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Modeling Terrorist Attacks: Assessing Statistical Models to Evaluate Domestic and Ideologically International Attacks

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ABSTRACT

Many prior studies have analyzed how country characteristics affect the rate of terrorist violence and there is a growing literature on how group traits influence terrorist violence. The current study expands on this literature by using multilevel modeling to assess both these units of analysis on the rate of domestic attacks and the rate of attacks against foreign targets. Using data from the Big Allied and Dangerous and the Global Terrorism Database, a cross-national sample of 224 terrorist groups are modeled in relation to their countries of origin to assess rates of domestic attacks. In this cross-sectional study many of these terrorist groups target multiple foreign countries. Multiple membership random effects modeling (MMREM) is used to assess the impact of multiple countries targeted by a group. The results of the study indicate that multilevel modeling provides an improved statistical fit and the MMREM model provides an improved measurement for analyzing attacks targeting foreign countries.

Terrorism researchers have long been interested in factors that influence violent group behavior; however, the empirical cross-national comparison of terrorist groups in relation to the unique social and political contexts they target has largely gone unstudied. Although terrorism is a topic studied by multiple academic disciplines using a variety of research methodologies,[1] reviews of the literature show there have been far fewer sophisticated statistical studies examining terrorism compared to other subject areas.[2] Most terrorism research is comprised of exploratory or descriptive case studies providing anecdotal evidence of trends, but lacking empirical validation or suitable statistical comparisons.[3] Previous research has generally focused on a single level of analysis, primarily looking at individuals labeled as terrorists (the individual level), and the rate of terrorism experienced by countries (the country level), and more recently at the behavior of terrorist groups (the group level). Although theories have suggested the importance of each of these levels of analysis in explaining terrorist violence, there is a lack of literature on this subject that uses analysis to properly assess multiple units of measurement.[4] This article expands on the prior literature by using multilevel modeling to evaluate how two levels of measurement, the terrorist group and the country targeted, influence terrorist attacks.

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Most quantitative studies of terrorism evaluate the rate of transnational terrorist attacks due to the availability of terrorist incident level data. Many studies use the International Terrorism: Attributes of Terrorist Events (ITERATE) data, which consist of transnational attacks between 1968 and 2009. Studies show, however, that domestic attacks far outnumber transnational attacks.[5] The Global Terrorism Database (GTD), is commonly used because it includes both domestic and international attacks between 1970 and 2014. Domestic and international attacks were not officially distinguished in the GTD prior to June 2015.[6] At this time the GTD was updated and now includes variables distinguishing domestic attacks from various types of international terrorist attacks. The current study expands on the literature by separating the analysis of two types of terrorist attacks, domestic attacks and ideologically international attacks, and compares the analyses to determine if there are different factors that affect the rate of attacks against domestic and international targets.

This article follows with four sections. The first section discusses the existing literature and theoretical arguments that lead to the aims of this study. The aims are to compare factors affecting the rate of domestic and ideologically international terrorist attacks, and to assess the methodological value of specific statistical techniques, multilevel modeling and multiple membership random effects modeling (MMREM), to evaluate these relationships. The second section describes the sources of data used in this study, the sample, the measures used in the analyses, and the methodology. The third section presents the results of the analyses comparing the rate of domestic attacks and the rate ideologically international attacks, and the last section is the discussion relating the findings to the existing literature.

Evaluating Domestic and Ideologically International Terrorist Targets

Terrorism is a coercive means of communication, once labeled propaganda by deed.[7] An attack is meant to display a show of force to the opposition. The target selected for an attack is often related to the group's ideology and the message the group seeks to convey. Some terrorist groups select specific targets, whether a distinct politician or a category of people like the police. These groups may intend to operate by attacking the perceived opposition while intending to avoid harming others. In contrast, some groups appear to attack indiscriminately by carrying out attacks on transport or in civilian populated areas seeking to cause mass casualties.[8] In either extreme, the targets serve a symbolic purpose. Specific targets may epitomize the ruling power in a country while nameless civilians may represent a group's social, political, and economic enemy. Terrorist groups select their targets in relation to their ideological predispositions and what they perceive as their opposition. Some groups' ideologies emphasize local issues and, relatedly, domestic targets to combat. Other groups' ideologies focus on the foreign enemy, whether due to perceived victimization from political or economic policies, or a perceived threat in a conflict between cultures. There are also groups with local and global grievances that may conduct attacks against domestic as well as international targets. In each case it is necessary to consider how a terrorist attack is related to both the group carrying it out as well as the target. Analyzing either the target or the group rather than both may pose significant measurement and theoretical concerns.

The relationship between the terrorist group and the target is used to distinguish domestic from international terrorist attacks.[9] Terrorist attacks involve at least three nationalities—the nationality of the group perpetrating the act, the nationality of the target(s), and the country in which the attack takes place. A terrorist attack is considered domestic when all three of these nationalities are the same. Attacks where at least one of the nationalities is not the same are considered international attacks. International terrorism takes a variety of forms.[10] One type, called an ideologically international terrorist attack, is when there is a difference between the nationality of the terrorist group and the target(s). These attacks indicate the intentions to inflict violence toward a symbol of a foreign country.

Domestic terrorism is often described as a cycle of violence and political conflict between extreme factions and the state.[11] I argue that terrorist groups' development and violent behavior is a product of the group in relation to the political and social context in which they operate. Similarly, international attacks imply unique relationships between the group and the foreign country being targeted, and imply the limitations of an analysis solely focused on a single unit of analysis.

Many theories focus on either the micro or macro factors influencing behavior. Ecological theory provides a comprehensive framework for explaining how both micro and macro factors in conjunction affect behavior. Ecological theory explains that all human activity is a product of the unique individual in relation to a specific environmental context.[12] This theory explains that there is a symbiotic relationship between units of analysis that affect behavior.

Applying ecological theory to terrorism implies that there is a symbiotic relationship between a terrorist group and the country targeted (whether domestic or foreign) that affects violent behavior.[13] Terrorist groups are clustered by countries they target with different social, political, and economic contexts that influence how groups develop and operate. The mechanism of exposure to these contextual factors differs for domestic terrorism and ideologically international terrorism. Groups focusing on domestic attacks develop within the social and political constructs it seeks to combat. In comparison, I argue that the social construction of foreign threats is different and based on exposure to members of the foreign country or the effects of foreign policy within the home base country (e.g.. military occupation, tourists, politicians) or to how a foreign culture and political agenda gets socially constructed in the media and second hand knowledge. Though both types of terrorist attacks are the product of the terrorist group and the symbolic target, the different means of exposure suggest the value of modeling these types of attacks separately for comparison. Ecological theory provides the conceptual framework for the measurement of how group traits and country traits influence domestic and ideologically international attacks that relates well to the data analysis used in this article.

This study seeks to identify group and country traits that influence terrorist attacks targeting the domestic country and foreign countries. Specifically, this study analyzes two different outcome variables to measure the impact of these distinct relationships on the rate of domestic and ideologically international attacks conducted by groups between 1998 and 2005. The analysis expands on the previous literature by using multilevel modeling to compare how two units of analysis, the terrorist group and the country targeted, influence the rate of terrorist attacks. These models show the direct effects of group traits as well as the direct effects of the country contextual factors on the outcome variable. Multilevel modeling assumes single-membership of level one units (i.e., that terrorist groups are situated in relation to a single country). This is a valuable statistical tool for analyzing these two units of analysis on the number of domestic attacks a group conducts, where the country of origin is the only nationality targeted in these attacks.

International attacks, however, may not be limited to attacks targeting a single foreign country (see Figure 1). In this cross-sectional study of ideologically international attacks there are many groups that target multiple foreign countries. For example, Al Qaeda has attacked many foreign targets, including the United States, France, and Turkey, far removed from the group's home base in Pakistan.[14] Ecological theory suggests that the frequency of international attacks targeting foreign countries is influenced by each of the countries targeted. To properly assess the influence of how country characteristics influence the rate of ideologically international attacks it is necessary to include all of these countries in the equation. This study contributes to the literature both methodologically and conceptually by using MMREM analysis to include the measures of multiple foreign countries and tests whether this is a more accurate method for modeling the rate of ideologically international attacks.

MMREM has been used predominantly in the education literature to model students' academic outcomes within schools, and include multiple schools for students who changed schools throughout the time period assessed.[15] Without MMREM only a single country can be modeled for all the attacks in the cross-sectional time period. Modeling international attacks with a single country, even if it is the most frequently targeted, may misestimate the influence of country level characteristics. The influence of regime type on ideologically international attacks, for example, will not be properly assessed if a group targets a foreign democratic country ten times and targets three foreign countries that are not democratic nine times each. In this case the influence of non-democratic regimes will be excluded simply because these states individually had fewer attacks than the democratic regime. In this analysis one cannot properly assess the effect of democratic regimes on the rate of ideologically international terrorist attacks. MMREM allows multiple countries that are targeted to be included in the analysis. Countries are weighted specific to each group in the MMREM analysis to ensure the countries, and the corresponding traits, are measured in proportion to the rate of ideologically international attacks associated with each country. Ecological theory provides the logical mechanisms underlying the use of MMREM analysis for properly assessing international attacks that typically involve multiple foreign countries.

The prior literature has investigated separate units of analysis in the quantitative study of terrorism. The following subsections discuss the literature on the two levels of measurement included in this study: the country at level two and the group at level one.[16]

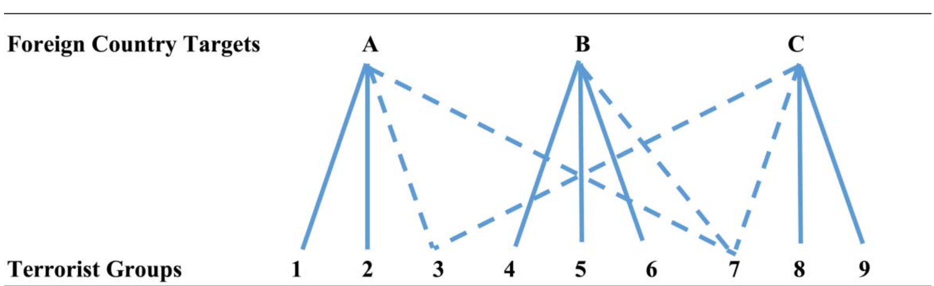

Figure 1. Multiple membership data structure depiction. The solid line depicts the terrorist groups that only target a single foreign country, while the dotted line indicates a terrorist group that targeted multiple foreign targets. This figure depicts terrorist group 3 targets both country A and country C. Terrorist group 7 targets countries A, B, and C. The remaining groups only conduct foreign attacks against a single country.

Country Factors

Terrorism has a small base rate compared to many other types of crime, making it difficult to conduct accurate statistical assessments.[17] Large samples are often obtained by analyzing terrorist attacks in the aggregate. For example, there are a number of studies that have evaluated the influence of country characteristics on the rate of terrorist attacks.[18] The rates of terrorism are not equal across nations, but rather terrorist attacks are concentrated in specific countries and regions.[19] Political scientists and economists dominate the empirical analysis of how structural factors influence terrorism rates. These studies highlight important theoretical constructs of how the social, political, religious and demographic characteristics in a country may influence the rate of violence in the region.[20] Sometimes these studies show consistent results, such as the statistically insignificant role of poverty.[21] There are other studies that, when compared with each other, show conflicting results. For example, there are studies that suggest democracies are more prone to terrorism, while other studies have found the democratic regime to be associated with fewer terrorist attacks.[22]

These studies highlight contextual factors that may be associated with the risk of terrorist violence. Countries differ dramatically in political structure, social demographics (population diversity and economic factors), as well as the methods used by the country to combat perceived opposition. By aggregating the terrorist attack data to the country level these studies rarely distinguish whether the attack is domestic and conducted by a group that developed in that region, or if an attack is international and carried out by a foreign group and/or against a foreign target.[23] Scholars have noted that these country characteristics may have differing effects on the likelihood of being targeted in domestic versus international attacks.[24] Few studies evaluate country-level predictors of terrorism separately modeling whether the country is where the perpetrating group originated (domestic attacks) or the country is the location or victim of international attacks.[25] These studies focus on the single unit of analysis, the country, and do not account for the different types of groups conducting attacks. The current study expands on this literature by comparing how country characteristics influence attacks targeting countries of origin to attacks targeting foreign countries while also modeling group-level indicators.

