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Recognizing & Resolving Issues in Terrorism Research, Data Collection, & Analysis

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ABSTRACT

In the years following 9/11, countries around the world sought to implement evidence-based counter-terrorism policy and practices. Political narratives suggest these measures have been effective in stemming the tide of extremist violence, often in the absence of empirical results supporting this claim. This chapter focuses on the need for appropriate and well-informed quantitative methods of assessment and analysis. The chapter begins with an introductory discussion about the collection of quantitative data; readers are introduced to data collection techniques and effective methods of quality control. The focus then expands to include appropriate quantitative techniques for addressing specific research questions, including the impact of policy, of diverse practices, as well as isolating the effects of political, economic, and social factors on extremist behavior. The chapter concludes with a series of cautionary tales regarding drawing conclusions from statistical results, lessons learned from the analytical field, and best practices moving forward.

INTRODUCTION

Many individuals view quantitative research, particularly data collection and analysis, as a daunting and anxiety-producing exercise best left to others. Although some frame their analytical allegiances positing qualitative against quantitative methods, many are simply uncomfortable with quantitative processes.[1] Is this aversion warranted? In this author's opinion, yes and no. On the one hand, there are a number of difficulties and pitfalls that the unseasoned researcher may encounter. On the other hand, with proper warning and instruction, researchers can minimize or avoid these problems altogether. Therefore, the goal of this chapter is twofold; first, to introduce the curious scholar to issues surrounding quantitative data collection and analysis in terrorism studies and second, through that introduction, to quell reservations about the inaccessibility of these practices. The purpose is not to create research experts (it would be impossible to accomplish that feat in a single chapter) but to equip readers with enough information to pause, reflect on the methods and strategies available, and seek out more information.

The first half of the chapter provides an overview of data collection considerations. Readers are introduced to a number of data sources and issues that influence which of those sources are best suited to answer the research question at hand, and factors that impact the quality of data. The goal of this discussion is to give new researchers the tools necessary to critically assess available data options. The second half of the chapter is devoted to analytical considerations. Readers are introduced to a number of broad questions that guide terrorism research and the quantitative methods traditionally used to address these questions. The goal of this section is to familiarize researchers with the options available to them so that

1 There is an ongoing debate within the research community regarding the strengths and weaknesses of qualitative and quantitative research; this often results in the statement that one approach is superior to the other. Fortunately, 21st century researchers are moving away from this historical divide, recognizing that one approach compliments the other.

they may seek out additional information as warranted. The chapter ends with a short narrative illustrating best practices and principles in terrorism research.

DATA COLLECTION

What data resources are available to researchers? How does a researcher select a data source? How do we determine the quality of data? This section seeks to address these and other similar questions about data collection and availability, while also identifying some of the considerations and concerns of which potential users of data should be aware. The section begins by looking at traditional data sources, then shifts to factors influencing data selection, and ends with data quality assessment.

Data Sources

Researchers examining individual and group-level violent crime traditionally use three primary sources of data: self-report data, official data, and victimization data. Although these are common sources for the examination of apolitical criminal offending, they may be less than ideal when examining terrorism.[2] As detailed below, these sources of data are difficult to collect, subject to censorship, or simply may not exist.

Self-report data involves collecting data through a survey or interview process; members of the population of interest report their thoughts, feelings, and behaviors in relation to a phenomenon of interest. In order to collect self-report data on terrorism, the researcher is most often required to solicit the participation of active or former extremists. As the reader can likely imagine, this is no small feat. Extremists are difficult to access, and identifying willing participants is a logistically and legally demanding task. Even if the researcher is able to identify and access extremists, they may be unwilling to participate in an interview process. In cases where they are amenable, generalizability remains a concern—how well do the select few that are willing to be interviewed represent all of those unwilling to cooperate? As such, it is difficult (and questionable) to draw inferences from self-report interviews and apply those inferences to a larger population.[3] In addition, the interview process may influence participant responses, introducing potential error. Social desirability bias and respondent bias is a concern in self-report data—the interviewee may want to present themselves in a positive way, disguise some of their activities, or protect members of their community through the omission of details, all leading to inaccuracies in responses. Therefore, although self-report data may be a potentially rich source of information, it is often difficult to collect and is subject to error. That is not to say that this approach is completely absent from or a futile

2 Gary LaFree and Laura Dugan, "How Does Studying Terrorism Compare to Studying Crime?," in *Terrorism and Counter-Terrorism*, ed. Mathieu Deflem (Amsterdam: Elsevier, 2004), 61-63.

3 Joshua D. Freilich and Gary LaFree, "Measurement Issues in the Study of Terrorism: Introducing the Special Issue," *Studies in Conflict & Terrorism* 39, nos. 7-8 (2016): 570.

endeavor in terrorism research. A number of researchers have been successful in soliciting the participation of current and former extremists, resulting in valuable insights on a variety of factors, including radicalization, disengagement, and group membership.[4] Still, the successful collection of terrorism-related self-report data is the exception, not the norm.

Official data, similar to self-report data, come with a host of cautionary considerations, although these caveats differ considerably from the concerns levied at self-report sources.[5] Official data refer to data sources built and distributed by government entities. Unfortunately, the first hurdle a researcher may face when relying on official data is that it simply may not exist. Many countries, for a variety of reasons, do not collect terrorism data. The United States government, for example, does not keep an official terrorism database for research purposes; nor do other countries, such as China, Canada, and Nigeria, to name an eclectic few. In addition, some nations may not be willing to share information on terrorism with the research community, limiting the ability to examine extremist violence in those areas.[6] Even if they do collect data and make it available for public use, governments are often swayed in the data collection process by a host of considerations that influence the accuracy of the data. For example, perhaps it is politically strategic at certain points in time or under specific administrations to underreport or over-report terrorist events, to inflate or deflate casualties and damages, or to acknowledge or mask the identity of perpetrators.[7] If so, official data cannot be used with any degree of confidence. In addition, some countries (such as the United States) do not always convict extremists of terrorism-specific offenses but, instead, will process political offenders under more traditional criminal statutes. These factors suggest that researchers should use official data cautiously, if it is available at all, or, if alternative data sources are available, pass over official sources entirely.

