	-1.23**	-4.93	-8.18
	(4.42)	(5.65)	(1.08)	(0.71)	(0.39)	(4.4)	(12.98)
Polity IV	1.57	-1.17	0.48	0.12	0.06	1.81	-7.62
	(1.43)	(0.69)	(0.33)	(0.09)	(0.05)	(1.58)	(4.6)
Polity IV^2	-0.55	0.070	0.09	0.00	-0.02*	-0.62	-0.32
	(0.42)	(0.09)	(0.09)	(0.02)	(0.01)	(0.42)	(0.26)
Pop. Density (log)	28.9	49.65**	3.04	4.28	-2.29*	27.68	8.30
	(22.29)	(17.53)	(2.94)	(2.74)	(0.89)	(22.34)	(85.57)
Temp. SD	0.42	3.03*	0.44	0.51	-0.09	-0.02	1.86
	(1.63)	(1.30)	(0.41)	(0.31)	(0.12)	(1.58)	(4.84)
Precipitation. SD	-1.04	1.62	-0.5	-0.05	-0.05	-0.73	4.71
	(2.62)	(1.51)	(0.58)	(0.29)	(0.12)	(2.32)	(3.72)
Constant	846.5*	-820.5	145.8*	-54.47	-49.43*	-632.1	-360.7
	(395.5)	(474.4)	(69.60)	(40.66)	(19.91)	(357.1)	(670.5)
Observations	4340	2551	3253	2013	3871	3927	495

Tran'l- Transnational
Standard errors in parentheses
* p<-0.05, ** p<0.01, *** p<0.001

protocol facilitates efforts to compare findings from datasets at more granular levels of spatial and temporal precision (e.g., grid-month or county-week).

To illustrate the utility of this feature, the author considers a variable that is easily scalable across different spatial units and where concerns of potential reverse causality are reduced–- temperature. Mean changes in climate and the number of extreme weather events, such as heat waves and droughts, are increasing (Fischer & Knutti, 2015). Extreme temperatures may exacerbate violence through a relative deprivation mechanism by decreasing income in agrarian societies or physiologically though a heat-aggression effect (Miguel et al., 2004; Buhaug & Rød, 2006; Craig et al., 2019). Although this relationship has been examined in the study of rebellion, the relationship, if any, between climate measures and terrorism is still an area that is understudied.

Then standard deviations of temperature are generated using data from the National Oceanic and Atmospheric Administration (NOAA) at each level of geographic specification (2022). The models continue to control for population, regime type, and economic wealth. However, for subnational models, an aggregate of gross cellular product (GCP) from the G-Econ v4.0 dataset aggregated to the

Table 9. Negative binomial model (ADM0-year) with common support

	Dependent Variable: Any Target						
	GTD	**MIPT**	**GTD**	**MIPT**	**ITERATE**	**GTD**	**MIPT**
	All	**All**	**Tran'l**	**Tran'l**	**Tran'l**	**Domestic**	**Domestic**
	(22)	**(23)**	**(24)**	**(25)**	**(26)**	**(27)**	**(28)**
GDPpc (log)	2.81**	3.12**	0.88	1.57	1.22	5.42***	5.08**
	(0.94)	(1.03)	(1.13)	(0.99)	(1.05)	(1.53)	(1.61)
$GDPpc^2$ (log)	0.17**	-0.18**	0.03	-0.08	-0.06	0.33***	-0.3**
	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.09)	(0.1)
Polity IV	0.10***	0.07***	0.06***	0.08***	0.04***	0.06***	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Polity IV^2	0.01***	-0.01	0.01	-0.01	-0.00	0.02***	0.00
	(0.0)	(0.01)	(0.0)	(0.0)	(0.0)	(0.01)	(0.01)
Pop. Density (log)	0.15	0.42***	0.31***	0.08	0.12	0.5***	0.61***
	(0.13)	(0.14)	(0.15)	(0.11)	(0.09)	(0.19)	(0.20)
Temp. SD	0.04	0.61***	0.02	0.08	-0.08	0.21	0.16
	(0.07)	(0.10)	(0.09)	(0.06)	(0.06)	(0.12)	(0.15)
Precipitation. SD	0.0	0.12	0.14	0.02	-0.0	-0.03	0.07
	(0.07)	(0.07)	(0.10)	(0.06)	(0.052)	(0.12)	(0.10)
Constant	8.61***	12.43***	-4.92	-5.95	-4.897	21.01***	20.94***
	(3.89)	(4.31)	(4.50)	(4.07)	(4.18)	(6.29)	(6.9)
lnalpha	1.34***	1.33***	1.29***	0.87***	0.76***	1.43***	1.21***
Constant	(0.07)	(0.07)	(0.10)	(0.08)	(0.09)	(0.12)	(0.09)
Observations	2312	2312	1755	1755	1755	498	498