Group Factors

Just as countries differ, there are substantial differences between terrorist groups. Group ideology is highlighted in the literature as the motive behind their actions and encompasses values and objectives behind the group's aims.[26] The decision of who to target in an attack may differ dramatically depending on the group's goals. The ability to conduct an attack may differ among terrorist groups that have different resources. Resources include, but are not limited to, the number and abilities of group members, the financial resources available to a group, and the number of alliances the group has with other terrorist groups. Group longevity differs substantially. Most terrorist groups exist for very short periods of time, while others operate for decades.[27] Older groups have longer time periods to carry out attacks than short lived groups, which may mean older groups will be associated with a higher rate of attacks. In contrast, older groups may be more strategic in limiting the amount of violence to maintain an optimal balance between financial and political support.[28]

Few studies, other than qualitative case studies, have focused on the terrorist group–level of analysis.[29] Case studies of terrorist groups offer valuable information comparing groups or explaining group behavior in relation to the larger political, social and historical context; however, the information cannot be generalized to contribute to the understanding of terrorist trends or distributions.[30] There are a few studies that have quantitatively analyzed how terrorist group traits influence whether a group is lethal, the degree of lethality, and the targets of attacks. These studies show that religious ideology and larger group size are significant predictors of fatalities,[31] while these traits as well as more alliances to other terrorist groups and religious-ethno-nationalist groups are associated with attacking unprotected facilities and people, often referred to as "soft targets."[32] These studies offer a significant contribution to the literature for empirically showing how violence differs across various types of terrorist groups. These studies include control variables for the home base country, such as a proxy for wealth, military spending, and the political regime.[33] These analyses, however, are single level models that do not include random intercepts to model differences between countries and are not designed to optimally handle unbalanced data where groups are not evenly dispersed among countries.[34]

In addition to these traits it is worth noting that not all terrorist groups conduct violence in the same way. Some groups use suicide attacks while other groups do not intend to physically harm people and call in warnings before a bomb explodes. Some groups target specific individuals while others attack indiscriminately. Similarly, some groups primarily conduct domestic violence, while other groups focus on foreign targets. The differences among terrorist groups and their behaviors indicates the potential problem of modeling all terrorist incidents the same and aggregating the total attacks conducted by a group. Similarly, modeling attacks in the aggregate at the country level does not account for the different types of groups carrying out attacks. Conceptually, it is important to model the different characteristics of the terrorist groups for drawing comprehensive understanding of terrorist violence. Methodologically, it is important to properly attribute statistical variance that may be better explained by the terrorist groups than the country characteristics. Aggregating terrorist attacks misestimates the model by including group and contextual characteristics in the same regression model. This misestimation is a significant problem because it reduces the ability to analyze the group and contextual factors that explain statistical variability unique to each level of analysis. The next sections of this article explain how this study aims to expand on this literature by using multilevel modeling and MMREM for measurement of the rate of domestic and ideologically international attacks.

Aims of the Study

The current study expands on prior literature by evaluating how the traits of a terrorist group as well as the characteristics of the targeted country affect the rate of domestic attacks and ideologically international terrorist attacks. The purpose of this study is to compare models evaluating the rates of attacks to determine the most appropriate form of measurement, conceptually as well as methodologically. This article has two related aims. The first is to determine if there are different predictors for domestic attacks compared to ideologically international attacks. The distinct relationships between terrorist groups and the different types of targets (i.e., domestic or foreign) suggests the conceptual value of modeling these outcome variables separately for comparison.

The second aim is to assess different statistical modeling techniques for measuring what factors influence the rate of different types of terrorist attacks per group. Multilevel modeling is a statistical method that disaggregates the data to evaluate how the variables of each level influence the dependent variable, controlling for all other variables in the model. The current study uses this methodology to measure the direct effects of traits at level one, the terrorist group, and the direct effects of the characteristics of countries targeted at level two on two separate outcome variables: the rate of domestic attacks and ideologically international attacks. Two-level and three-level models are very common in literature evaluating crime and criminal justice as well as other fields of study, such as education.[35] Multilevel modeling, however, has only been used in a few studies on terrorism that focus on the United States.[36] Multilevel modeling has not yet been used to study terrorism cross-nationally and account for the unique relationships between terrorist groups and the countries targeted in attacks. This study evaluates the use of this statistical modeling for these outcome variables and assesses if these models have a preferred statistical model fit.

As previously discussed, the methodological and theoretical benefits of including additional country contexts for groups that conduct attacks against multiple foreign countries suggest MMREM should improve the analysis of ideologically international attacks. This study tests the statistical fit of the MMREM model in comparison to the multilevel model that assumes single membership to address the second aim of the study. The following sections detail the data, sample, and research design used to assess these aims.

Data and Methods

Most of the research on terrorism relies on open-source data, which is information accessible from the media, government reports, nongovernmental organizations, and other relevant secondary sources.[37] These types of sources have limitations regarding scope, bias, and difficulty verifying accuracy; however, Silke emphasizes the benefit of using inferential statistics that add a level of control when working with data obtained from open-source research.[38] The following sections of this article discuss the sources of data for the study, the variables being measured, and the data analysis.

Global Terrorism Database (GTD)

The GTD is an event database that codes information on domestic and international terrorist attacks around the world from 1970 to 2014. The GTD is one of the most often cited terrorist incident databases and is the most comprehensive and frequently used incident dataset that includes both domestic and international terrorist attacks.[39] In total, the dataset includes over 141,900 cases. For each attack, the GTD includes information on where and when the incident occurred, the weapons used, the target(s) of the attack, the number of fatalities, and the perpetrator (i.e., group name) when it is known. The most recently released version of the GTD includes variables indicating if an attack is domestic or international.[40] The data are collected via open-source research, and use information reported by the media, government, and nongovernmental sources.[41]

Big Allied and Dangerous (BAAD)

The BAAD dataset is one of very few cross-national terrorist group–level datasets.[42] The dataset was created to examine what factors contribute to group lethality. The BAAD dataset quantified information from the Memorial Institute for the Prevention of Terrorism (MIPT)'s Terrorism Knowledge Base ® (TKB®), and then extended the data through verification and open-source coding. These researchers used a list of databases, websites, and search engines for coders to use when collecting data. The prior cross-national studies on lethality and soft-targets described previously used the BAAD dataset.[43]

There are 395 terrorist organizations that conducted at least one attack and operated between 1998 and 2005 in the cross-sectional dataset.[44] The dataset lists the country of origin, referred to as the home-base country, for each group and includes information on each group's ideology, size, the number of allies with other terrorist groups, the age of the group, state financial sponsorship, and whether the group ever controlled territory.

Quality of Government (QoG): Country Data

Most of the information regarding country characteristics used in this project come from multiple datasets made available by the QoG Institute at the University of Gothenburg in Sweden.[45] The data are described as a "pool of variables gathered from other original or secondary sources."[46] The QoG Institute is primarily interested in research on good governance and has multiple datasets publically available for researchers. Country level measures in this dataset span a wide variety of topics, including measures of regime type, Gross Domestic Product (GDP), social diversity, and measures of human rights violations.

Sample Description

This study looks at the measurement of terrorist group traits and country characteristics on the rate of domestic and ideologically international terrorist attacks. Terrorist groups were selected that are included in both the BAAD and GTD datasets.[47] This study is a cross-sectional analysis of groups between 1998 and 2005 because this is the time period for which the BAAD data are available. It is important to acknowledge that over half of the attacks in the GTD are conducted by unknown perpetrators. In this time period, specifically, 5,069 of the total 11,819 attacks are coded as perpetrators unknown.[48] The perpetrators coded for attacks in the GTD are not all due to groups claiming responsibility, but rather include an educated guess by START staff members based on the information found in media sources. Some of these attacks without known perpetrators may have been conducted by groups included in this study, but based on the information available these attacks were not attributed to these groups. To measure the influence of group traits this study only includes attacks where responsibility was attributed to groups in the sample. This study does not account for the attacks conducted in this time period by unknown perpetrators, or by groups that are not in the BAAD dataset.[49]

In this study the sample is 224 terrorist groups, listed in Appendix A.[50] These groups conducted 2,758 domestic attacks and 1,293 ideologically international attacks between 1998 and 2005. Table 1 shows how many of the groups in the sample conducted domestic attacks (60.71 percent) and ideologically international attacks (55.80 percent).

The number of countries included in the analysis differs according to the dependent variable. The analysis of domestic terrorist attacks includes 54 countries of origin, which are depicted in Figure 2. India is the home base country to 22 groups in the sample, while some

Table 1. Sample depicting the number of groups that conduct domestic and ideological international attacks ($N = 224$).

Target of attacks	Number of groups	Percentage of sample
Domestic attacks	136	60.71
Ideologically international attacks	125	55.80
Ideologically international attacks targeting one foreign country	69	30.80
Ideologically international attacks targeting two foreign countries	25	11.16
Ideologically international attacks targeting three foreign countries	8	3.57
Ideologically international attacks targeting four foreign countries	23	10.27

countries have only a single group. The number of terrorist groups varies across countries, which means the data are unbalanced for both dependent variables (see Appendices B and C). Fortunately, multilevel modeling is able to operate with unbalanced data. Tabachnick and Fidell state that "unequal sample sizes at each of the levels poses no problems and are, indeed, expected."[51]

There are 66 foreign countries that were targeted by these groups between 1998 and 2005 and modeled in the ideologically international attacks.[52] A graphic depiction of the foreign countries is shown in Figure 2 and are listed with the number of groups in the sample that targeted each foreign country in Appendix C.[53] There are some groups that did not conduct any ideologically international terrorist attacks. Rather than excluding these groups from the

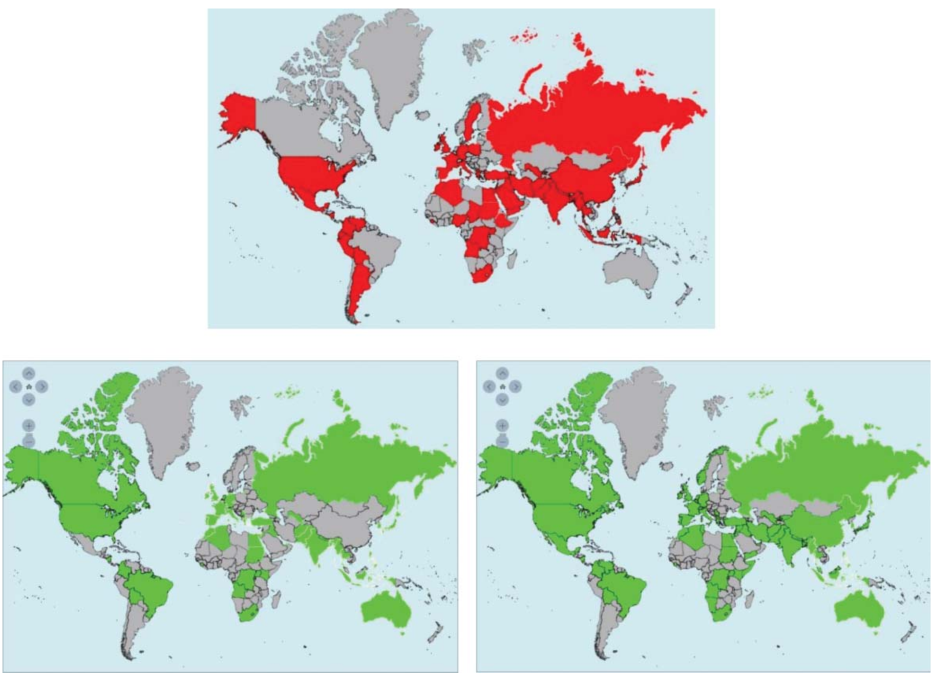

Figure 2. Maps with shaded countries included in the models. Red countries ($N = 54$) are the home base countries for domestic attacks included in Models 1 and 2. The first map of green countries ($N = 54$) depicts the most frequently attacked foreign target by each group, which are included in models 3 and 4 of the ideologically international attacks. The second map of green countries ($N = 66$) depicts all the foreign targets included in the MMREM analysis in model 5.

analysis, which would misestimate the effects of group traits on international attacks, the average values for the countries in these analyses are input for these groups. This method was selected to ensure the analysis of country traits are not unduly affected by these groups. Table 1 shows that 55.8 percent of the terrorist groups in this sample conducted attacks targeting one or more foreign countries in ideologically international attacks. Although 44.2 percent of groups in this sample did not conduct any ideologically international attacks, 25 percent of the sample conducted attacks targeting two or more foreign countries. These sizeable percentages suggests the potential value of including the influence of multiple countries in the analysis. Figure 3 shows the distribution of groups in this sample conducting any domestic and/or ideologically international attacks between 1998 and 2005.

As previously discussed, multilevel modeling can only model the groups in relation to a single target country. The sample data show how modeling terrorist groups in respect to the foreign country they target the most frequently in this time period may produce serious inaccuracies. In this sample of ideologically international attacks the United States is the most frequently targeted foreign country. The United States is the exclusive foreign target for 12 of the terrorist organizations in the sample. There are seven more groups for whom the United States is the target in the largest proportion of ideologically international attacks. Using multilevel modeling these 19 groups are modeled in relation to the United States alone, despite the fact that one group targeted the United States in only one-third of attacks against foreign targets. In these cases there are other countries that are also being targeted that are not being modeled when MMREM is not used in the analysis. Similarly, there are an additional 14 groups in this sample that targeted the United States, though not as often as at least one other foreign target. Multilevel modeling without MMREM does not account for the effect the United States had on these groups' behavior. The sample data show the value of using MMREM to model the groups in relation to multiple foreign targets in proportion to how often these targets were attacked.