The last source of traditional data, victimization data, is very rare in terrorism research. Victimization data refer to information gathered directly from the victims of crime, usually through survey or interview techniques. Victims of terrorism are, however, unique when compared to victims of apolitical crimes. Unfortunately, the most obvious characteristic (and hinderance) is that terrorism victims are often killed in attacks, eliminating them as a potential source of information.[8] In addition, since terrorism is usually focused on sending a message to an audience that extends beyond the immediate victims, attackers often choose victims at random or as a matter of convenience rather than intentionally or based on prior personal interactions. This limits the amount of valuable information victims can provide given their peripheral relationship to the perpetrator of extremist violence. Lastly, victims who are strategically targeted by perpetrators and actually survive the attack are so rare that collecting a large enough sample to warrant quantitative analysis is nearly impossible.

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4 See, for example, John G. Horgan, *Walking Away from Terrorism: Accounts of Disengagement from Radical and Extremist Movements* (Abingdon: Routledge, 2009).

5 LaFree and Dugan, 62.

6 Freilich and LaFree, 571.

7 Gary Ackerman and Lauren E. Pinson, "Speaking Truth to Sources: Introducing a Method for the Quantitative Evaluation of Open Sources in Event Data," *Studies in Conflict & Terrorism*, 39, no. 7-8 (2016): 618.

8 LaFree and Dugan, 62-63.

Given the difficulties in collecting self-report, official, or victimization data, researchers have turned to other sources of data, including media reports, arrest and conviction data, journals, and books. With enough time, perseverance, and diligence, these early collections have become established databases that are now key sources of terrorism data[9]. Although these databases do not necessarily suffer from the same issues noted above, they come with their own host of considerations and caveats, as described below.

User's Choice

Databases are collections of topic-specific data organized to facilitate ease of access and management. The information stored in a database is usually organized in a vertical and horizontal fashion with rows denoting the unit of analysis or metric of observation and columns denoting variables. For example, if the database is an event database that reports terrorist attacks, each row would represent an attack (the unit of analysis) and each column would record details of that attack (variables). Databases allow researchers to easily access and analyze records on aggregations of the unit of analysis. A popular event-based terrorism database, for example, is the Global Terrorism Database (GTD) collected and distributed by the National Consortium for the Study of Terrorism and Responses to Terrorism (START). The GTD reports all terrorist attacks committed between 1970 and present day and contains, at the time of writing this chapter, nearly 200,000 incidents. As the reader can well imagine, researchers would be hard pressed to effectively answer a number of meta-questions about terrorism without access to a database of this kind with such a volume of information. Of course, as discussed below, while databases are not an infallible resource, they are a necessary tool for the quantitative examination of political violence in the absence of surveys and other means of gathering quantitative data.

A database ideally contains valid and reliable content. There are a number of factors that influence the quality of data outlined in the next section. Before discussing quality, however, there are a handful of considerations for which the database user (rather than that database developer) bears responsibility. A conscientious user should be aware that databases differ considerably in a number of ways, which introduces inconsistencies across datasets. The researcher should be informed about the sources of these potential inconsistencies and their relevance to her/his research so that, when she/he selects a database, the selected database is appropriate for the research question. Inconsistencies can arise due to multiple factors, including diversity in operational definitions, units of analysis, and coding strategies.

There is no universal definition of terrorism, and different states and research projects will vary in how they conceptualize the phenomenon[10]. Schmid and Jongman noted that definitions may vary on 22

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9 Joe Whittaker, "Building Secondary Source Databases on Violent Extremism: Reflections and Suggestions," RESOLVE, July 9, 2019. https://resolvenet.org/research/building-secondary-source-databases-violent-extremism-reflections-and-suggestions

10 J.M. Berger, "Researching Violent Extremism: The State of Play," RESOLVE Network, June 23, 2019. https://resolvenet.org/research/researching-violent-extremism-state-play

unique elements, resulting in more than a hundred variations.[11] Terrorism databases are no exception to this finding. Database developers use different definitions and thus different exclusion and inclusion rules resulting in diversity across databases. Studies have shown that databases appearing similar in nature often report dramatically different rates and types of attacks, likely due at least in part to definitional criteria.[12] For example, the GTD excludes state-sponsored attacks while early versions of the RAND Database of Worldwide Terrorism Incidents (WTI) includes attacks perpetrated by the state. Other sources of definitional variation may arise in regard to, among other factors, the inclusion or exclusion of insurgencies, intergroup violence, and purely criminal activities carried out by extremist groups.

A second source of inconsistency lies with the unit of analysis or the entity of interest. Databases may vary considerably in this regard; some focus on individual perpetrators, while others focus on groups or attacks. The Profiles of Individual Radicalization in the United States (PIRUS) database, for example, reports on individual extremists in the United States, while the Big Allied and Dangerous (BAAD) dataset captures information on terrorist organizations.[13] Although there may be some overlap between the two databases, their units of analysis ensure they are measuring different entities.

A third consideration includes case creation and coding strategies; databases employ unique strategies that affect the number and type of observations included. For example, one database may code a coordinated attack as a single event, while another may code it as multiple separate events. Comparing the International Terrorism: Attributes of Terrorist Events (ITERATE) database with the WTI provides a ready example of this issue. Jenkins and Johnson, upon examining these databases, discovered that ITERATE had created forty separate incidents for a coordinated bombing while the WTI coded it as a single event.[14] This is not an error on the part of either database per se but simply reflects different strategies in action.

These points of inconsistency may not appear particularly problematic at first glance, but the caution presented here is threefold. First, database users should review definitional criteria to ensure that the database is compatible with the researcher's interests. Is the user interested in including or excluding particular events or observations, such as state-sponsored terrorism or insurgent attacks? Second, users should attend to the unit of analysis and ensure that they select a dataset that best matches the research question at hand. If, for example, the researcher is interested in exploring factors that facilitate individual-level radicalization, the PIRUS database will likely be a more appropriate choice than the BAAD dataset. Third, researchers should be mindful of their choices and how it can affect their results. In the case of coordinated attacks, for example, selecting one database over another will influence reported rates of terrorism, particularly in areas where coordinated attacks are commonplace. Therefore, it falls on the

11 Alex P. Schmid and Albert J. Jongman, *Political Terrorism: A New Guide to Actors, Authors, Concepts, Data Bases, Theories, & Literature* (New Brunswick: Transaction Publishers, 1988).

12 See, for example, Ivan Sascha Sheehan, "Assessing and Comparing Data Sources for Terrorism Research" in *Evidence-Based Counterterrorism Policy*, eds. Cynthia Lum and Leslie W. Kennedy. (New York: Springer, 2012).