Tran'l- Transnational
Standard errors in parentheses
* p<-0.05, ** p<0.01, *** p<0.001

same levels of analysis is used (Nordhaus, 2006). It should be noted again that due to the limitations of common support (common spatial and temporal coverage across all five datasets), the findings presented in this section are based on analysis of events in 27 African countries between 1997 and 2009 (the full list of country-years is in the online appendix), as ACLED data was initially limited to countries in Africa when it began in 1997, and MIPT ended in 2009.

Figure 1 reports the predicted shape of the temperature-violence relationship. At the country-year level, no clear pattern emerges, even when analysis restricted to common support. However, at the subnational level, there emerges a consistent positive linear relationship between standard deviations in temperature and the occurrence of violent events. This effect is not exclusive to terrorism databases;

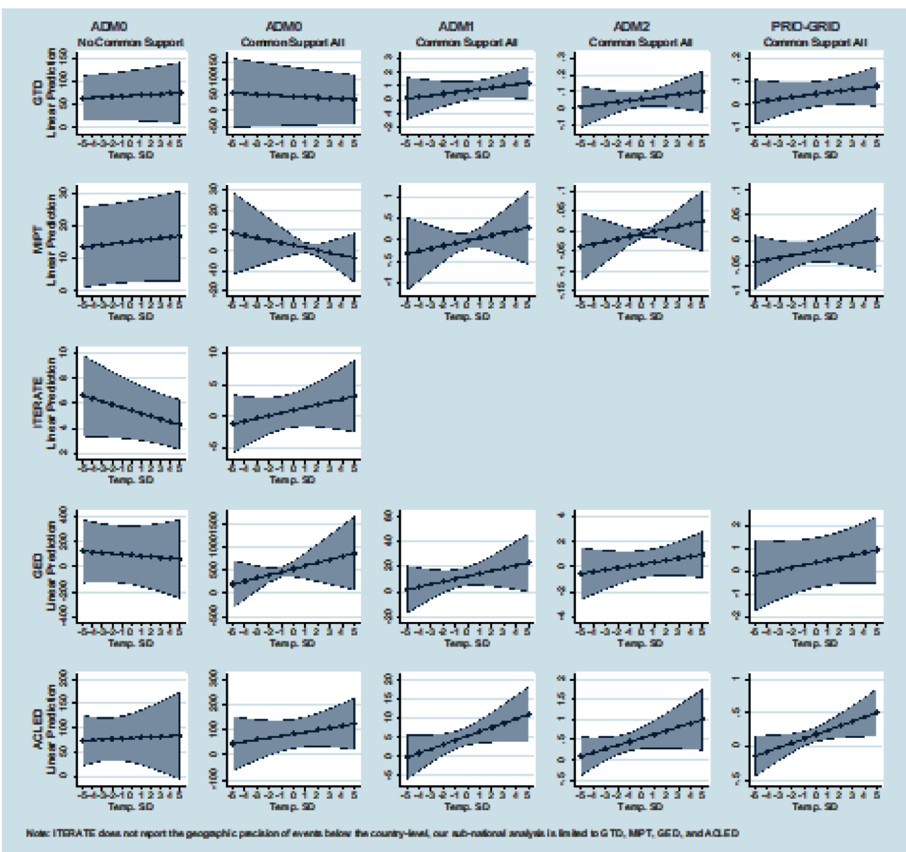
a similar relationship is found when using events from GED and ACLED. This example highlights two additional benefits of this protocol. First, new patterns can emerge when analysis is conducted at the subnational level, which is useful when determinants are theorized to have local effects and there is significant variation within countries. Second, comparing findings from specialty terrorism datasets with general political violence datasets at the same units of analysis can help researchers evaluate whether findings are distinct to terrorism or more generalizable to rebellion.