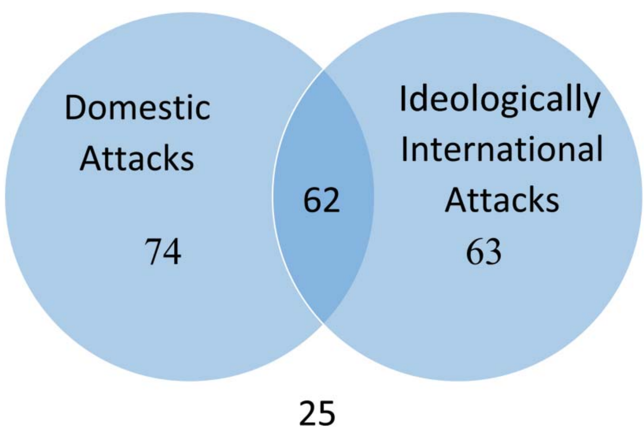

Figure 3. Graphic display of frequency of groups conducting domestic and/or ideologically international attacks between 1998 and 2005. *25 groups in the sample did not conduct any domestic or ideologically international attacks during this time period. This does not mean that the group did not conduct any attacks in this time period. A group may have conducted a logistically international attack by targeting a domestic target in a foreign country, which would not be included in either of the two categories of attacks analyzed in this study.

Measures

The data for this project consists of two units of analysis. The first level is the terrorist group. Terrorist groups are clustered within target countries, which is the second unit of analysis. The next sections will elaborate on the measures for the dependent variables and the independent variables for each level of analysis.

Dependent Variables

The data on terrorist attacks are from the GTD. The first dependent variable is the rate of domestic attacks per year conducted by the group between 1998 and 2005.[54] The total number of domestic attacks per group throughout this time period range from zero to 406.[55] Some groups developed within the time duration being analyzed and therefore did not exist for the entire eight year period. The rate was computed by dividing the total number of attacks conducted by the group in this time period by the number of years the group was in operation between 1998 and 2005. Roughly 39 percent of the sample did not conduct any domestic attacks in the time-span, and 25 percent of the sample have more than four domestic attacks in this duration.

The second dependent variable is the rate of ideologically international terrorist attacks coded for each group in the same time period, between 1998 and 2005.[56] Forty-two percent of the sample did not attack foreign targets in this time period, while roughly 10 percent attacked 10 or more foreign targets between 1998 and 2005.[57] The descriptive statistics for the dependent variables and the group level traits are provided in Table 2.

Table 2. Descriptive statistics for the dependent variables and group level traits.

Level One Variables	Minimum	Maximum	Mean/Proportion	*SD*
Dependent Variables				
Rate of domestic attacks per year[1]	0	50.75	1.70	5.25
Rate of ideologically international attacks per year[2]	0	21.75	0.85	2.26
Group Variables ($N = 224$)				
Ideology				
Religious	0	1	0.16	
Ethno-nationalist	0	1	0.28	
Religious-ethno-nationalist	0	1	0.18	
Left wing	0	1	0.21	
Other	0	1	0.17	
Group Size				
Small	0	1	0.52	
Medium	0	1	0.29	
Large	0	1	0.19	
Number of Alliances (logged)[3]	0	3.53	0.79	0.72
Group Age (logged)[4]	0	4.47	2.25	1.00
State Financial Support	0	1	0.12	0.32
Territorial Control	0	1	0.18	0.39

[1]Total number of domestic attacks for groups between 1998 and 2005 range from 0 to 406 ($M = 12.31$, $SD = 41.28$).
[2]Total number of ideologically international attacks for groups between 1998 and 2005 range from 0 to 174 ($M = 5.77$, $SD = 17.34$).
[3]The number of alliances range from 0 to 33. The distribution is severely skewed to the right so the variable is logged for analysis.
[4]The groups range in age from 1 to 87 years. The distribution of this variable is severely skewed to the right so the variable is logged for analysis.

Independent Variables

Level One: Terrorist Group Trait Variables. The first level of analysis is the terrorist group. A series of binary variables are included to capture the ideology of the group deriving from the BAAD data. Binary variables indicate if the group is religious, ethno-nationalist, religious-ethno-nationalist, left wing, or of some other ideology.[58] The proportions of each ideology in this sample range from 16–28 percent.[59]

Additional variables from the BAAD dataset are included to assess the association between terrorist group traits' and group violence. The size of the group is recoded into three dummy variables: small groups with 1–100 members (and low confidence), medium size groups with 100–1,000 members, and large groups with more than 1,000 members.[60] The number of alliances the group has with other groups, which ranges from 0 to 33 alliances, is logged for analysis because the variable is skewed to the right. The BAAD dataset also has a variable for group age that is coded as the number of years since the group was founded until 31 December 2005. Like the number of alliances, the age of groups is skewed so the variable is logged for analysis.[61] Last, two binary variables included indicate if the group received financial support from a state and if the group ever controlled any territory.

Level Two: Country Characteristic Variables. The second unit of analysis is the country.[62] Table 3 provides the descriptive statistics for the country characteristics used for the domestic and international attacks being analyzed. The first measure indicates the degree to which the country violates human rights. Specifically, the Physical Integrity Rights Index includes measures of torture, extrajudicial killing, political imprisonment, and disappearance in a country. The measure is recoded such that it ranges from 0 = "full government respect for these four rights" to 8 = "no government respect for these four rights."[63]

There are two variables measuring how wealth influences group violence: the Gini index which measures "the extent to which the distribution of income among

Table 3. Descriptive statistics for the countries included in analyses for each dependent variable.

	Minimum	Maximum	Mean/Proportion	*SD*
Domestic Attacks Country Variables ($N = 54$)				
Human Rights Abuse	0.00	7.50	3.92	2.17
Gini Index	26.78	62.59	40.31	8.50
GDP (logged)	20.22	29.75	24.80	2.14
Democracy	0.00	1.00	0.56	0.50
Ethnic Fractionalization	0.01	0.93	0.44	0.27
Religious Fractionalization	0.00	0.86	0.36	0.24
Population Size (logged)	7.03	14.07	10.39	1.41
Ideologically International Attacks ($N = 66$)				
Human Rights Abuse	0.00	7.50	3.48	2.22
Gini Index	27.82	63.90	39.93	8.71
GDP (logged)	10.83	29.75	24.60	2.80
Democracy	0.00	1.00	0.53	0.50
Ethnic Fractionalization	0.00	0.93	0.46	0.27
Religious Fractionalization	0.00	0.86	0.40	0.25
Population Size (logged)	7.57	14.06	10.10	1.44

individuals or households within an economy deviates from a perfectly equal distribution," and the log of the GDP that measures each country's wealth.[64] Some countries have the Gini index data and the GDP for numerous years, so this study uses the average of all these values for all the years between 1998 and 2005.[65] To estimate the degree of political freedom, a dichotomous variable indicates if the country is a democracy in this time period.[66]

There are two continuous variables that measure heterogeneity in a country: the degree of ethnic fractionalization, and the degree of religious fractionalization.[67] Fractionalization is the "probability that two randomly selected people from a given country will not share a certain characteristic, the higher the number the less probability of the two sharing that characteristic."[68] Ethnicity incorporates racial and linguistic traits and in some areas ethnic diversity reflects greater differences in race while in other areas diversity indicates differences primarily in language.[69] The data on religious fractionalization distinguishes 294 religions based on distinctions noted in the 2001 Encyclopedia Britannica.[70] These measures indicate differing forms of diversity that may have unique influences on terrorist violence. Last, this study includes the logged population of the country as a control variable.[71]

Data Analysis

This study uses Markov Chain Monte Carlo (MCMC) methods in a Bayesian framework in MLwiN software to run multilevel modeling.[72] The Bayesian approach works well with small samples and provides more accurate estimates for parameters in nonlinear models.[73] There are a series of models run to address the aims of this study. Model one includes the level one predictors with a random intercept for the rate of domestic terrorist attacks.[74] Model two adds the level two predictors, characteristics of the country of origin. Model three shows the level one predictors with a random intercept for the number of ideologically international terrorist attacks, while model four adds the country level data for the single foreign country most targeted for each group.[75]

The last model includes predictors for both levels using MMREM to model multiple foreign target countries for ideologically international attacks. Ignoring multiple membership, as is shown in the fourth model, often provides an underestimation of the variance for the macro level, foreign target countries.[76] MMREM modeling includes a weight for each macro-level (country) to account for the amount of influence each country should have on the dependent variable. The weights for all the foreign countries targeted by a group must all add to one. In this study the weights were calculated as the proportion of attacks by the group between 1998 and 2005 related to each foreign country. A group that targeted two foreign countries has these two countries in the analysis for ideologically international attacks. If 75 percent of the attacks targeted country one, it is weighted 0.75 while country two is weighted 0.25.[77]

Before providing the statistical equations for the models used in this study, it is necessary to describe the outcome distributions for these analyses. The dependent variables used in this study are discrete response count variables modified as the rate of attacks (domestic and ideologically international attacks) conducted by each group between 1998 and 2005. The descriptive statistics for these variables, shown in Table 2, indicate that the outcomes are both skewed to the right (Domestic: $M = 1.70$, $SD = 5.25$; International: $M = 0.85$, $SD = 2.26$). This study uses a Poisson distribution that includes a log link function to properly model the count data.[78] As previously stated, the dependent variable is a rate to account for the different amount of exposure to conduct attacks in this time period. This study includes the log (base e) of the number of years the group is operating during this time period as the offset in the analysis.

Equations

The level one equation with a random intercept for both dependent variables is:

$$Rate\ of\ Attacks_{ij} \sim Poisson(\pi_{ij})$$

$$\begin{aligned}\log(\pi_{ij}) = off_{ij} + \beta_{0j} + \beta_{1j-4j}(Ideologies_{ij}) + \beta_{5j-6j}(Group\ Size\ Dummy\ variables_{ij}) \\ + \beta_{7j}(Alliances_{ij}) + \beta_{8j}(Group\ Age_{ij}) + \beta_{9j}(Financial\ support_{ij}) \\ + \beta_{10j}(Territorial\ Control_{ij})\end{aligned}$$

$$\beta_{0j} = \gamma_0 + u_{0j}$$

The subscript i refers to the specific terrorist group, while the subscript j refers to the country. π_{ij} is the dependent variable, the rate of attacks for terrorist group i from country j, and the natural log link function is used to transform the dependent variable for the Poisson distribution. off_{ij} is the natural log transformation of the offset variable described previously. β_{0j} is the intercept of the equation, or the average rate of attacks for country j. The second equation shows that β_{0j} is equal to the average rate of attacks across countries, β_0, plus random error, u_{0j}. The error term is assumed to be normally distributed at level two with a mean of zero and a constant variance. β_{1j} through β_{10j} represent the level-one variables added to the equation. Dichotomous and dummy variables (i.e. ideology, group size dummy variables, financial support, and territory control) are uncentered, while the other variables (i.e. the natural log of number of alliances, and group age) are grand mean centered ($X_{ij} - \overline{X}_{..}$). These betas represent country j's average for each of the variables.

The level two, country level, equation for both dependent variables is:

$$\begin{aligned}\beta_{0j} = \gamma_{00} + \gamma_{01j}(Lack\ of\ Human\ Rights) + \gamma_{02j}(GINI\ Index) + \gamma_{03j}(GDP) \\ + \gamma_{04j}(Democracy) + \gamma_{05j}(Ethnic\ Fractionalization) \\ + \gamma_{06j}(Religious\ Fractionalization) + \gamma_{07j}(Population\ size) + u_{0j}\end{aligned}$$

The gammas are the level two variables, represented by γ_{01j} through γ_{07j}. These gammas refer to the average for each of the country level variables across all of the countries. These variables are all grand mean centered, except for democracy which is a binary variable.

When including multiple membership random effects modeling, the equation for a two level model is:

$$\log(\pi_{i\{j\}}) = \text{off}_{ij} + \gamma_{00} + \gamma_{10}(Group\ trait\ X)_{i\{j\}} + \gamma_{01} \sum_{h\in\{j\}} w_{ih}(Country\ trait\ Z)_{.h} + \sum_{h\in\{j\}} w_{ih}\ u_{0h}$$

In this equation, the first sigma represents the level two predictor that is a weighted average of this variable across the countries in which group i has attacked. The second sigma represents the weighted error for all of those countries.[79] For example, if a group conducted the same number of attacks in two foreign countries the equation would be as follows:

$$\log(\pi_{i\{j\}}) = \text{off}_{ij} + \gamma_{00} + \gamma_{10}(Group\ trait\ X)_{i\{j\}} + \gamma_{01}(0.5\ Z_{.1} + 0.5\ Z_{.2}) + (0.5\ u_{01} + 0.5\ u_{02})$$

The country variable Z is weighted 0.5 for the first country and 0.5 for the second country and the error terms are similarly weighted. If a group conducted 75 percent of the attacks in one foreign country and 12.5 percent of attacks in a second foreign country and 12.5 percent of attacks in a third foreign country the equation would be:

$$\log(\pi_{i\{j\}}) = \text{off}_{ij} + \gamma_{00} + \gamma_{10}(Group\ trait\ X)_{i\{j\}} + \gamma_{01}(0.75\ Z_{.1} + 0.125\ Z_{.2} + 0.125\ Z_{.3}) + (0.75\ u_{01} + 0.125\ u_{02} + 0.125\ Z_{.3})$$

In this case country variable Z is weighted 0.75 for the first country and 0.125 for the second and third countries, and the weights for the error terms are weighted comparably.