13 The BAAD database name reflects a tongue-in-cheek recognition that terrorist organizations are undesirable and unwelcome entities.

14 Brian Michael Jenkins and J. J. Johnson, *International Terrorism: A Chronology, 1968-1974* (Santa Monica: Rand Corporation, 1975).

user to carefully consider characteristics unique to the data and, in light of these factors, to determine if the data are appropriate to address the research question at hand.

Caveat Emptor: Quality Considerations

When reviewing data options, users need to ensure a good fit to their research question, while also critically assessing the quality of the data. There are many factors that influence quality, and it is beyond the scope of this chapter to create an exhaustive list (if such a task were even possible); however, there are a number of areas of concern to which researchers typically attend, including the characteristics of the original source material, the potential for coding errors, and possible conflicts of interest.

Most terrorism databases rely on open source material, particularly media reports.[15] Although open sources are an inexpensive and accessible way to gather data, they can also be problematic. One issue that causes data producers concern is coverage; in many cases, data are either missing or incomplete. In the case of terrorist attacks, media often underreport foiled or failed attacks, limiting the presence of these types of incidents in event databases. In addition, in certain areas of the world political violence is prevalent, such as remote areas in Nigeria, Iraq, and Afghanistan, but media representation is limited or nonexistent due to accessibility issues, which results in underreporting in these regions.

The attack on the *Charlie Hebdo* magazine headquarters in Paris in January of 2015 provides an example of this concern. On January 7th, 2015, assailants opened fire in the satirical magazine headquarters, resulting in a two-day chase and 17 victim fatalities. The event dominated headlines for weeks afterwards and even now, several years later, a media search of "Charlie Hebdo attack" results in nearly 100,000 individual hits.[16] Three days before the Paris attacks, Boko Haram raided Baga city in Nigeria, killing upwards of 2000 people over four days. In contrast to the Paris attacks, Western media failed to report on the Baga events until a week after the spree had ended and these reports were, for the most part, limited to a simple paragraph due to lack of information. BBC news, for example, first reported the attack on January 15th, stating that it was "faced with the challenge of trying to piece together the details so…[it]… can provide the most accurate picture of what really happened."[17] A media search of "Baga 2015 attack" produces less than 5,000 individual hits, even though the fatalities eclipsed Paris by more than 1,000 percent.[18] Quite simply, accurate and complete information on the Baga attack is not available. The stark contrast between Paris and Baga illustrates an important point: while there is little a researcher can do about the ability of the media to capture and accurately report terrorist activities around the globe, it would behoove the user to familiarize her/himself with the data producer's approach to potentially inaccurate and incomplete sources, as would be found in some remote areas. Does the data producer acknowledge issues related to coverage? Does it take measures to overcome

15 Neil G. Bowie, "Terrorism Events Data: An Inventory of Databases and Data Sets, 1968-2017," *Perspectives on Terrorism* 11, no. 4 (2017): 50.

16 The search was conducted by the author of this chapter while composing the first draft in the summer of 2019.

17 BBC, "Nigeria Boko Haram: What Really Happened in the Baga Attack," 2015.

18 The search was conducted by the author of this chapter while composing the first draft in the summer of 2019.

these issues whenever possible? In a similar vein, even if events are reported, databases often rely heavily on English-speaking sources, leading to an underrepresentation of information about foreign nations that have limited language sources. This results in an overrepresentation of information on terrorist events in Western nations or targeting Anglo-Western victims and an underrepresentation of data in non-Western and non-English settings. Is the data collection agency or institution capable of multilingual data collection? Does it report the use of non-English sources and/or does it have collection capacities in non-Western nations?

In addition to coverage, sources also influence data accuracy. Data accuracy may refer to missing values, factual errors, and inherent uncertainty. Do databases use valid sources? Do they triangulate their information using multiple sources? And do they use current and updated sources? Validity is a difficult metric to assess but some databases provide a source validity rating.[19] If they do not, the astute user will likely have informed opinions that can guide her/his assessment of potential source bias. Centrist media sources are ideal in comparison to left- or right-leaning sources but, when the latter are used, are they used together to present a balanced summary of each data point? Even if there is no discernible bias, databases should, whenever possible, employ multiple sources for each observation to ensure complete and accurate information about an event, person, or group. They should also prioritize current sources. It may take some time for complete and updated information to become available to the public, and if database producers rely on early media releases, they will likely report, among other factors, inaccuracies or uncertainties in casualties and perpetrator information.

In light of concerns about data accuracy, researchers should look for source information in potential datasets. Is the database transparent about the sources used? Does it provide a validity scoring metric and if so, is the researcher in agreement with that metric? Is triangulation required and is a premium placed on current sources? These are all source-related factors that can and should guide the assessment of data quality.

In addition to source characteristics, coding practices also impact data quality. Human coders are not infallible; they are subject to error and bias. Although this cannot be entirely eliminated, it can be minimized through a variety of ways. First, careful training is key; database producers are responsible for ensuring that coders take part in rigorous instruction and practice periods before coding real data. In addition, datasets should be assessed for interrater reliability or the degree of agreement or similarity between coders. This may involve having more than one trained person code the same dataset and then assessing the results using Krippendorff's alpha procedure or a similar statistical test.[20] Data users should, whenever possible, inquire about coder training processes and interrater reliability metrics.

19 A source validity rating refers to an explicit scoring system that ranks sources from low to high credibility. Each observation in the database, for example, will be informed by one or more external sources. When a source validity rating is included, the database will report the external sources and inform the user of the level of confidence the data collectors have in those sources.

20 Freilich and LaFree, 574. Krippendorf's Alpha is a statistical test that determines interrater reliability. It compares variable values across multiple coding sets and determines whether there is a significant difference in those values. If the differences across sets are minimal, interrater reliability is high and the coding strategy is considered reliable.

Some researchers advocate the use of computer algorithms and data crawlers to overcome human error.[21] Unfortunately, automated data collection methods also introduce error and are not a particularly sound option. In a study that compared automated, human, and hybrid data collection of suicide attacks, researchers found that automated processes exaggerated the number of attacks by creating duplicate and false events and reported inaccurate event characteristics.[22] Using five separate databases as a reference, the research team identified 136 unique suicide attacks that occurred globally over a two-month period in 2015. They then compared the number and characteristics of suicide attacks that each collection and coding process produced. Automated processes resulted in the erroneous identification of more than 5000 suicide attacks over the two-month period, including the successful assassination of the United States President Obama several times over, while human and hybrid processes were much more conservative, reporting between ten and 443 incidents, depending on the database. As for coding details, the automated process often led to inaccurate location information, erroneous attack resolution and outcomes, and the lack of topic segmentation. In other words, automated processes are not a panacea solution and may introduce a degree of error that exceeds human or hybrid processes.