AN INTEGRATED PICTURE OF TERRORISM

In 2008, the Department of Justice (DOJ) funded a RAND effort to integrate the GTD and MIPT datasets from 1970 to 2006 (Dugan et al., 2008). After accounting for differences in inclusion criteria, a RAND computer program spent 10 days running to identify matches and recorded a 28% match rate. The analysts manually reviewed each record and found a high rate of false negatives. The process was repeated, leaving the computer program to run for 30 days, followed by another manual review. In Dugan et al. (2008), the final match rate was 33.5%. The resulting integrated dataset was touted as the "most extensive set of open-source data on both international and domestic global terrorist attacks ever assembled," and the authors demonstrated some of the ways the new dataset could identify unique trends associated with terrorism (Dugan et al., 2008).

Figure 1 reports the predicted shape of the temperature-violence relationship.

Figure 1. Analysis of temperature and terrorism



Integrating data from conflict event datasets has the potential to improve the measurement and understanding of different patterns and causes of violence by accounting for missingness inherit with the use of a single event dataset and allow researchers to analyze terrorism alongside other forms of conflict (Donnay et al., 2018). There is an interest in the terrorism research community in obtaining integrated datasets, but efforts have been stymied as integration and validation have historically been cumbersome, time-consuming, and difficult to replicate (Dunford et al., 2019). Even with the assistance of computer programmers and funding from the federal government, it took 30 days for RAND to integrate MIPT and GTD datasets in 2008, and this does not account for the time spent by analysts manually reviewing results. Additionally, researchers today do not have access to the program used and cannot independently validate or replace this effort.

The xSub protocol facilitates the integration of terrorism datasets using the MELTT automated software (Donnay et al., 2018; Dunford et al., 2019). Integration now takes minutes on a standard personal computer, and built-in functions in MELTT allow the researcher to validate matches and non-matches. Most importantly, this process is transparent and replicable. If scholars disagree with some of the decisions made in the pre-processing or coding of taxonomies or contend that the parameters are mis-specified, they can adjust the process accordingly.

As an example, this section integrates events from GTD, MIPT, ACLED, and GED in Somalia for years in which there is common support (1997-2009). In keeping with recent work by Dunford et al. (2019), a spatio-temporal window of 25 kilometers and two days is set (see Figure 2) (Donnay et al., 2018; Dunford et al., 2019). When integrating GTD with MIPT, a taxonomy that draws on the target types and weapon systems is used to identify candidate matches and consolidate entries that are deemed duplicates. These duplicates are then validated using MELTT's built-in functions to randomly sample and review potential candidates. As an additional validation measure, the author also manually validates each candidate match for GTD and MIPT in Somalia.

Table 10 summarizes the results of the integration including matching and unique entries across each dataset. A match rate of 24.8% is found between GTD and MIPT in Somalia for 1997-2009. This is comparable to the 2008 study that also finds incompleteness when relying on solely GTD or MIPT to account for terrorism (Dugan et al., 2008). Using the MELTT built-in function to randomly sample and review potential matches, a 95% accuracy rate is recorded, and when each candidate match is manually validated, the author finds there is a 91.9% accurate match rate (see Table 11). Figure 2 shows the number of unique and duplicate entries, by dataset, for each year.