After these models are generated the Deviance Information Criterion (DIC) diagnostic for each model is calculated and used to assess the statistical goodness of fit for each model. The DIC provides a method of comparing models that use Bayesian estimation.[80] It is used to determine how well the model fits the data by measuring deviance, as well as measuring complexity (pD). The pD is an estimate to measure the "effective number of parameters."[81] An improvement in the model is identified by the DIC decreasing, and the pD increasing. The second aim of this study is assessed by comparing the DIC and pD for the models with only level 1 predictors and the corresponding models with level 2 predictors, and then the model with MMREM for the measurement of ideologically international attacks.

Results

Correlations were analyzed between the dependent variables, and group-level and country-level variables. The strongest correlation among variables in this sample is between country GDP and population size ($r = 0.674$, $p < .001$), which is strong but sensitivity analysis showed it did not unduly influence the results.[82]

Table 4. Results of Terrorist Group and Country level predictors on the rate of domestic terrorist attacks and ideologically international terrorist attacks conducted between 1998 and 2005.

Fixed effect	Model 1: Domestic attacks level 1 Exp(B)	Model 2: Domestic attacks full model (Country $n = 54$) Exp(B)	Model 3: Ideologically international attacks Level 1 Exp(B)	Model 4: Ideologically international attacks full model (Country $n = 52$) Exp(B)	Model 5: Ideologically international attacks MMREM model (Country $n = 67$)[c] Exp(B)
Intercept	0.088***	0.039***	0.021***	0.012***	0.021***
Level 1: Group (n= 224)					
Group ideology[a]					
Religious	0.393**	0.377**	1.461	1.672	1.401
Ethno-nationalist	0.282***	0.278***	2.465*	2.514*	1.350
Religious-Ethno-nationalist	0.525**	0.512***	2.061	2.096	1.283
Other	0.678	0.691	3.823**	3.823**	2.192
Group size[b]					
Medium Group	1.155	1.120	1.365	1.445	0.994
Large Group	9.052***	8.628***	2.702**	2.713**	2.197*
Alliances (logged)	3.068***	3.133***	1.939***	1.978***	1.917***
Group Age (logged)	0.666***	0.665***	0.641**	0.668**	0.536***
State Financial Support	0.503***	0.499***	0.456*	0.429**	0.583
Territory Control	0.673	0.654*	1.935*	1.895*	2.036*
Level 2: Country					
Human Rights Abuse		1.573		1.377	1.161
Gini Index		0.970		0.975	0.973
GDP (logged)		1.065		1.467	0.956
Democracy		3.401		2.020	2.111
Ethnic Fractionalization		7.576		5.474	3.504
Religious Fractionalization		1.029		21.434*	42.436**
Population size		0.819		0.597	1.051
Variance Components					
Level 2 Intercept	40.488**	74.888**	14.806**	12.705*	83.436**
Level 1	1.000	1.000	1.000	1.000	1.000
−2*loglikelihood					
Deviance (DIC)	717.798	716.135	432.339	433.104	407.562
Effective No. of Parameters (pD)	43.673	43.932	39.608	40.038	41.726

[a]The reference category for group ideology is Left wing.
[b]The reference category for group size is small (0–100 members).
[c]Model 5 includes the 66 countries shown in the map in Figure 2 as well as the proxy country consisting of the averages for variables used for groups that did not conduct an attack. The 66 countries and the proxy country total 67 level 2 units.
*$p \leq .05$ **$p \leq .01$ ***$p \leq .001$

The first model, shown in Table 4, shows the influence of terrorist group traits on the rate of domestic terrorist attacks. This model includes a random intercept that allows for variation in the rate of attacks across countries. In comparison to the left-wing group reference category, religious, ethno-nationalist, and religious-ethno-nationalist groups are associated with a lower rate of attacks, holding all other variables constant. In contrast, groups categorized as other do not significantly differ from the rate of domestic attacks by left-wing groups.

The results highlight the significant impact of the other group traits on the rate of domestic terrorist attacks. Specifically, groups with more alliances, and larger groups are associated with a higher rate of attacks, controlling for the other variables in the model. In contrast, older groups and those that have controlled territory are associated with a lower rate of domestic attacks.

Model two introduces the country level variables into the model of domestic attacks. The results for the terrorist group traits are rather similar to model one. In addition to the group traits discussed above, a group controlling territory is associated with a lower rate of domestic attacks when country characteristics are included in the model. Model two shows there are no significant country level characteristics of domestic traits. The lack of significant measures at level two may be because a wide variety of countries experience domestic terrorism, or because the measures selected for country traits are not capturing the most important features of a country that significantly elevate or decrease the likelihood of domestic terrorism.

The third model includes level one, group traits, on the rate of ideologically international attacks conducted by terrorist groups. The model shows that in comparison to the left-wing reference group, ethno-national groups and groups of an other ideology are associated with more attacks directed at foreign targets, controlling for all other variables in the model. Large groups, in comparison to groups with fewer than 100 members, are associated with a higher rate of ideologically international attacks, as are groups with more alliances and groups that have controlled territory. Older groups and terrorist organizations that have been financially supported by a state are associated with a lower rate of attacks against foreign targets, controlling for other variables in the model.

The fourth model adds the country characteristics of a foreign target to the analysis of ideologically international attacks. As previously explained, multilevel modeling assumes single membership, so the foreign target included in this analysis is the foreign target with the largest proportion of attacks. In this analysis there are 52 foreign target countries modeled. The results for group level traits in this model are comparable to those in prior model. The results in this model show that one country trait, religious fractionalization, is a significant predictor of ideologically international terrorist attacks (Exp(B) $= 21.434$, $p < .05$), controlling for all other variables in the model. This result means the predicted number of ideologically international attacks targeting a country with greater religious fractionalization (one standard deviation above the mean $= 0.65$) is 2.152 times greater than a country with average religious fractionalization (Mean $= 0.40$).[83]

The last model uses MMREM to model the influence of multiple foreign targets attacked by a group, rather than only measuring influence of the foreign country most frequently targeted. This model includes 67 units (i.e., countries) at level two, while the prior models of ideologically international attacks include 52 units.[84] There are some differences in the influence of group traits on the rate of ideologically international attacks. This model shows that there are no longer any significant differences between left-wing groups, the reference category, and the other ideological groups in the analysis. Similarly, financial support from a state is no longer a significant influence on the rate of ideologically international attacks. The changes in significance for these variables suggests that the variance explained by these variables is explained by the larger contextual factors included in this model. Similar to model four, the results in the MMREM model show that larger groups, groups with more alliances, and terrorist organizations that have controlled territory are still significant predictors of a higher rate of ideologically international attacks, controlling for all other variables in the model. Group age remains a significant predictor of a lower rate of attacks against foreign targets. The MMREM model shows that religious fractionalization is still a significant predictor of a higher rate of ideologically international attacks (Exp(B) $= 42.436$, $p < .01$), controlling for other variables in the model. These results show that modeling the influence of all foreign countries targeted means the risk of an ideologically international attack targeting a foreign country is 2.552 times greater in a religiously diverse country (one standard deviation above the mean = 0.65) than in a country with the average degree of religious diversity (Mean = 0.40).

The first aim of the study is to determine if there are different significant predictors for the two separate types of terrorist attacks assessed: domestic attacks and ideologically international attacks. A comparison of predictors across the two outcome variables suggests the importance and value of separately modeling domestic attacks and ideologically international attacks. The meaning and relevance of these findings is elaborated on in the discussion section of this article.

The DIC diagnostic for each model is provided and used to assess the second aim in this study. Comparing the DIC between the two models for domestic attacks we see the DIC for the first model is 717.798, which decreases to 716.135 in the second model. This is not a large difference, which is likely related to the fact that there are no significant level two predictors in the model. The decrease, however, indicates that the inclusion of level two variables makes the second model a better fit to the data. The number of effective parameters (pD) also increased a small amount from 43.673 to 43.932. Although the changes are small, they support the proposition that a two level model improves the analysis as the second model has less deviance and is less complex. I also ran the level one model for the rate of domestic attacks without a random intercept in OLS format that does not account for clustered observations. The DIC for this model is 1102.988 while the pD is 10.89, suggesting that the model fit improves dramatically by including a random intercept. In comparison, the results for the ideologically international attacks show partial support for the proposition that multilevel modeling improves the analysis. The DIC increased slightly from 432.339 to 433.104 indicating there is more deviance in this model, while the pD increased from 39.608 to 40.038 suggesting this model is less complex. Like the domestic attacks, I ran the level one model analyzing the rate of ideologically international attacks in model three that did not include a random intercept. The DIC for this model is 741.208, which is much larger than the reported model that includes the random intercept, and the pD is 10.903 which indicates there are fewer effective parameters than in the reported model. Including a random intercept for both the domestic and ideologically international attacks reduces the amount of deviance in the models and increases the number of effective parameters, which further supports the value of using multilevel modeling to analyze this clustered data.

Also to address the second aim the DIC of the fourth model is compared to the fifth model. Model five shows an increase in the effective parameters (pD = 41.726) and a large decrease in the deviance (DIC = 407.562), indicating that this model improves the statistical fit for the data more than the two prior models. This result supports the idea that the multilevel model with MMREM is a superior measurement of factors predicting the rate of ideologically international terrorist attacks.

Discussion

The current study contributes to reducing the gap in the literature, noted by Lum et al., by evaluating terrorism in relation to unique religious, socioeconomic, and political contexts. [85] By using multilevel modeling this study evaluates the direct effects of group traits and country characteristics on the rate of group terrorist attacks. The findings contribute to prior research that has generally focused on one of these units of analysis in the study of terrorism. At the group level the results indicate that there is variation among different ideologies and the rate of domestic terrorist attacks. In this analysis religious, ethno-nationalist, and religious-ethno-nationalist groups have lower predicted rates of domestic attacks than the left-wing group reference category. In comparison, model three and four show that ethno-nationalist and groups categorized as other have greater predicted rates of targeting foreign countries than the left-wing groups. In model five that includes multiple membership, however, there are no ideologies that significantly differ in the rate of ideologically international attacks from left-wing groups. The change in significance suggests that the variance these variables accounted for in model four are better explained in the MMREM model by other variables. MMREM analyses show greater differences in parameter estimates between models when the rate of multiple membership is higher.[86] In this study the number of groups attacking multiple foreign targets is quite large (25 percent of groups attacked multiple foreign countries), which helps explain the changes in parameter estimates.

Consistent across models, groups of large size with more than 1,000 members, and groups with more alliances to other terrorist organizations predict a higher rate of both domestic and ideologically international attacks. These findings resemble prior studies of terrorist groups showing how group size and alliances are significant predictors of group lethality and attacking soft targets.[87] These results suggest logistical resources play a significant role in the ability of carrying out numerous terrorist attacks. It has been suggested that large terrorist groups may limit terrorist violence because of the complications with organizing clandestine operations; however, this study shows that larger groups are associated with more violence.[88] In contrast, most models show that the financial support of a state predicts fewer domestic and ideologically international attacks. This may be explained by the power dynamics involved by accepting funds from an authority, rather than the influence of financial means. Some groups have significant resources available from independent sources, so future research should try to identify an additional measure to distinguish the effects of financial resources and power dynamics. Group age is consistently associated with a lower rate of attacks, both domestic and ideologically international alike. This result suggests that older groups have survived because they are strategic. They may conduct fewer attacks to optimize maintaining support from their sympathizers and decreasing operational risks. The findings in this study identify group traits that are significant predictors across both types of terrorist attacks measured. Modeling these types of attacks separately also identifies predictors that differ in effect across outcomes.

Interestingly, the results show that a group that has controlled territory is predicted to a have a lower rate of domestic attacks than a group that has not controlled territory. In contrast, a group that has controlled territory has a higher rate of ideologically international attacks compared to a group that has not controlled any territory. The difference in direction indicates the value of modeling domestic and international targets separately. This may indicate that groups controlling territory have been given concessions by the domestic country and so the group reduces or maintains a low rate of domestic attacks. In contrast, a group controlling territory may have significant resources and security to plan attacks against foreign targets. For example, Al Qaeda controlled territory in Afghanistan and was able to devote significant resources and time to planning against foreign targets.

The results for level two show that there are no country characteristics that are significant predictors of domestic terrorist attacks. It may be that there are other measures that may better capture factors that influence groups carrying out domestic attacks. For example, Li suggests that different features of democratic regime may enable terrorism, such as institutional constraints on the government, while other features may reduce terrorist attacks, such as voter turnout and proportional representation in government.[89] Li's study used ITERATE data to analyze how these country characteristics influence transnational attacks. Future research should investigate these type of regime related variables with the GTD data that distinguishes domestic and international attacks. Future research on domestic terrorism could include a measure of systematic group exclusion and evaluate if there is an interaction with the terrorist group identification. For example, many ethno-nationalist groups identify themselves based on their physical and ethnic traits that differentiate them within their society. These groups may be mobilized to conduct acts of terror if they perceive oppression or injustice directed at their group. Future research on domestic terrorism should expand the variables at level two to include factors unique to local conflict.