Regardless of the method, researchers should carefully assess the data and look for potential inconsistencies (such as the successful assassination of President Obama). If there are inconsistencies, are they explained by coding strategies? In order to address this question, the data user will likely need to familiarize her/himself with the codebook and coding practices used by data developers.[23] Does the codebook describe how coders address ambiguities, a key source of coding inconsistency? Does it summarize the coder training process? Lastly, it is never a bad idea to discuss potential databases with other researchers. What impressions do others have of the data and do they have any cautionary tales to share?

The last area of concern relates to potential conflicts of interests.[24] Data users should consider the identity of the agency that produced the data and the characteristics unique to that agency. Is the agency independent or is it influenced by other groups or actors? Does it report its funding sources? Lastly, are there incentives to report the data in a particular way? For example, as described previously, a state-coordinated database may have reason to omit or edit events and details. However, state-generated data are not the only sources subject to reliability issues. Independent institutions may be funded by state or corporate interests, suggesting the potential for a conflict of interest. In simple terms, consider the credibility of the data producer before relying on the data.

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21 See, for example, Idean Salehyan, "Best Practices in the Collection of Conflict Data," *Journal of Peace Research* 52, no. 1 (2015). Also see Philip A. Schrodt, "Automated Production of High-Volume, Near-Real-Time Political Event Data," in *APSA 2010 Annual Meeting Paper*, 2010.

22 Brian Wingenroth, Erin Miller, Michael Jensen, Omi Hodwitz, and Kieran Quinlan, "Event Data and the Construction of Reality," in *International Conference on Social Computing, Behavioral-Cultural Modeling, & Prediction and Behavior Representations in Modeling and Simulation (SBP-BRiMS)*, 2016.

23 Quality public access databases will provide a codebook with the data that describes each variable, coding strategies, and database history and sponsorship. If a database does not provide a codebook…caveat emptor (buyer beware).

24 Yoshiko Herrera and Devesh Kapur, "Improving Data Quality: Actors, Incentives, and Capabilities" *Political Analysis* 15, no. 4 (2007): 372-82.

NAVIGATING ANALYSIS

After selecting a quality data source, the researcher can begin analyzing the data and testing relationships. At this point it might be wise to reiterate the caveat expressed in the chapter introduction: the goal of this section is not to produce quantitative experts but, instead, to offer some analytical options that the reader should explore further once she/he formalizes her/his research question and selects her/his data. Therefore, for the ease of instruction, this section will first identify broad research questions that often inform terrorism inquiries and suggest quantitative methods appropriate for addressing these questions. Before doing so, it is helpful to deal with a small amount of quantitative housekeeping, specifically differentiating between descriptive and inferential statistics and providing a brief introduction to control variables.

As the name suggests, descriptive or summary statistics describe a phenomenon of interest. For instance, what is the typical age, gender, and socioeconomic background of convicted extremists? How long, on average, do terrorist organizations last before they disband? Descriptive statistics involve the simple calculation of a number of metrics, including (but not limited to) the average (the mean), the most common occurring value (the mode), and the middle value in a ranked set of values (the median). Often, the research question can be addressed through the use of descriptive statistics alone, although using descriptive statistics is becoming increasingly more common in step with inferential statistics.

Inferential statistics go beyond simple description. Researchers take samples from larger populations of interest and make inferences or generalizations about the larger population based on the sample. Inferences may involve deriving estimates or assessing relationships between variables and outcomes. Many terrorism-related research questions rely on inferential statistics. For example, if a researcher is interested in assessing the relationship between aviation security measures and political violence, they may craft a research questions such as: do aviation security measures influence terrorist attacks on airports? In order to address this question, the researcher may select a sample of aviation security measures and (mindfully) select a database that reports terrorist attacks on airports. Using inferential statistics, the researcher can then examine whether terrorist attacks on airports increase or decrease following the implementation of these security measures. If results suggest a relationship, the researcher can then (cautiously) infer that aviation security measures influence terrorism.

Inferences can only be drawn when alternative explanations have been ruled out. Continuing with the example from the previous paragraph, it may be that political violence shifts due to other events that coincide with the implementation of aviation security measures but are not part of those measures, such as the introduction of cost-effective alternative means of travel or an outbreak of disease in the area of study that dissuades tourist travel. Results may show a relationship between security measures and political violence directed towards airports, but the relationship is actually due to another factor: a reduction in air travelers, thus decreasing the appeal of airports as a potential target for extremists. Researchers are required to consider alternative explanations or factors that may influence the outcome of interest and control for those influences.

Controlling for other factors means including a variable for each factor in the analysis. Control variables are kept constant (unchanging) so that they do not unduly influence the outcome of interest, allowing researchers to conclude that any observed variation or change in the dependent variable (the outcome variable) is due to the influence of the independent variable (the main explanatory variable). For the airport example, this would require including variables that recorded variations in alternative means of travel and outbreaks of disease or other health-related issues in the area of interest. If terrorist attacks on airports (the outcome or dependent variable) decrease following the implementation of security measures (the explanatory or independent variable), while holding stable any influence from alternative travel means and health-related issues (the control variables), the researcher can infer a relationship. The lesson here is to carefully consider other important influences and control for them; a failure to do so may produce results that do not accurately portray the relationship of interest.

With those clarifications in mind, the remainder of this section will focus on broad research questions and analytical strategies that can be used to address these questions. One cautionary note is necessary: analytical models or methods are not sentient entities, they will unquestioningly process data and produce statistics regardless of the fit between the data and the model. In other words, the analytical model or statistical test does not know when it is an inappropriate match for the research question or the data—only the researcher knows this. Therefore, it is the responsibility of the researcher to ensure that the analytical method is suitable for the question and data. Unfortunately, providing a detailed and exhaustive list of analytical models and their suitability for particular research questions and data is beyond the scope of this chapter. However, recommendations for additional readings are included when appropriate and the reader is encouraged to consult these resources.