Figure 2 shows the number of unique and duplicate entries, by dataset, for each year.

The author repeats the process with general conflict event datasets ACLED and GED; however, as GED provides less details about events, the taxonomy here is limited to target types using the same spatial and temporal window (25km, two days). Results are presented in Table 12. There

Table 10. Summary data integration (25km, two days) in Somalia (1997-2009)

GTD	MIPT	N Matches	N Entries
X		0	397
	X	0	202
X	X	99	198
Total number of entries: 797			
Total number entries after de-duplication: 698			
Number of duplicate entries removed: 99			
Percent of entries that matched: 24.8%			
Percent reduction in the size of the pooled dataset: 12.42%			

Table 11. Integration results for Somalia (1997-2009)

Country-years	Window	Total Events	Matches	Accuracy (%)
Somalia, 1997-2009	25km, 2 days	797	198 (24.8%)	91.9%

Figure 2. Unique and duplicate entries by year

Table 12. Summary data integration (25km, two days) in Somalia (1997-2009)

GTD	MIPT	ACLED	GED	N Matches	N Entries
X				0	284
	X			0	127
		X		0	768
			X	0	269
X	X			62	114
X		X		39	78
X			X	36	72
	X	X		17	34
	X		X	19	38
		X	X	65	130
X	X	X		18	54
X	X		X	11	33
		X	X	24	72
	X	X	X	25	75
X	X	X	X	22	88
Total number of entries: 2246					
Total number entries after de-duplication: 1786					
Number of duplicate entries removed: 460					
Percent of entries that matched: 35.1%					
Percent reduction in the size of the pooled dataset: 20.5%					

is significant overlap between ACLED and the two terrorism datasets, which is not surprising as ACELD attempts to cover a broad range of conflict event types including acts of terrorism. Still, despite this broad scope, there remain potentially hundreds of events ACLED did not record in Somalia during this period.

Figure 3 shows the number of unique and duplicate entries, by dataset, for each year, and Table 13 shows the match accuracy rate. The y-axis is negative in the bottom panel to denotate these are identified as duplicate events. All databases show events increase substantially beginning in 2007, most likely due to an increase in media coverage of al-Shabaab, as it came to prominence and subsequently designated a foreign terrorist organization (FTO) by the US Department of State in 2008 (Department of State, 2022).

Again, the intent of this illustration is not to critique any dataset over the other but to highlight the potential value in integrating datasets to measure and analyze different forms of political violence in the same location and time. Researchers interested in political violence, broadly defined, would benefit from a more complete picture of violence and related metrics that this process provides.[6]

In each case, relying upon a single dataset would potentially result in an underestimation of the level of violence in Somalia. Additionally, deconflicting matches between terrorism and non-terrorism event databases could help terrorism scholars put the rates of terrorism into greater context for researchers, policymakers, and partitioners in comparison to other forms of violence. Questions like, "Are non-state actors increasingly relying upon terrorism?" could be better addressed with this process.

As an example of the utility of this process, consider a recent retrospective look at terrorism in Sub-Saharan Africa from 1970 to 2020 published by the World Association for Disaster and Emergency (Hata et al., 2023). The study sought to understand how Counter-Terrorism Medicine (CTM) initiatives might improve health care outcomes through an analysis of types of terrorism that occurred in the region over the last 50 years using the Global Terrorism Database. However, as we just demonstrated, any conflict event database alone may underestimate the number of attacks and related deaths that may be pertinent to the study's conclusions and recommendations.

Figure 3 shows the number of unique and duplicate entries, by dataset.

CONCLUSION

An understanding of how the selection of different data sources at different times influences empirical findings in terrorism has been limited due to challenges in conducting a systematic comparison across datasets with variations in scope and coverage. The intent of this analysis is to illustrate how applying xSub protocols to existing terrorism event databases can improve the ability of terrorism researchers to assess the relationship between variables of interest across data sources and different levels of analysis and facilitate comparative analysis with other forms of political violence.