The results of this study show that countries with greater religious fractionalization predict a higher rate of ideologically international terrorist attacks. Religious diversity may be socially constructed as an ideological conflict with religious freedom and/or as a threat of opposing religions. These explanations suggest a religious motivations underlying terrorist action, but in the models for ideologically international attacks groups with religious ideology do not differ significantly from the reference left-wing, political groups. This may be due to the fact that religious groups are categorized separately from groups that have both religious and ethno-nationalist agendas in the BAAD dataset. Future research should determine if different ideological categories can be used to refine the types of motivations underlying group behavior. It is also possible that the significant influence of religious diversity is due the changing demographics during this period of globalization. The results of this study suggest, however, that this is unlikely due to the fact that ethnic fractionalization is not a significant predictor of ideologically international attacks.

The findings of this study indicate the methodological and theoretical value of modeling domestic and ideologically international attacks separately. Similarly, the findings indicate that modeling the data in multilevel form and with MMREM improves the statistical fit and the structure to the data where there is multiple membership. Multilevel modeling with MMREM is a methodological technique that may be useful for modeling the location of international attacks as some groups conduct attacks in multiple foreign countries. Logistically international attacks are attacks that take place outside of the perpetrating group's country of origin. Group traits, such as alliances and resources, may explain the number of attacks conducted abroad. Similarly, certain country characteristics, such as freedom of assembly or a lack of government capacity or difficulty controlling borders, may facilitate foreign groups to operate within a country. Multilevel modeling with MMREM can model these two levels of analysis and incorporate multiple countries of operation. Additionally, this form of statistics can include a spatial matrix to determine if proximity also affects how and where groups operate. Additionally, multilevel modeling enables one to assess moderation hypotheses using cross-level interaction equations. Moderation hypotheses test whether the size of a relationship between the independent variable and dependent variable changes depending on a third variable, the "moderator" variable. Future research should test moderation relationships suggesting that a specific country characteristic may have varying effects on different types of groups to contribute to theory development in terrorism studies.

There are limitations to this study. First, the study was limited by the data that were available. As previously mentioned, there are many attacks in the GTD that are conducted by unknown perpetrators. Some of these may have been conducted by groups included in this study, but were not attributed to these groups. This is a significant limitation that can only be acknowledged with the hope that law enforcement and surveillance improves cross-nationally. Although there were few, there are some attacks conducted by groups included in this sample that are coded as unknown for whether they are domestic and/or ideologically international. This study is limited to including the attacks with known information for these variables. Similarly, the terrorist group data are limited by what information is publically available. There are other traits that may be of particular relevance to this study, such as a better measure of financial resources, or skilled membership, or a measure of group structure. Unfortunately this information is not included in the BAAD dataset and may be difficult to accurately collect.

Counterterrorism measures likely have significant influence on the rate of terrorist attacks. Although there are researchers collecting data on counterterrorism legislation cross-nationally,[90] as well as counterterrorism measures being directed toward groups,[91] or in various areas, the data are not yet publically available. Future research should include counterterrorism measures into the model.

It is necessary to point out that the group data and country characteristics are included as cross-sectional measurements. Although some group traits, such as ideology, are less likely to significantly shift into a differing category, other traits, like group size, may experience significant change over time. Likewise, the country characteristics included in the model may not be static. The time-frame for this study is only eight years, however, and although these characteristics are not static, dramatic changes in regime type or economic conditions are often very gradual. This study uses the mean of country level variables measured within this time frame for all of the countries included in the analysis. There are some changes, however, that future research should investigate further. The findings for religious diversity may be related to the increase in migration of people in this time period due to globalization. Future research should evaluate if the impact of religious fractionalization is better explained by the change in diversity.

Another limitation is that there are some groups that may be best associated with a territory or region, rather than a country (e.g., Northern Ireland, Kashmir, West Bank/Gaza Strip). Unfortunately there are no country level measures for these regions. The country of origin for these groups was kept the same as the BAAD assigned for consistency. The country assigned is often the neighboring country or the country that legally controls the territory, such as the United Kingdom for groups in Northern Ireland.

Conclusion

The results of this study show the conceptual as well as the methodological value of using multilevel modeling to include several units of analysis in the study of terrorism. The study shows similarities and differences in group traits and country characteristics predicting domestic and ideologically international attacks. MMREM facilitates the measurement of additional macro-level units to model the effect of multiple foreign countries targeted in international attacks. MMREM structures the multilevel data optimally to account for the influence of very different country contexts that are excluded in analysis that only accounts for a single target country. The results of the study indicate that the MMREM model provides an improved statistical fit to the data. Based on the results of this study, multilevel modeling and MMREM are valuable tools to improve measurement in the study of terrorism.

Notes

1. Adam Roberts, "Terrorism Research: Past, Present, and Future," *Studies in Conflict & Terrorism* 38(1) (2015), pp. 62–74; Cynthia Lum, Leslie W. Kennedy, and Alison Sherley, "Are Counter-Terrorism Strategies Effective? The Results of the Campbell Systematic Review on Counter-Terrorism Evaluation Research," *Journal of Experimental Criminology* 2(4) (5 December 2006), pp. 489–516. doi:10.1007/s11292-006-9020-y
2. Andrew Silke, "Research on Terrorism: A Review of the Impact of 9/11 and the Global War on Terrorism," in *Terrorism Informatics* (New York: Springer, 2008), pp. 27–50. Available at http://content.schweitzer-online.de/static/content/catalog/newbooks/978/038/771/9780387716121/9780387716121_Excerpt_001.pdf; Andrew Silke, "The Devil You Know: Continuing Problems with Research on Terrorism," *Terrorism and Political Violence* 13(4) (2001), pp. 1–14; Alex Schmid, "Statistics On Terrorism: The Challenge of Measuring Trends in Global Terrorism," *Forum on Crime & Society* 4(1/2) (December 2004), pp. 49–69; Lum, Kennedy, and Sherley, "Are Counter-Terrorism Strategies Effective?"
3. Lum, Kennedy, and Sherley, "Are Counter-Terrorism Strategies Effective?"; Alex P. Schmid and Albert J. Jongman, *Political Terrorism: A New Guide to Actors, Concepts, Data Bases, Theories, and Literature* (New Brunswick, NJ: Transaction Books, 1988); Alex P. Schmid and A. J. Jongman, *Political Terrorism: A New Guide to Actors, Authors, Concepts, Data Bases, Theories, & Literature*, 2nd ed. (New Brunswick, NJ: Transaction Publishers, 2005); Silke, "The Devil You Know: Continuing Problems with Research on Terrorism."
4. For example see Robert Agnew, "A General Strain Theory of Terrorism," *Theoretical Criminology* 14(2) (2010), pp. 131–153; Martha Crenshaw, "The Causes of Terrorism," *Comparative Politics* 13(4) (1981), pp. 379–99, doi:10.2307/421717
5. See Gary LaFree and Laura Dugan, "Introducing the Global Terrorism Database," *Terrorism and Political Violence* 19(2) (2007), pp. 181–204. doi:10.1080/09546550701246817; A. J. Jongman, "Trends in International and Domestic Terrorism in Western Europe, 1968–1988," *Terrorism and Political Violence* 4(4) (1992), pp. 26–76. doi:10.1080/09546559208427174
6. In 2011 Enders, Sandler, and Gaibulloev published an article where they created a method of distinguishing domestic and transnational attacks in the GTD to compare the GTD transnational incidents with the ITERATE data. Following the ITERATE operationalization, the authors define a transnational attack as an attack where there is a difference in the nationality of the perpetrator and the victim(s), the victim and the location of the attack, or the perpetrator and the location. The updated variables released with the most recent GTD distinguish these specific types of international attacks so that researchers can distinguish attacks against foreign targets from those that crossed borders to attack a domestic target. Walter Enders, Todd Sandler, and Khusrav Gaibulloev, "Domestic versus Transnational Terrorism: Data, Decomposition, and Dynamics," *Journal of Peace Research* 48(3) (May 1, 2011), pp. 319–337. doi:10.1177/0022343311398926
7. Matthew Carr, *The Infernal Machine: A History of Terrorism* (New York: New Press, 2007).
8. Peter R. Neumann, *Old & New Terrorism* (Malden, MA: Polity, 2009).
9. For a thorough review of domestic and international attacks see chapter 8, "International and Domestic Terrorism," in Gary LaFree, Laura Dugan, and Erin Miller, *Putting Terrorism in Context: Lessons from the Global Terrorism Database* (New York: Routledge, 2014).

10. International terrorist attacks are called logistical when the group's nationality differs from the country in which the attack occurs. In these cases the group crosses a border to carry out an attack. Indeterminate international attacks are when there is a difference in nationality between the target(s) and the location of the attack. See ibid.
11. Scholars and politicians have referred to terrorist conflict as cycles of violence. Sometimes this phrase is used in relation to specific conflicts, such as the Israeli–Palestinian conflict, and other times in relation to terrorist conflicts in general. For example, following the suicide attack in Tel Aviv in June 2001 UN Secretary-General Kofi Annan said that the attack "underlines the urgency of breaking the cycle of violence" and the European Union released a statement describing the conflict the same. UN Secretary-General press release, 1 June 2001; European Union press release, 2 June 2001. See also David A. Jaeger and Marco Daniele Paserman, "The Cycle of Violence? An Empirical Analysis of Fatalities in the Palestinian-Israeli Conflict" (IZA Discussion Papers, No. 1808, 2005). Available at http://hdl.handle.net/10419/33236. Academics have studied the terrorism–counterterrorism cycle in multiple parts of the world. For example, Hewitt studied long-term conflicts in Cyprus, Uruguay, Northern Ireland, Spain, and Italy. Christopher Hewitt, *Effectiveness of Anti-Terrorist Policies* (Lanham, MD: University Press of America, 1984). Available at https://www.ncjrs.gov/App/publications/abstract.aspx?ID=96049. Similarly, Chalk has evaluated methods of dealing with terrorism in conflict zones, such as Peru, Spain, and Italy. Peter Chalk, "The Response to Terrorism as a Threat to Liberal Democracy," *Australian Journal of Politics & History* 44(3) (1 September 1998), pp. 373–388. doi:10.1111/1467-8497.00027
12. Urie Bronfenbrenner, *The Ecology of Human Development: Experiments by Nature and Design*, 9th ed. (Cambridge, MA: Harvard University Press, 1979); Urie Bronfenbrenner, "Ecological Systems Theory," in *Annals of Child Development: Six Theories of Child Development: Revised Formulations and Current Issues* (Greenwich, CT: JAI Press, 1989), pp. 1–103; Frank S. Pearson and Neil Alan Weiner, "Toward an Intergration of Criminological Theories," *Journal of Criminal Law and Criminology* 76 (1985), p. 116; Bryan Vila, "A General Paradigm for Understanding Criminal Behavior: Extending Evolutionary Ecological Theory," *Criminology* 32(3) (August 1994), pp. 311–359.
13. Ecological theory provides the framework for the development of the Minorities at Risk Organizational Behavior (MAROB) database, which codes country behavior in relation to both violent and nonviolent ethnic minority groups situated in countries in the Middle East and North Africa. Victor Asal, Amy Pate, and Jonathan Wilkenfeld, "Minorities at Risk Organizational Behavior Data and Codebook Version 9/2008," 2008. Available at http://www.cidcm.umd.edu/mar/data.asp#marob
14. Although Al Qaeda is associated with Afghanistan, the group originally formed in Peshawar, Pakistan between 1988 and 1989.
15. Matthew W. Grady and S. Natasha Beretvas, "Incorporating Student Mobility in Achievement Growth Modeling: A Cross-Classified Multiple Membership Growth Curve Model," *Multivariate Behavioral Research* 45(3) (28 May 2010), pp. 393–419. doi:10.1080/00273171.2010.483390; Lindsey Janae Smith, "A Comparison of Procedures for Handling Missing School Identifiers with the MMREM and HLM," May 2012. Available at http://repositories.lib.utexas.edu/handle/2152/ETD-UT-2012-05-5153; Lindsey J. Wolff Smith and S. Natasha Beretvas, "The Impact of Using Incorrect Weights with the Multiple Membership Random Effects Model," *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences* 10(1) (2014), pp. 31–42.
16. Group behavior is likely influenced by the individuals that comprise the group and it would be worthwhile to include this level of analysis as well, however, no cross-national dataset with a representative sample of individuals from terrorist groups is currently available. The John Jay and ARTIS Transnational Terrorism database (JJATT) has information collected on individuals within terrorist groups, however, this is for a select network of groups and it is difficult to determine if these individuals are representative of all those participating in a clandestine group. For more information see Scott Atran, "John Jay & ARTIS Transnational Terrorism Database" (Sponsored by the Air Force Office of Scientific Research [AFOSR], 2009). Available at http://doitapps.jjay.cuny.edu/jjatt/index.php.