Research Question: *How does one variable influence another variable?*

Analytical Strategy: Regression analysis

One of the more traditional questions asked of researchers is how one factor influences another or, in more concrete terms, how social, political, psychological, and economic variables impact terrorist-related events and developments. Does the accessibility of certain weapons influence incidents of political violence? Are national metrics of press freedom related to terrorist activity? Does terrorism affect tourism? These are all questions that can be answered using various methods of regression analysis.

Regression techniques examine the effects that one or more independent (explanatory) variables have on the dependent (outcome) variable, holding all else constant (controlling for alternative explanations). More specifically, regression techniques explore how variations in the value of the independent variable influence values on the dependent variable. A helpful way to understand regression is to refer to cross-tabulation (crosstabs) as a point of comparison. A crosstab is a descriptive tool that displays the relationship between two variables in a table.

For example, assume a researcher is interested in studying the influence of unemployment on terrorism and hypothesizes that an increase in unemployment results in an increase in terrorism. The researcher will gather unemployment rates (independent variable) from a number of countries and compare those to terrorism rates (dependent variable) in those same countries. A crosstab function would create a table that summarizes every possible combination between those two variables and how many countries fall within each of those categories. For the unemployment example, the first cell of the crosstab may denote low unemployment and low terrorism. The value in the cell will report the number of countries that fit that criteria. The next cell may record low unemployment and medium terrorism, with a third reporting low unemployment and high terrorism, and so on until all possible combinations are reported. If the relationship is supported, the researcher would expect to see more countries in the low unemployment/low terrorism and high unemployment/high terrorism categories than in the remaining cells.

Although this is useful when seeking an overview of a potential relationship, it does not tell us if that relationship is noteworthy or significant. In other words, how much do values between cells need to differ in order to conclude that there is a relationship? Regression analysis is designed to answer this specific question. It assesses whether increases or decreases in unemployment are significantly related to increases or decreases in terrorism. If changes in the former influence changes in the latter in a consistent manner (in the same direction with some degree of frequency), the model will determine there is a relationship that can be inferred from the results. If a relationship can be inferred, then we can form expectations based on that inference, allowing researchers to predict the circumstances under which they would expect to see changes in the dependent variable.

In addition, unlike crosstabs, regression allows researchers to include and control for the influence of additional variables. Unemployment may show a consistent relationship to terrorism rates but a number other forces could be at play (e.g. health metrics, participation in national and international conflicts, political cycles). Controlling for those factors increases confidence in resulting predictions. In other words, regression analysis does the work for the researcher; it tells the researcher whether, across countries, the values tell similar stories and if they do, what predictions can be made about countries not included in the sample, while also controlling for other factors.

There are different regression techniques, and researchers should be careful to select the appropriate option. Selections are based on the features of the dependent variable and the relationship assumed between the independent and dependent variables. Regarding the features of the dependent variable, this is determined by how the variables are measured. They may be nominal (they are dichotomous and only have a value of yes/no or 0/1), ordinal (the values can be rank-ordered, but that ordering does not have quantitative significance, such as small/medium/large), or interval/ratio (the values are continuous or have no upper limit, such as the annual income).

For example, binary logistical regression is ideal for a dichotomous or nominal dependent variable, one that assumes only two discrete outcomes. This statistical strategy would be suitable for studying factors that influence successful assassinations, hostage-takings, or other forms of political violence (these events did or did not occur resulting in a yes/no or 0/1 coding strategy). In contrast, ordinal logistical regression is appropriate for ordinal dependent variables only. A researcher interested in examining the relationship between democratic characteristics and citizen dissatisfaction with the government, for example, may hypothesize that more democratic countries will experience less citizen dissatisfaction. Although quantitative values can be assigned to the dependent variable (citizen dissatisfaction), it may be more accurate and/or efficient to rank satisfaction on a non-quantitative scale, such as low/medium/high.

Lastly, when addressing an interval/ratio or continuous variable, the researcher may opt for standard linear regression. This would be an ideal model if a researcher is exploring the influence of terrorism on, for example, tourism, as measured by tourist spending. In this example, terrorism is the independent variable and tourism spending is the dependent variable. Financial transactions of this sort have quantitative significance (the value between one dollar and two dollars is quantitatively informative) and no upper limit or cap and, therefore, is potentially a good fit for linear regression.

Linear regression, although often used in terrorism research, may not be appropriate for all studies involving continuous variables. This is due to the fact that, in addition to the features of the dependent variable, researchers can also often make an educated guess about the expected shape of the relationship and should select a statistical model that is appropriate for that shape. Linear regression assumes a linear relationship between variables (as the independent variable increases, the dependent variable is expected to increase or decrease in relative lockstep) and requires a continuous dependent variable (it has an infinite number of possible values). If a researcher is interested in examining the relationship between state oppression and citizen dissatisfaction with the government, the researcher will likely assume a linear relationship (as a metric of oppression increases, so too does citizen dissatisfaction). However, not all relationships are linear in nature. Polynomial regression, for example, allows for a curvilinear (bending) relationship between variables. An example of a potential curvilinear relationship might be found between state oppression and political violence. As state oppression increases, we would expect to see an increase in political violence; however, at a certain point, political violence may begin to decrease as the threat of incarceration, torture, or death at the hands of the state serves to deter further political protest.

This is, by no means, an exhaustive list of regression decisions, but it does illustrate the number of options available to researchers and that the selection of the appropriate model is informed by the characteristics of the dependent variable and the assumed relationship between variables. Regression models are some of the more popular analytical tools available to quantitative researchers and there are numerous texts that provide detailed summaries of these models. Some suggested sources for further reading include Richard Berk's book titled *Regression Analysis: A Constructive Critique* and Joshua Angrist and Jorn-Steffen Pischke's book *Mostly Harmless Econometrics: An Empiricist's Companion*.