Table 13. Terrorism + general political violence integration results for Somalia (1997-2009)

Country-Years	Window	Total Events	Matches	Accuracy (%)
Somalia, 1997-2009	25km, two days	2246	788 (35.1%)	94.1%

Figure 3. Unique and duplicate entries by year

Just as Geddes (1990) observes that the cases one selects affect the answers they get in small-n studies, the author finds that the dataset one selects affects the answers they get when conducting large-N terrorism research. Heterogeneity in findings appears to be driven by differences in coverage and model specification rather than differences in inclusion standards or original sources across datasets. As such, discrepancies may be reduced when conducting analysis across common support and units.

Scholars of terrorism and other forms of political violence might consider this process as part of a robustness check. If findings are consistent across various specifications, datasets, locations, and time periods, it can enhance researcher'' confidence in the validity of their theories and results. If the same empirical regularities are identified in multiple datasets, assembled by different research teams, and during different time periods, levels of analysis, and using different methodologies, it bolsters the understanding of causes of political violence. Conversely, when findings are not generalizable, it still provides researchers with valuable means by which to articulate the scope of any conclusions.

This article also reinforces that new patterns may emerge when analysis is conducted at the subnational level, and processing terrorism event data using the xSub protocol facilitates analysis of micro-foundations of terrorism. To build upon this study, future research should also assess the generalizability of empirical results at different levels of temporal specification, particularly if explanatory variables are available at more finite temporal units. For example, there may be unique relationships between climate measures that emerge when analysis is conducted at the month or week level. Moreover, using this protocol to process events into common units and then pool events from disparate datasets can also offset underreporting and missingness by facilitating the use of automated integration software available to scholars (Donnay et al., 2018; Dunford et al., 2019).

Finally, the ability to conduct cross-data comparisons could improve research that asks whether terrorism is an effective strategy (Stanton, 2013). There are a range of strategies that challengers can employ, concurrently and sequentially. By adopting the data integration protocols put forth here and conducting cross-dataset comparison with general political violence datasets, terrorism scholars can evaluate political violence more holistically and employ a systematic means by which to identify variables that explain a group's choice to privilege a certain violent strategy over another. This would also free researchers to exert energy towards uncovering determinants that resolve the use of terrorism post rebellion.

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CONFLICT OF INTEREST

The author declares that they have no conflict of interests.

AUTHORS NOTE

Data is available on request.

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ENDNOTES

1 List of current data sets available in xSub: https://cross-sub.org/about/data-sources.

2 Replication code available on GitHub: https://github.com/timothyleejones/xSub_Terrorism/

3 Source-specific dictionaries for existing xSub datasets are online at: https://github.com/zhukovyuri/xSub_ReplicationCode and for terrorism event databases at: https://github.com/timothyleejones/xSub_Terrorism/.

4 For additional details on how geo-precision codes from each dataset are used to aggregate data to different levels of spatial specification (e.g., country, province, district, grid) see Zhukov, Y.M. et al. (2019), op. cit. pp. 609 and replication code for how this is implemented at: https://github.com/zhukovyuri/xSub_ReplicationCode.

5 Additional tables can be found at https://github.com/timothyleejones/xSub_Terrorism/.

6 A 5% sample of the matched pairs from the integrated data were manually reviewed using MELTT's validation function using the candidate match and two control events (entries not identified as candidate matches) randomly drawn from the pool of events in a similar spatial and temporal proximity for each match. A true positive rate of 94.1% and false positive rate of 5.9% were identified in the sample.

Timothy Jones is currently a Donald R. Beall Defense Fellow at the Naval Postgraduate School in Monterey, California. He received his PhD in Political Science from the University of Michigan in 2023. His research interests encompass the causes, dynamics, and outcomes of political violence with an emphasis on civil and conventional wars, insurgency, terrorism, countermeasures, and the peace-building process.