17. The low base rate is not unique to terrorism. There are other types of crime that have low base rates, such as spree killing, serial killing, and school shootings.
18. See Joe Eyerman, "Terrorism and Democratic States: Soft Targets or Accessible Systems," *International Interactions* 24(2) (1998), pp. 151–70. doi:10.1080/03050629808434924; Quan Li, "Does Democracy Promote or Reduce Transnational Terrorist Incidents?," *Journal of Conflict Resolution* 49(2) (2005), pp. 278–297. doi:10.1177/0022002704272830; Stephen Nemeth, "Adaptive Tactics: Terrorist Targeting and Regime Type" (Paper, Midwest Political Science Association Annual Meeting, Chicago, IL, April 20, 2006). Available at http://scholar.googleusercontent.com/scholar?q=cache:0VJdScD0eGsJ:scholar.google.com/+terrorist+targets,+politicians&hl=en&as_sdt=0,33; Stephen Nemeth, "A Rationalist Explanation of Terrorist Targeting," *Theses and Dissertations*, 1 January 2010. Available at http://ir.uiowa.edu/etd/718; Alan B. Krueger, *What Makes a Terrorist: Economics and the Roots of Terrorism* (Princeton, NJ: Princeton University Press, 2008); Alan B Krueger and Jitka Maleckova, "Education, Poverty, Political Violence and Terrorism: Is There a Causal Connection?," *Journal of Economic Perspectives* 17(4) (2003), pp. 119–144; James A. Piazza, "Rooted in Poverty?: Terrorism, Poor Economic Development, and Social Cleavages 1," *Terrorism and Political Violence* 18(1) (2006), pp. 159–177. doi:10.1080/095465590944578; Alberto Abadie, "Poverty, Political Freedom, and the Roots of Terrorism," *American Economic Review* 95(4) (2005), pp. 50–56.
19. Gary LaFree, Nancy A. Morris, and Laura Dugan, "Cross-National Patterns of Terrorism: Comparing Trajectories for Total, Attributed and Fatal Attacks, 1970–2006," *The British Journal of Criminology* 50(4) (2010), pp. 622–649.
20. For more on the theoretical contribution of these factors see also Agnew, "A General Strain Theory of Terrorism"; Jessica Stern, "Being Feared Is Not Enough to Keep Us Safe," *Washington Post*, 15 September 2001; Scott Atran, "Genesis of Suicide Terrorism," *Science* 299(5612) (2003), pp. 1534–1539.
21. Abadie, "Poverty, Political Freedom, and the Roots of Terrorism"; Krueger, *What Makes a Terrorist: Economics and the Roots of Terrorism*; Krueger and Maleckova, "Education, Poverty, Political Violence and Terrorism"; Piazza, "Rooted in Poverty?"
22. Eyerman, "Terrorism and Democratic States"; Li, "Does Democracy Promote or Reduce Transnational Terrorist Incidents?"; Nemeth, "Adaptive Tactics"; Nemeth, "A Rationalist Explanation of Terrorist Targeting." Prior research has been done using different datasets, some of which only include transnational attacks (e.g. ITERATE), and may help explain inconsistent results in the literature.
23. This is the case for studies using GTD data, while studies using ITERATE data only include transnational attacks and exclude domestic attacks.
24. Todd Sandler, "Poverty as a Cause of Terrorism and MIND/FIND as an Inhibitor of Transnational Terrorism," *Current Research Project Narratives* (2014). Available at http://research.create.usc.edu/current_synopses/81; Walter Enders, Gary A. Hoover, and Todd Sandler, "The Changing Nonlinear Relationship between Income and Terrorism," *Journal of Conflict Resolution*, (26 May 2014), 0022002714535252, doi:10.1177/0022002714535252
25. Alan B. Krueger and D. D. Laitin, "Kto Kogo?: A Cross-Country Study of the Origins and Targets of Terrorism," in E. M. Myersson Milgrom, ed., *Suicide Missions and the Market for Martyrs, A Multidisciplinary Approach* (Princeton, NJ: Princeton University Press, 2007); Enders, Hoover, and Sandler, "The Changing Nonlinear Relationship between Income and Terrorism"; Enders, Sandler, and Gaibulloev, "Domestic versus Transnational Terrorism."
26. For an elaborate discussion of terrorist ideology see C. J. M. Drake, "The Role of Ideology in Terrorists' Target Selection," *Terrorism and Political Violence* 10(2) (1998), pp. 53–85. doi:10.1080/09546559808427457
27. Gary LaFree, "The Global Terrorism Database: Accomplishments and Challenges," *Perspectives on Terrorism* 4(1) (29 November 2010); Erin Miller, "Patterns of Onset and Decline Among Terrorist Organizations," *Journal of Quantitative Criminology* 28(1) (18 November 2011), pp. 77–101. doi:10.1007/s10940-011-9154-6
28. For a more detailed look at factors that influence terrorist group decision making see Jacob N. Shapiro, *The Terrorist's Dilemma Managing Violent Covert Organizations* (Princeton, NJ:

Princeton University Press, 2013). Available at http://public.eblib.com/choice/publicfullrecord.aspx?p=1189075

29. Victor Asal and R. Karl Rethemeyer, "The Nature of the Beast: Organizational Structures and the Lethality of Terrorist Attacks," *Journal of Politics* 70(2) (April 2008), pp. 437–449; Tore Bjørgo and John Horgan, *Leaving Terrorism behind: Individual and Collective Disengagement* (New York: Taylor & Francis, 2009); Gary LaFree and Erin Miller, "Desistance from Terrorism: What Can We Learn from Criminology?," *Dynamics of Asymmetric Conflict* 1(3) (2008), pp. 203–230. doi:10.1080/17467580902718130; Miller, "Patterns of Onset and Decline Among Terrorist Organizations"; Marisa Reddy Pynchon and Randy Borum, "Assessing Threats of Targeted Group Violence: Contributions from Social Psychology," *Behavioral Sciences and the Law* 17(3) (1999), pp. 339–355.
30. Miller, "Patterns of Onset and Decline Among Terrorist Organizations."
31. Asal and Rethemeyer, "The Nature of the Beast"; see also Victor Asal and R. Karl Rethemeyer, "Dilettantes, Ideologues, and the Weak: Terrorists Who Don't Kill," *Conflict Management and Peace Science* 25(2) (July 2008), pp. 244–263. doi:10.1080/07388940802219000
32. Victor Asal et al., "The Softest of Targets: A Study on Terrorist Target Selection," *Journal of Applied Security Research* 4(3) (2009), pp. 258–278. doi:10.1080/19361610902929990
33. Asal and Rethemeyer, "Dilettantes, Ideologues, and the Weak"; Asal and Rethemeyer, "The Nature of the Beast"; Asal et al., "The Softest of Targets: A Study on Terrorist Target Selection."
34. The quantitative research on cross-national terrorism has adjusted standard errors to account for country-level clustering. This is a worthwhile effort, but may not optimally account for clustering and may fail to capture the unique trajectories between different types of groups operating in different environments.
35. For a thorough review of the literature until 2010 see Brian D. Johnson, "Multilevel Analysis in the Study of Crime and Justice," in *Handbook of Quantitative Criminology*, eds. Alex R. Piquero and David Weisburd (Springer Science & Business Media, 2010), pp. 615–648; Adam Whitworth, "Inequality and Crime across England: A Multilevel Modelling Approach," *Social Policy and Society* 11(1) (January 2012), pp. 27–40. doi:10.1017/S1474746411000388; see also Jihyung Shin, "Mixed-Effects Models For Count Data With Applications To Educational Research" (Statistics, Florida State University, 2012), Electronic Theses, Treatises and Dissertations (Paper 5181). Available at http://diginole.lib.fsu.edu/etd/5181; Stephen W. Raudenbush, *Hierarchical Linear Models: Applications and Data Analysis Methods*, 2nd ed, Advanced Quantitative Techniques in the Social Sciences 1 (Thousand Oaks, CA: Sage Publications, 2002).
36. Johnson analyzed case proceedings of indicted terrorists across different jurisdictions in the United States were analyzed. Brian D. Johnson, "Cross-Classified Multilevel Models: An Application to the Criminal Case Processing of Indicted Terrorists," *Journal of Quantitative Criminology* 28(1) (30 November 2011), pp. 163–189. doi:10.1007/s10940-011-9157-3. Using GTD data, LaFree et al. (2015) analyzed county level predictors of terrorist incidents in the United States between 1990 and 2011. This article uses multilevel modeling to conduct longitudinal analysis with years clustered within counties. Gary LaFree and Bianca E. Bersani, "County-Level Correlates of Terrorist Attacks in the United States," *Criminology & Public Policy* 13(3) (1 August 2014), pp. 455–481. doi:10.1111/1745-9133.12092; Joshua D. Freilich, et al., "Investigating the Applicability of Macro-Level Criminology Theory to Terrorism: A County-Level Analysis," *Journal of Quantitative Criminology* (2014). doi:10.1007/s10940-014-9239-0. Joshua D. Freilich et al., "Investigating the Applicability of Macro-Level Criminology Theory to Terrorism: A County-Level Analysis," *Journal of Quantitative Criminology* (2014). doi:10.1007/s10940-014-9239-0
37. Silke, "The Devil You Know."
38. Ibid.
39. Other incident databases include TWEED, ITERATE, RAND, PGIS, U.S. Department of State, RAND-MIPT, and WITS. For thorough comparison of terrorist incident databases see the forthcoming paper by LaFree, "The Future of Terrorism Event Databases." Unpublished paper prepared for conference on The Future of Terrorism, Pennsylvania State University (2011).

40. This study uses the Global Terrorism Dataset publically released in June 2015. This cross-sectional study uses GTD data from 1998–2005 because this is the time period for the group-level data. This time duration corresponds to the time period used for prior studies using the BAAD data. Between 1998 and 2005 the GTD has 11,819 total attacks cross-nationally.
41. LaFree and Dugan, "Introducing the Global Terrorism Database"; LaFree, Morris, and Dugan, "Cross-National Patterns of Terrorism." The GTD data on incidents since 1998 was collected by research assistants from a variety of institutions. The initial data recorded between 1970 and 1997 came from the Pinkerton Global Intelligence Service (PGIS), which was digitized by National Consortium for the Study of Terrorism and Responses to Terrorism (START). The GTD data for attacks between 1998 and 2008 began as a collaboration between START and the Center for Terrorism and Intelligence Studies (CETIS). The Institute for the Study of Violent Groups (ISVG) was the primary data collector with START for attacks between 2008 and 2011. Attacks since 2011 have been collected by START. The GTD provides the bibliographic information for multiple sources used to code for each terrorist incident since 1998. Terrorist incidents included in the GTD are reviewed by members of the START staff in efforts to ensure credible sources are used and information is accurately coded, increasing the reliability of the data.
42. Victor Asal, R. Karl Rethemeyer, and Ian Anderson, "Big Allied and Dangerous(BAAD) Database 1 - Lethality Data, 1998–2005 - START Terrorism Data Archive Dataverse—IQSS Dataverse Network" (2009). Available at http://hdl.handle.net/1902.1/16062UNF:5:2Z77QCNImKUu2OVS6hqccw==
43. Asal and Rethemeyer, "Dilettantes, Ideologues, and the Weak"; Asal and Rethemeyer, "The Nature of the Beast"; Asal et al., "The Softest of Targets."
44. Note that these groups may not have carried out an attack in this time period, but must have been in operation in this time period.
45. Jan Teorell et al., "The Quality of Government Dataset, Version 15May13" (University of Gothenburg: The Quality of Government Institute, 2013), 3. Available at http://www.qog.pol.gu.se
46. Ibid.
47. I searched for each group in the BAAD dataset in the GTD. The GTD codes up to 3 groups involved in an attack. I searched through each of these to ensure I counted the number of attacks each group took part in, even if the group was not listed first. Many groups had the same group name in both datasets; however, there are some groups that had different spellings (e.g., Hizballah; Hezbollah), or listed by translations (e.g., Grupo de Combatientes Populares; Group of Popular Combatants [GPC]), or are listed in the GTD with an alias listed in the original Memorial Institute for the Prevention of Terrorism (MIPT)'s Terrorism Knowledge Base ® (TKB®)Terrorist Organization Profiles dataset (e.g., Kayin National Union [KNU]; Karen National Union). The group names listed in Appendix A are from the BAAD dataset when inconsistencies are found.
48. National Consortium for the START, *Global Terrorism Database [Data File]* (2015). Retrieved from http://www.start.umd.edu/gtd. Note that the number of recorded terrorist attacks is lower in this time period than in others. This may be in part due to the limited resources of the CETIS, which was collecting this data.
49. Within this time period, at least 1,094 attacks are coded as attacks with "generic" perpetrators, such as student radicals or Islamic extremists.
50. The final sample of groups in both the BAAD and GTD was 229 groups; however, five of these groups have attacks that could not be confirmed as domestic or transnational. These five groups were excluded from the analysis because they are missing the attack counts for the dependent variables.
51. Barbara G. Tabachnick and Linda S. Fidell, *Using Multivariate Statistics* (Boston: Pearson/Allyn & Bacon, 2007), 788. Available at http://tocs.ulb.tu-darmstadt.de/135813948.pdf.
52. There are 67 foreign countries targeted in ideologically international attacks in the analysis shown in model 5 that uses MMREM. In model 4 there are only 52 foreign countries targeted as this model assumes single membership.
53. The data are unbalanced, meaning the number of terrorist groups varies substantially across countries. Fortunately, multilevel modeling is equipped to model this type of data.