Research Question: *How do trends or patterns change over time? How do select factors influence trends or patterns?*

Analytical Strategy: Time-series analysis

Time-series refers to a group of regression methods that can be used to identify and describe events across time and to predict or forecast future values of the phenomenon of interest. Time series models assume that the data will consist of: a) a pattern, and b) random noise, also known as unexplained variation in the sample data (in simple terms, there a great deal of change in the variables that could be due to random irregularities). This analytical strategy involves diminishing or muting the random noise in order to detect an underlying pattern. For example, when examining terrorist attacks, researchers have discovered that separating incidents involving casualties from those that do not involve casualties increases the predictability of incidents involving casualties, given that non-casualty events are largely random, consisting of irregular noise.[25]

If the goal of a particular study is to describe events across time, the pattern may be reflected by a trend (a linear or nonlinear change that does not systematically repeat itself, such as an observed decrease in voter turnout situated within a larger trend of increased voter turnout) or by seasonality (systematic repetition or cyclical change, such as violence consistently increasing in the hot summer months). Research has indicated that terrorism experiences cyclical patterns or seasonality that has little do with the research question at hand and, because of this, scholars tend to focus more on trends.[26] For example, how does terrorism change over time on a global scale? How does it change in individual countries?

In addition to describing changes over time, the researcher may also be interested in assessing factors that facilitate these changes. Time-series methods are popular for assessing the impact of policy on subsequent events or behavior. For example, how does the implementation of counterterrorism policy influence rates of terrorism? Do specific security measures decrease attacks? Does group decapitation influence political violence? Time series allows for the examination of the variable of interest (e.g. policy or leadership decapitation) on the lagged (temporally delayed) value of the phenomenon of interest (terrorism).

In order to use time series models, the researcher must have data reported in temporal intervals or in an equally spaced order. In other words, the data are observed at consistent successive points in time, such as daily, monthly, or annually. A database that reports monthly terrorism rates would be appropriate for time series analysis since it gives consistent temporally-anchored metrics. A database that reported single terrorist events would not be suitable since it reports observations that are not rooted in temporal intervals. However, the latter could be recoded from single events to rates in order to address pattern-related questions using time series analysis. For example, researchers often convert single event data from

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25 Walter Enders and Todd Sandler, "Is Transnational Terrorism Becoming More Threatening? A Time-Series Investigation," *Journal of Conflict Resolution* 44, no. 3 (2000): 307-32.

26 Enders and Sandler, 307-32.

the GTD into aggregate attack numbers simply by calculating the number of events listed within the temporal unit of interest (e.g. month) and recording that information in a new dataset. In addition to the number of attacks, the users may also calculate additional variables, such as the number of casualties or the frequency of attack and weapon types found within each temporal unit, increasing the scope of analysis that can be conducted with the aggregated temporal set.

In addition to ensuring that the researcher has temporally-defined data, she/he will need to consider whether the dependent variable is a rare event. It is difficult to conclusively detect patterns in rare events given that, by definition, they do not occur frequently enough for a consistent pattern to emerge. For example, if a country only experiences two terrorist attacks in one year but one of them occurs during a change of administration, can we confidently conclude that a change in leadership influences terrorism? Fortunately, there are analytical approaches designed to assess and predict rare events, such as a Poisson model. When assessing rare events over time, the researcher should explore rare event time series models as the appropriate choice.

To learn more about these considerations and the factors that influence model selection, readers are encouraged to review the following sources: Chatfield's *The Analysis of Time Series: An Introduction* and Brockwell, Davis, and Fienberg's *Time Series: Theory and Methods*.

Research Question: *How do patterns shift across space?*

Analytical Strategy: Geospatial analysis

Oftentimes, a researcher is interested in exploring spatial patterns of terrorism locally and around the world. While point maps (imagine sticking pins into a map) can help illustrate obvious clusters of terrorism, assessing whether these clusters are random and/or how they evolve over time entails a more sophisticated approach. Spatial data analysis techniques and programs can assist in evaluating spatial nuances. Geographic information systems (GIS) technology, a popular method of assessing geospatial data, maps longitude and latitude events, creating a final map that can be analyzed using tools that distinguish between random and non-random patterns. For example, researchers may choose to engage in geospatial analysis to determine if there is a pattern to terrorist violence in a select region or country. This can be used to identify hot spots of activity to which counterterrorism resources can be directed.

While many of the geospatial methods are cross-sectional (no temporal component), there are some analytical alternatives that allow for the assessment of spatial patterns over time, creating the opportunity to examine the evolution of patterns.[27] This kind of analysis offers researchers the chance to examine a number of fascinating questions. What is the spatial distribution of terrorism, for example, in multiple cities? How do those spatial distributions change over time? With this kind of analysis, researchers may begin to predict where additional points of activity will appear given the historical development of

27 See, for example, Jacqueline Cohen and George Tita, "Diffusion in Homicide: Exploring a General Method for Detecting Spatial Diffusion Processes" *Journal of Quantitative Criminology* 15, no. 4 (1999).

patterned violence. One cautionary note is necessary: although spatial analysis can facilitate understanding of and predictions about spatial patterns over time, it is not designed to assess the relationship between variables. In other words, if researchers were interested in examining whether the implementation of a particular policy halted the spread of terrorism in a specific region, they could use spatial analysis to observe patterns over time but not to statistically determine the significance of those changes.

To conduct spatial analysis, researchers need data that include geographical coordinates and, for more sophisticated analysis, user-friendly software with the capacity to assess data as the research question requires. There are a number of different sources that will aid the new researcher in working with geospatial data and in selecting appropriate analytical techniques and software. Recommended sources include De Smith, Goodchild, and Longley's *Geospatial Analysis: A Comprehensive Guide to Principles, Techniques, and Software Tools* and Haggett, Cliff, and Frey's *Locational Analysis in Human Geography*.

Research Question: *How do behaviors change over time? Are there distinct groups that experience similar changes? What factors influence behavioral changes?*

Analytical Strategy: Life-course analysis

One area of interest involves looking at how behaviors change over the life course or over time. Life-course analysis consists of several different modeling options. One method that is particularly relevant for terrorism research is trajectory analysis. This method gives researchers the opportunity to explore the trajectory or course of a variable over time as well as the influence of other variables on that course. Group-based trajectory modeling is particularly relevant, as it allows for the identification of distinct groups with similar trajectories of a phenomenon of interest, the assessment of the impact of different variables on that trajectory, and the influence of key factors on group membership.[28] Group-based trajectory models can be used, for example, to group extremist organizations based on their attack patterns and to identify factors that influence those patterns. It may also be used to examine geographical groups, such as nations that experience a particular kind or frequency of violence and the factors that facilitate membership in these groups.

Researchers considering this method should assess the dependent variable of interest and ascertain whether it is binary, continuous, or count—this will influence the type of model used.[29] In addition,

28 Daniel S. Nagin, *Group-Based Modeling of Development Over the Life Course* (Cambridge, MA: Harvard University Press, 2005).