54. The definition of terrorism for the purposes of this study comes from an existing dataset, the GTD. The GTD defines terrorism as "the threatened or actual use of illegal force and violence to attain a political, economic, religious or social goal through fear, coercion or intimidation," (PGIS definition cited in LaFree and Dugan, "Introducing the Global Terrorism Database," p. 184). Although an explicit definition is in dispute, scholars have generally had similar tenets in defining terrorism and this definition has been used in the development of the GTD and in many scholar writings.
55. The number of domestic attacks for each group is calculated by totaling the number of attacks by the group between 1998 and 2005 in the latest GTD that have a 0 for the International-Any variable, which indicates that "the attack was domestic on *all* of the dimensions described… (logistically, ideologically, miscellaneous)" (GTD codebook, 2016, p. 57, emphasis original). There are a few groups that had an attack coded 0, meaning it was a domestic incident, but the location and/or target of the attack are not the same as the home base country listed in the BAAD dataset. In these cases I did research to confirm the home base country for the group and properly total the number of domestic attacks and ideologically international attacks accordingly.
56. The GTD codes ideologically international attacks as those where the perpetrating group and the target in an attack are of different nationalities. The GTD codebook notes that for attacks involving groups in contested areas, such as Corsica, Northern Ireland, or West Bank and Gaza Strip, the perpetrating group's nationality is coded as the parent country and attacks coded targeting the parent country (e.g., France) are coded as domestic. Similarly, international logistic attacks are when a border is crossed to conduct an attack. Unlike those cases above, if an attack occurred in a territory that is not contested, the groups' nationality is coded as belonging to the territory rather than the parent country. In these cases, attacks against the parent country are coded as being logistically international (see GTD codebook, June 2015 for more explanation).
57. The ideologically international attack variable in the GTD indicates if the attack is against a foreign target. I looked at each attack coded as 1 for this variable for each group conducted in this time frame to count the foreign nationalities targeted and how often each foreign country was targeted. Note that the GTD codes the target that "reflects [the] motive" of the terrorist group, so some incidents that victimize dozens of nationalities (e.g., 9/11 attacks) are coded for the top three targets related to the motive of the group.
58. To elaborate, the left-wing groups are those following a Marxist, Maoist, and Leninist economic and social philosophy. Ethno-nationalist groups seek to establish a new political order based, in part, on ethnic dominance and/or desires for ethnic homogeneity. Religious groups derive their ideology, at least in part, from their interpretation of a spiritual faith. Religious-ethno-nationalist groups have both religious and ethno-nationalist agendas. The "other" ideology includes groups with an anarchist, antiglobalist, racist, rightist, or environmentalist agenda. For more information see Asal and Rethemeyer, "The Nature of the Beast."
59. I coded groups based on the ideological variables included in the BAAD1 data (i.e., ContainRelig, ContainEthno, LeftNoReligEthno, PureRelig, PureEthno, ReligEthno, ContainRelig2, ContainEthno2, and Islam). I found there is no overlap between left-wing and religious, or left-wing and ethno-nationalist groups. The groups that contain religious ideology, and are not ethno-nationalist, were combined with pure religious groups for the Religious category in this study. The groups that contain ethno-nationalist ideology, and are not religious, are combined with the pure ethno-nationalist groups to make the Ethno-nationalist category in this study. Groups that are inspired by both religious and ethno-nationalist ideologies are coded as Religious-ethno-nationalist groups. Left-wing groups are coded in the BAAD dataset as pure left-wing groups. The Other category is derived from groups that are coded as 0 on all the ideological categories included in the BAAD dataset. These ideological categories are mutually exclusive because groups are coded as 1 for only a single ideological category.
60. The group size variable derives from the BAAD dataset, which has four categories (I combined the largest two as there were so few groups with 10,000 or more members). The original data have the categories overlapping with groups coded as 0–100 (low confidence); 100–1000; 1000–10,000; and 10,000 or more. It is likely the measure was coded in categories because it is often difficult to accurately obtain a definitive number of group members in a clandestine group, and the

number of members changes over time. Many groups would likely have missing values if this variable was coded as a continuous measure. In contrast, estimations of group size are much easier to make from open source data.

61. The year the groups were founded range substantially. The oldest group was founded in 1918 (age is coded 87), while there are 11 groups that were founded in 2005 (age is coded 1). The 25th percentile for group age is 5 years, while the 50th percentile is 9 years, and the 75th percentile is 23.75 years.
62. Some of the country-level variables fluctuate over time. This cross-sectional study is unable to capture the variation over time, however, this study uses the mean value for each variable throughout the time period (aside from Democracy, which is selected based on whether it was a democracy or not during the majority of the duration). The benefits of using multilevel modeling and MMREM outweigh the benefits of capturing what are small variations in country characteristics over time.
63. D. L. Cingranelli and D. L. Richards, *CIRI Human Rights Data Project [Data File]*, 2010. Available at http://www.humanrightsdata.org/
64. World Bank, "Countries Ranked by GINI Index," 2014. Available at http://iresearch.worldbank.org/PovcalNet/index.htm
65. Some of the countries do not have a Gini index measure. The Gini index of countries with similar demographics, economic background, and/or geography were used as proxies. The Gini index for Syria was used for Lebanon, Thailand for Myanmar, Jordan for Saudi Arabia, Morocco for Qatar, Colombia for Kuwait, Germany for South Korea, Venezuela for United Arab Emirates, and Algeria for Portugal. Also note that multiple measures of poverty in each country were found (World Bank data); however, there is no measure that has consistent data available for all the countries in this dataset in the time frame. Other poverty measures had missing values for a large proportion of the countries in this analysis, so this study includes only the Gini index and the Gross Domestic Product (GDP).
66. J. A. Cheibub, J. Gandhi, and J. R. Vreeland, "Democracy and Dictatorship Revisited," *Public Choice* 143(1) (2010), pp. 67–101. Note the HDI is not used in the analyses because it is strongly correlated with other indicators included in the model.
67. Alberto Alesina et al., "Fractionalization," *Journal of Economic Growth* 8 (2003), pp. 155–194.
68. Ibid., 158–159.
69. Language diversity has been used in studies as a measure of diversity, but this study opted to include measures of ethnic and religious heterogeneity because they are each associated with specific terrorist group ideologies. Ethno-nationalist groups and religious terrorist groups distinguish themselves based on their ethnicity and/or religion, while there are few if any groups that solely identify with language.
70. The article does not specify what religious faiths are included in the 294 religions identified in the data for this variable. Although it is unclear whether some variations of faith, such as Sufi Sunni and Salafist Sunni Muslims, would be distinguished, the sheer number of religious faiths suggest that more general differences in faith, such as Sunni and Shi'ite Muslims, would be differentiated.
71. J. Bolt and J. L. van Zanden, "The First Update of the Maddison Project; Re-Estimating Growth Before 1820" (Maddison Project Working Paper 4, 2013). Available at http://www.ggdc.net/maddison/maddison-project/home.htm
72. Multivariate analysis is used to statistically evaluate the relationship between a dependent variable and one or more independent variables. Ordinary Least Squares (OLS) is used in multivariate analysis to determine the best-fitting regression line by minimizing error. OLS, however, requires that the sample consist of independent observations. If these observations (terrorist groups) are not independent then there may be correlated error, which may underestimate the standard error. Type I error, the false rejection of the null hypothesis, is increased if the OLS assumption of independence is violated. Terrorist groups are clustered within countries such that they are not independent. Therefore, proper analysis modeling nested data, multilevel modeling, is required.
73. W. J. Browne, *MCMC Estimation in MLwiN v2.1* (University of Bristol: Centre for Multilevel Modelling, 2009). Available at http://www.bristol.ac.uk/cmm/software/mlwin/refs.html; W. J.

Browne, *MCMC Estimation in MLwiN, v2.26* (University of Bristol: Centre for Multilevel Modelling, 2012). Available at http://www.bristol.ac.uk/cmm/media/migrated/2-31/mcmc-web.pdf

74. Note a model was run with these data without a random intercept to compare measures of deviance and effective parameters. Although this model was not reported in the table, the findings are compared in the results section of this article.
75. As noted in the descriptive statistics there are a number of groups that do not conduct any ideologically international attacks. In these cases there is no country context to include in the analysis, but the analysis requires level two parameters. The average values for the country traits are used for these groups so that the parameters of the foreign countries being targeted (ideological) can be appropriately assessed.
76. Browne, *MCMC Estimation in MLwiN, v2.26*.
77. Note that MMREM in MLwiN software is only able to include a total of four countries in the analysis. There are some groups that conducted international attacks that targeted more than four foreign countries. In these cases the countries with the largest number of attacks were included in the model using MMREM and weights were distributed according to the number of attacks the group conducted in each country in relation to the number of attacks among these four countries so that the weights add to one. A recent study on MMREM weights shows that the "choice of weight pattern did not greatly impact relative parameter bias," Wolff Smith and Beretvas, "The Impact of Using Incorrect Weights with the Multiple Membership Random Effects Model," 31. To assess if this is the case with this data, this analysis was run with equal weights arbitrarily used for multiple membership. In this analysis if two foreign countries were targeted they were each weighted 0.5, while if three were targeted they were weighted 0.34, 0.33, and 0.33, and groups that targeted four foreign countries were each weighted 0.25. Unlike the prior study analyzing weights in MMREM, the results of this analysis show some dramatic differences in the estimation of country-level variables. These different results are likely due to two factors. First there is a large proportion of groups in the sample that qualify for multiple membership because they targeted multiple foreign countries. Second the weight distributions differ significantly from the equal weightings as some groups may have attacked multiple foreign targets but not to the same degree. For example, the United States may have been targeted by four groups who attacked two foreign countries. If these groups attacked the other countries 80 percent of the time and the United States only 20 percent of the time, then equal weights dramatically overestimates the influence of the U.S. characteristics while underestimating the other country targeted. The weights selected for this study properly attribute the influence of country characteristics in proportion to the extent the group targets that country because it is theoretically and methodologically more justifiable.
78. The descriptive statistics for the dependent variable indicate that the data are overdispersed. This is not a concern in this model as a multilevel Poisson model allows for overdispersion by including random effects, which allows the variance to be larger than the mean (see J. Rasbash et al., *A User's Guide to MLwiN, v2.26* (University of Bristol: Centre for Multilevel Modelling, 2012). Available at http://www.bristol.ac.uk/media-library/sites/cmm/migrated/documents/manual-web.pdf; W. A. Link and J. R. Sauer, "A Hierarchical Analysis of Population Change with Application to Cerulean Warblers," *Ecology* 83 (2002), pp. 2832–2840; Junfeng Liu and Dipak K. Dey, "Hierarchical Overdispersed Poisson Model with Macrolevel Autocorrelation," *Statistical Methodology* 4 (2006), pp. 354–370; H. Huang and M. Abdel-Aty, "Multilevel Data and Bayesian Analysis in Traffic Safety," *Accident Analysis and Prevention* 42 (2010), pp. 1556–1565; Andrew Gelman and Jennifer Hill, *Data Analysis Using Regression and Multilevel/hierarchical Models* (New York: Cambridge University Press, 2007),https://books.google.co.uk/books?id=c9xLKzZWoZ4C&printsec=frontcover&dq=Data+analysis+using+regression+and+multilevel/hierarchical+models&hl=en&sa=X&ei=QTazVLSoH9exaZTEgdgG&ved=0CCkQ6AEwAA#v=onepage&q=Data%20analysis%20using%20regression%20and%20multilevel%2Fhierarchical%20models&f=false.
79. S. N. Beretvas, "Cross-Classified and Multiple Membership Random Effects Models," in J. Hox and J. K. Roberts, eds., *The Handbook of Advanced Multilevel Analysis* (New York: Routledge, 2010), pp. 313–334.

80. David J. Spiegelhalter et al., "Bayesian Measures of Model Complexity and Fit," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 64(4) (2002), pp. 583–639. See also Browne, *MCMC Estimation in MLwiN, v2.26*, 28.
81. Rasbash et al., *A User's Guide to MLwiN, v2.26*; ibid.; Spiegelhalter et al., "Bayesian Measures of Model Complexity and Fit."
82. Sensitivity analyses were conducted to ensure the results are robust and accurate.
83. This was calculated by using the equation: $\hat{e}(3.065^{*}.25) = 2.152$.
84. Note there are 51 and 66 distinct countries being modeled in these analyses. The average for each country trait is used for groups that did not conduct any ideologically international attacks in this time period.
85. Lum, Kennedy, and Sherley, "Are Counter-Terrorism Strategies Effective?," 9; 34.
86. Rasbash et al., *A User's Guide to MLwiN, v2.26*.
87. See Asal et al., "The Softest of Targets: A Study on Terrorist Target Selection"; Asal and Rethemeyer, "Dilettantes, Ideologues, and the Weak"; Asal and Rethemeyer, "The Nature of the Beast."
88. Kent Layne Oots, *A Political Organization Approach to Transnational Terrorism* (New York: Greenwood Press, 1986).
89. Li, "Does Democracy Promote or Reduce Transnational Terrorist Incidents?"
90. Eran Shor, "Constructing a Global Counterterrorist Legislation Database: Dilemmas, Procedures, and Preliminary Analyses," *Journal of Terrorism Research* Volume 2, no. Issue 3 (2011).
91. Asal and Rethemeyer are creating an extension of the BAAD database (BAAD2) that includes longitudinally coded group traits as well as a series of counterterrorism variables that have been directed toward each group.

Appendix A. Sample of terrorist groups. Terrorist group name and the number of domestic and ideologically international attacks between 1998 and 2005.

Terrorist group name	Number of domestic attacks	Number of ideologically international attacks
1920 Revolution Brigades	0	2
Abu Hafs al-Masri Brigade	0	11
Abu Sayyaf Group (ASG)	73	19
Achik National Volunteer Council (ANVC)	1	1
Action Committee of Winegrowers	3	0
Action Directe	3	0
Aden Abyan Islamic Army (AAIA)	2	1
Akhil Krantikari	0	0
al-Aarifeen	4	1
al-Aqsa Martyrs Brigades	61	7
al-Badr	0	3
Albanian National Army (ANA)	0	6
Alex Boncayao Brigade (ABB)	2	1
al-Fatah	9	0
al-Gama'a al-Islamiyya (GAI)	0	2
al-Haramayn Brigades	3	0
al-Intiqami al-Pakistani	2	0
All Tripura Tiger Force (ATTF)	4	2
al-Madina	0	4
al-Mansoorain	0	16
al-Nawaz	1	0
Al Qaeda	0	64
Al Qaeda in the Arabian Penninsula (AQAP)	0	4
al-Umar Mujahideen	0	3
Amal	1	1
Anarchist Faction	0	2
Anarchist Struggle	0	1
Andres Castro United Front (FUAC)	1	1
Angry Brigade	2	0
Animal Liberation Front (ALF)	0	55
Ansar al-Islam	5	2
Ansar al-Jihad	1	0
Ansar Allah	0	0
Ansar al-Sunnah Army	11	6
Anti-Authority Erotic Cells	0	1
Anti-Communist Command (KAK)	1	0
Anti-Racist Guerrilla Nuclei	1	0
Anti-State Action	3	0
Anti-Zionist Movement	2	0
Arbav Martyrs of Khuzestan	1	0
Armata Corsa	1	0
Armata di Liberazione Naziunale	7	1
Armed Forces Revolutionary Council (AFRC)	2	1
Armed Islamic Group	114	3
Army of God	2	0
Asbat al-Ansar	0	1
Autonomous Decorators	1	0
Babbar Khalsa International (BKI)	0	0
Baloch Liberation Army (BLA)	11	1
Basque Fatherland and Freedom (ETA)	0	174
Bersatu	0	0
Black Panthers (West Bank/Gaza)	0	0
Black Star	4	3
Black Widows	0	0
Bodo Liberation Tigers (BLT)	0	6
Brigades of Imam al-Hassan al-Basri	1	0
Cambodian Freedom Fighters (CFF)	0	0
Catholic Reaction Force (CRF)	0	2

(*Continued on next page*)

Appendix A. (*Continued*)

Terrorist group name	Number of domestic attacks	Number of ideologically international attacks
Chukakuha	1	0
Clandestini Corsi	2	0
Coalition to Save the Preserves (CSP)	8	0
Communist Party of India-Maoist (CPI-M)	5	1
Communist Party of Nepal-Maoists (CPN-M)	14	2
Conscientious Arsonists (CA)	3	2
Continuity Irish Republican Army (CIRA)	0	0
Democratic Front for the Liberation of Palestine (DFLP)	7	0
Democratic Karen Buddhist Army (DKBA)	0	1
DHKP-C	9	1
Earth Liberation Front (ELF)	0	65
East Turkistan Liberation Organization	0	1
Egyptian Islamic Jihad (EIJ)	0	0
Ethnocacerista	1	0
Fighting Ecologist Activism	0	0
Fighting Guerillas of May	2	0
First of October Antifascist Resistance Group (GRAPO)	17	0
Free Aceh Movement (GAM)	106	5
Free Papua Movement (OPM)	0	7
Front for Defenders of Islam (FPI)	1	0
Front for the Liberation of the Cabinda Enclave	2	1
Fronte di Liberazione Naziunale di a Corsica (FLNC)	44	2
Gazteriak	1	0
Global Intifada	1	1
God's Army	0	2
Group of Popular Combatants (GPC)	2	0
Hamas	67	8
Harakat ul-Mudjahidin (HuM)	0	5
Hezbollah	0	68
Hizb-I-Islami	5	8
Hizbul Mujahideen (HM)	0	53
Indigenous People's Federal Army (IPFA)	1	0
Informal Anarchist Federation	4	3
International Solidarity	1	1
Iparretarrak (IK)	0	3
Irish National Liberation Army (INLA)	0	0
Irish Republican Army (IRA)	0	4
Islamic Army in Iraq	0	5
Islamic Great Eastern Raiders Front	12	3
Islamic Jihad Brigades	0	1
Islamic Movement of Uzbekistan (IMU)	0	5
Jagrata Muslim Janata Bangladesh	15	0
Jaime Bateman Cayon Group (JBC)	1	0
Jaish al-Taifa al-Mansoura	1	1
Jaish-e-Mohammad (JeM)	2	16
Jaish-ul-Muslimin	0	2
Jamatul Mujahedin Bangladesh	15	0
Jamiat ul-Mujahedin (JuM)	0	8
Janashakti	2	0
Jemaah Islamiya (JI)	0	56
Jenin Martyrs' Brigade	1	0
July 20th Brigade	2	0
Jund Allah Organization for the Sunni Mujahideen in Iran	0	0
Jund al-Sham	0	0
Justice Army of the Defenseless People	0	0
Kach	1	0
Kakurokyo	1	1
Kanglei Yawol Kanna Lup (KYKL)	2	0
Kangleipak Communist Party	0	0

(*Continued on next page*)

Appendix A. (*Continued*)

Terrorist group name	Number of domestic attacks	Number of ideologically international attacks
Kayin National Union (KNU)	8	5
Kosovo Liberation Army (KLA)	0	39
Kuki Liberation Army (KLA)	0	1
Kurdistan Freedom Hawks	0	6
Kurdistan Workers' Party (PKK)	82	10
Lashkar-e-Jhangvi (LeJ)	13	3
Lashkar-e-Taiba (LeT)	0	70
Lashkar-I-Omar	1	1
Laskar Jihad	7	0
Liberation Tigers of Tamil Eelam (LTTE)	280	10
Lord's Resistance Army (LRA)	87	15
Loyalist Volunteer Force (LVF)	0	2
Macheteros	0	0
Mahdi Army	1	2
Maoist Communist Center (MCC)	22	2
Mariano Moreno National Liberation Commando	0	3
May 98	2	0
Moro Islamic Liberation Front (MILF)	163	8
Moro National Liberation Front (MNLF)	5	0
Movement for Democracy and Justice in Chad (MDJT)	2	0
Muslim United Army	0	1
Muslims Against Global Oppression (MAGO)	0	1
Muttahida Qami Movement (MQM)	9	0
National Army for the Liberation of Uganda (NALU)	0	1
National Democratic Front of Bodoland (NDFB)	26	1
National Liberation Army (Colombia)	158	27
National Liberation Front of Tripura (NLFT)	0	41
National Socialist Council of Nagaland-Isak-Muivah (NSCN-IM)	2	0
New People's Army (NPA)	83	4
New Revolutionary Alternative	1	0
New Revolutionary Popular Struggle (NELA)	1	0
Odua Peoples' Congress	2	0
Orange Volunteers (OV)	0	0
Oromo Liberation Front (OLF)	3	1
Palestinian Islamic Jihad (PIJ)	32	2
Pattani United Liberation Organization (PULO)	7	0
People Against Gangsterism And Drugs (PAGAD)	9	0
People's Revolutionary Militias	4	1
People's War Group (PWG)	62	0
Popular Front for the Liberation of Palestine (PFLP)	32	0
Popular Liberation Army	10	1
Popular Resistance	2	0
Popular Resistance Committees	6	1
Popular Self-Defense Forces (FAP)	0	4
Proletarian Nuclei for Communism	2	0
Protectors of Islam Brigade	0	1
Purbo Banglar Communist Party (PBCP)	3	0
Real Irish Republican Army (RIRA)	0	1
Red Brigades	0	0
Red Hand Defenders (RHD)	0	1
Red Line	0	1
Resistenza Corsa	0	4
Revolutionary Armed Forces of Colombia (FARC)	406	38
Revolutionary Armed Forces of the People (FARP)	3	0
Revolutionary Army	0	0
Revolutionary Cells Animal Liberation Brigade	1	0
Revolutionary Liberation Action	0	0
Revolutionary Nuclei	4	6
Revolutionary Organization 17 November (RO-N17)	9	7

(*Continued on next page*)

Appendix A. (*Continued*)

Terrorist group name	Number of domestic attacks	Number of ideologically international attacks
Revolutionary Perspective	0	4
Revolutionary Proletarian Initiative Nuclei	2	0
Revolutionary Struggle	6	0
Revolutionary United Front (RUF)	15	18
Revolutionary Violence Group (RVG)	0	1
Riyad us-Saliheyn Martyrs' Brigade	5	0
Saif-ul-Muslimeen	0	1
Salafia Jihadia	0	5
Salafist Group for Call and Combat (GSPC)	0	0
Sardinian Autonomy Movement (MAS)	1	0
Save Kashmir Movement	4	0
Self-Defense Groups of Cordoba and Uraba (ACCU)	1	0
Shining Path	17	1
Shurafa al-Urdun	0	1
South Londonderry Volunteers (SLV)	0	2
Students Islamic Movement of India (SIMI)	4	2
Sudan People's Liberation Army	0	11
Tanzim	6	0
Tawhid and Jihad	19	31
Territorial Anti-Imperialist Nuclei	2	0
The Holders of the Black Banners	0	1
The Inevitables	0	1
The National Anti-Corruption Front	0	1
Tigers	1	0
TKP/ML-TIKKO	7	0
Totally Anti-War Group (ATAG)	1	0
Tupac Amaru Revolutionary Movement	0	0
Tupamaro Revolutionary Movement - January 23	1	3
Ulster Defence Association/Ulster Freedom Fighters	0	0
Ulster Volunteer Force (UVF)	0	2
Ummah Liberation Army (ULA)	1	0
UNITA	82	56
United Kuki Liberation Front (UKLF)	1	0
United Liberation Front of Assam (ULFA)	78	1
United National Liberation Front (UNLF)	1	0
United People's Democratic Solidarity (UPDS)	6	0
United Self-Defense Forces of Colombia (AUC)	57	0
Vigorous Burmese Student Warriors	1	1
White Legion	1	0
Young Liberators of Pattani	1	0

Appendix B. Countries included in the assessment of domestic terrorist attacks with the corresponding number of groups and percentage of groups in the sample.

Country	Frequency	Percent
Afghanistan	5	2.2
Algeria	2	.9
Angola	2	.9
Argentina	1	.4
Bangladesh	3	1.3
Bolivia	2	.9
Chad	1	.4
China	1	.4
Colombia	7	3.1
Congo, Democratic Republic of / Zaire	1	.4
Ecuador	3	1.3
Egypt	2	.9
El Salvador	1	.4
Ethiopia	1	.4
France	10	4.5
Germany	1	.4
Greece	17	7.6
India	22	9.8
Indonesia	7	3.1
Iran	2	.9
Iraq	14	6.3
Ireland	1	.4
Israel	11	4.9
Italy	12	5.4
Japan	3	1.3
Jordan	1	.4
Lebanon	4	1.8
Macedonia	2	.9
Mexico	2	.9
Morocco	1	.4
Myanmar (Burma)	4	1.8
Nepal	2	.9
Nicaragua	1	.4
Nigeria	1	.4
Pakistan	16	7.1
Peru	3	1.3
Philippines	6	2.7
Russia	3	1.3
Saudi Arabia	2	.9
Sierra Leone	2	.9
South Africa	2	.9
Spain	3	1.3
Sri Lanka	1	.4
Sudan	2	.9
Swaziland	1	.4
Sweden	1	.4
Thailand	3	1.3
Turkey	5	2.2
Uganda	2	.9
United Kingdom	11	4.9
United States of America	7	3.1
Uzbekistan	1	.4
Venezuela	2	.9
Yemen	1	.4
Total	224	100.0

Appendix C. Countries included in the assessment of ideologically international terrorist attacks with the corresponding number of groups that targeted the country.

Country	Frequency
Afghanistan	4
Algeria	1
Angola	2
Australia	4
Bangladesh	2
Belgium	2
Bhutan	1
Bolivia	1
Brazil	1
Canada	6
China	2
Colombia	1
Congo, Democratic Republic of / Zaire	1
Egypt	1
France	13
Germany	6
Greece	4
India	16
Indonesia	3
Iran	1
Iraq	3
Ireland	7
Israel	9
Italy	10
Japan	2
Jordan	3
Kenya	1
Kuwait	1
Kyrgyzstan	1
Lebanon	2
Macedonia	2
Malaysia	1
Mexico	1
Morocco	1
Myanmar (Burma)	3
Namibia	1
Nepal	3
Netherlands	1
Nicaragua	1
Norway	1
Pakistan	5
Philippines	3
Portugal	2
Russia	6
Serbia-Montenegro	4
Sierra Leone	1
Singapore	1
Somalia	1
South Africa	1
South Korea	2
Spain	3
Sri Lanka	2
Sudan	3
Switzerland	3
Syria	1
Thailand	5
Tunisia	1
Turkey	8
Uganda	1

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Appendix C. (*Continued*)

Country	Frequency
United Kingdom	16
United Arab Emirates	1
United States of America	33
Uzbekistan	1
Venezuela	1
Yemen	1