29 Similar to other analytical strategies, the characteristics of the dependent variable determine the appropriate model. Logistic models are suitable for dichotomous or binary variables, censored normal models are appropriate for continuous variables, and Poisson models are ideal for count data. Laura Dugan and Sue-Ming Yang, "Introducing Group-Based Trajectory Analysis and Series Hazard Modeling: Two Innovative Methods to Systematically Examine Terrorism over Time," in *Evidence-Based Counterterrorism Policy,* ed. Leslie W. Kennedy (New York: Springer, 2012), 122.

researchers need to decide the number of groups they would like the model to identify and the shape that the trajectory can take. Making these decisions requires testing a variety of combinations to ensure the best fit. Although group-based trajectory models are necessary to answer key questions relating to extremist violence, they are not for the faint of heart. Any researcher considering their use would be best served by reviewing the pivotal piece by Daniel Nagin titled *Group-Based Modeling of Development Over the Life Course*.

Research Question: *How do the type and intensity of group ties influence politically violent groups?*

Analytical Strategy: Network analysis

The last research question discussed in this chapter involves examining the structure and characteristics of social networks. Network analysis focuses on the network structure or how individuals or groups are connected or linked. It consists of two layers: a graphical component that can map the relational connections or links between people and a statistical component that allows the researcher to examine how these ties shape individual behavior, group dynamics, and collective action. For example, network analysis can be used to assess the centrality of a particular person in relation to others in the network, to detect subnetworks within the larger network, and to assess the development of networks through new links. One timely use of network analysis is the examination of online behavior through the assessment of social media sites and other websites. Another important application involves the use of computer simulations of violent networks to assess the effectiveness of proposed counterterrorism strategies on group survival and continued violence. For example, running simulations with varying counterterrorist approaches can indicate how networks will respond and adapt to state opposition.

To use this method, researchers need to define the boundaries of the network. What decides the inclusion or exclusion of specific individuals? Is this determined based on the preexisting knowledge of the researcher? Or should it be determined by the subjects themselves or more, specifically those that claim membership? Both options require some consideration. Regarding the former, the researcher may not be fully aware of the extent of the network and regarding the latter, there are those who claim and deny membership falsely.

Another issue arises if the data for the network are not complete. It is difficult or, in many cases, impossible to gather comprehensive information on terrorist networks. Results may be incomplete or misleading if key nodes and subsequent links are not included in the analysis. Fortunately, there are analytical strategies that allow the researcher to examine covert organizations when information is limited.[30]

A third area of consideration is the ties or links included in the analysis. When using network analysis, researchers must decide if they are interested in a variety of characteristics including, among others, cen-

30 To do so, the researcher must have knowledge of traditional network structures and predictive modeling.

trality (the number of links or connections to the node or actor), influence or strength (the influence of one node on the neighboring nodes), direction (unidirectional or bidirectional), and symmetry (equal or unequal in directional strength or influence). These decisions will determine the appropriate analytical strategy to apply to the data.

Given the graphical component of this analytical approach, researchers generally use sophisticated software to conduct network analysis. Researchers interested in the technique should exercise care when selecting the appropriate software and analytical strategy. A good place to start would be to read Wasserman and Faust's book titled *Social Network Analysis: Methods and Applications*.

BEST PRACTICES

Ideally, by this time, the reader has concluded that carrying out quantitative research requires careful consideration and know-how but is not an inaccessible means of examining terrorism. Although this chapter did not provide an exhaustive list of all the factors that may be important when researching terrorism, it did highlight some of the key issues that regularly arise. These frequently occurring issues have resulted in a set of best practices or principles that, although applicable to all forms of research, are particularly salient when using quantitative methods. These principles are an ideal way to compartmentalize and address the various concerns raised above and, therefore, the chapter will conclude with a brief description of three particularly significant principles. These include: knowing your data, knowing your methods, and being transparent about your decisions.

Know your data. As summarized previously, knowing your data refers to a number of factors, including knowing the unit of analysis, variable definitions, the codebook and coding strategies, source information, and so on. A failure to familiarize yourself with the data can lead to erroneous decisions that make analysis difficult or subject to error. To briefly illustrate this point, this author was invited to consult on a project that involved the amalgamation of two datasets, the first of which was produced by a non-governmental organization and the second by a governmental organization. The two parties had been working on the project for some time before asking for assistance. Upon reviewing the datasets, it became clear that they could not be easily merged; the two parties had failed to recognize that each dataset reported a different unit of analysis (terrorist attacks for one and annual metrics of terrorism for the other) and had, up until that point, been attempting to mash them together to no avail.

Know your methods. Knowing your methods can be a difficult and time-consuming but absolutely necessary endeavor. You should consider the research question and the group of analytical strategies or models available to address the question. You will need to think about the characteristics of the dependent variable and the relationship that it is believed to have with the independent variable. With these factors in mind, you should select the method that appears appropriate and then engage in further study of it to confirm that it is the best fit for the question and the data. You may want to review studies that describe the method to ensure that you are versed in its use and, when possible, consult with colleagues who have quantitative backgrounds. Lastly: practice. This can be accomplished by finding and replicating a study that uses your chosen analytical model or method and has publicly available data. If you can replicate the results reported in the study, you are likely using the model correctly. This author's own experiences demonstrate the importance of this practice or principle. Within the parameters of a quantitative research methods course, this author gave her students an often-cited terrorism-related empirical study to critique. Although the students were expected to focus only on the relationship between the research question and variable selection, one enthusiastic student opted to replicate the analysis with the publicly available dataset. Much to the student's surprise, his results did not match the results reported in the original article. Upon closer inspection, it became clear that, although the dependent variable was ordinal, the original author had erroneously applied a regression model that was appropriate for continuous dependent variables only, resulting in biased or erroneous outcomes. The original author had reported significant results when, in fact, the relationship disappeared when the proper analytical strategy was applied. On a side note, the student did quite well in the course and continued on to become an analyst.

Be transparent. If you are transparent about the decisions that you make at key points in the research process, it lends credibility to your choice of data and methods and, thus, your results. In addition to the choices that you make, you should be explicit about weaknesses inherent in your research. If there are issues that arise in your study, you should acknowledge them and provide justification for proceeding with your research. If you do not acknowledge potential shortcomings, it is likely that someone else will. An example from this author's days as a student demonstrates this awkward possibility. An applicant for a faculty position presented his research on radical individuals to a group of quantitatively-inclined students. What the applicant failed to acknowledge during his presentation (but was pointed out by one of the graduate students) was the uncomfortable fact that he was missing information on the vast majority of his sample. The researcher had treated the missing information as a non-issue and proceeded with his analysis, concluding that his results applied to all radical individuals in his study and, to a lesser extent, to the larger population. Perhaps not surprisingly, the applicant did not get the faculty position for which he was applying.

The final message of this chapter is to pair the cautions and considerations described throughout the chapter with the best practices summarized above. Doing so will better prepare the reader to engage in high-quality and well-informed research. Doing 'bad' research can have damaging effects to the researcher, the practitioner, and the policymaker. Doing 'good' research, although difficult, can contribute in significant ways to our understanding of radical violence.

SOURCES

Ackerman, Gary A. and Lauren E. Pinson. "Speaking Truth to Sources: Introducing a Method for the Quantitative Evaluation of Open Sources in Event Data." Studies in Conflict & Terrorism, 39, no. 7-8 (2016): 617-40.

Angrist, Joshua D. and Jorn-Steffen Pischke. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton: Princeton University Press, 2008.

BBC. "Nigeria Boko Haram: What Really Happened in the Baga Attack." January 15, 2015. https://www.bbc.com/news/av/world-africa-30838153/nigeria-boko-haram-what-really-happened-in-baga-attack

Berk, Richard A. Regression Analysis: A Constructive Critique (vol. 11). Thousand Oaks: Sage Publications, 2004.

Bowie, Neil G. "Terrorism Events Data: An Inventory of Databases and Data Sets, 1968-2017." Perspectives on Terrorism 11, no. 4 (2017): 50-72.

Brockwell, Peter J. and Richard A. Davis. Time Series: Theory and Methods. New York: Springer Science & Business Media, 1991.

Chatfield, Chris. The Analysis of Time Series: An Introduction. Boca Raton: Chapman and Hall/CRC, 2016.

Cohen, Jacqueline and George Tita. "Diffusion in Homicide: Exploring a General Method for Detecting Spatial Diffusion Processes." Journal of Quantitative Criminology 15, no. 4 (1999): 451-93.

De Smith, Michael J., Michael F. Goodchild, and Paul A. Longley. Geospatial Analysis: A Comprehensive Guide to Principles, Techniques and Software Tools. Kibworth: Troubador Publishing Ltd, 2007.

Dugan, Laura, and Sue-Ming Yang. "Introducing Group-Based Trajectory Analysis and Series Hazard Modeling: Two Innovative Methods to Systematically Examine Terrorism over Time." In Evidence-Based Counterterrorism Policy, 113-49. Edited by Leslie W. Kennedy. New York: Springer, 2012.

Enders, Walter and Todd Sandler. "Is Transnational Terrorism Becoming More Threatening? A Time-Series Investigation." Journal of Conflict Resolution 44, no. 3 (2000): 307-32.

Freilich, Joshua D. and Gary LaFree. "Measurement Issues in the Study of Terrorism: Introducing the Special Issue." Studies in Conflict & Terrorism 39, nos. 7-8 (2016): 569-79.

Haggett, Peter, Andrew David Cliff, and Allan E Frey. Locational Analysis in Human Geography. New York: John Wiley and Sons, 1977.

Herrera, Yoshiko and Devesh Kapur. "Improving Data Quality: Actors, Incentives, and Capabilities." Political Analysis 15, no. 4 (2007): 365-86.

Horgan, John G. Walking Away from Terrorism: Accounts of Disengagement from Radical and Extremist Movements. Abingdon: Routledge, 2009.

Jenkins, Brian Michael and J. J. Johnson. International Terrorism: A Chronology, 1968-1974. Santa Monica: Rand Corporation, 1975.

LaFree, Gary and Laura Dugan. "How Does Studying Terrorism Compare to Studying Crime?" In Terrorism and Counter-Terrorism, 53-74. Edited by Mathieu Deflem. Amsterdam: Elsevier, 2004.

Nagin, Daniel S. Group-Based Modeling of Development Over the Life Course. Cambridge: Harvard University Press, 2005.

Salehyan, Idean. "Best Practices in the Collection of Conflict Data." Journal of Peace Research 52, no. 1 (2015), 105-09.

Schmid Alex, P. and Albert J. Jongman. Political Terrorism: A New Guide to Actors, Authors, Concepts, Data Bases, Theories, & Literature. New Brunswick: Transaction Publishers, 1988.

Schrodt, Philip A. "Automated Production of High-Volume, Near-Real-Time Political Event Data." In APSA 2010 Annual Meeting Paper. 2010.

Sheehan, Ivan Sascha. "Assessing and Comparing Data Sources for Terrorism Research." In Evidence-Based Counterterrorism Policy, 13-40. Edited by Cynthia Lum and Leslie W. Kennedy. New York: Springer, 2012.

Wasserman, Stanley and Katherine Faust. Social Network Analysis: Methods and Applications. Cambridge: Cambridge University Press, 1994 .

Wingenroth Brian, Erin Miller, Michael Jensen, Omi Hodwitz, and Kieran Quinlan. "Event Data and the Construction of Reality." In International Conference on Social Computing, Behavioral-Cultural Modeling, & Prediction and Behavior Representations in Modeling and Simulation (SBP-BRiMS). 2016.Implications for Policy and Practice

INSIGHT INTO VIOLENT EXTREMISM AROUND THE WORLD

The RESOLVE Network is a global consortium of researchers and research organizations committed to delivering fresh insight into violent extremism around the world. The Network provides access to open-source data, tools, and curated research to ensure policy responses to violent extremism are evidence based. Members of the Network work in parts of Africa, Asia, Europe, and the Middle East to promote empirically driven, locally defined responses to conflict and to support grassroots research leadership on violent extremism.

Our partners operate in more than 25 countries where challenges with conflict are an everyday reality. We are passionate about amplifying credible local voices in the fight to mitigate the destabilizing risks of social polarization and political violence. The RESOLVE Network Secretariat is housed at the U.S. Institute of Peace, building upon the Institute's decades-long legacy of deep engagement in conflict-affected communities.

To learn more about the RESOLVE Network, our partners and how to get involved visit our website, www.resolvenet.org, and follow us on Twitter: @resolvenet.

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