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Transnational Terrorism Hot Spots: Identification and Impact Evaluation

ALEX BRAITHWAITE

Lecturer
Department of Political Science
University College London
London, UK

QUAN LI

Associate Professor
Department of Political Science
Pennsylvania State University
University Park, Pennsylvania, USA

To combat transnational terrorism, it is important to understand its geography. The extant literature on the geography of terrorism, however, is small and focuses on the distribution and diffusion of terrorism among aggregate regions such as Europe and the Middle East. In this analysis, we study transnational terrorism hot spots at the country level. We employ local spatial statistics to identify terrorism hot spot neighborhoods and countries that are located within. We also assess empirically the impact of these hot spots on future patterns of terrorist incidents. We find that countries with significant experiences with terrorism are often located within these hot spots, but that not all countries within the hot spots have experienced large numbers of terrorist incidents. We also find in a pooled time-series analysis of 112 countries from 1975 to 1997 that when a country is located within a hot spot neighborhood, a large increase in the number of terrorist attacks is likely to occur in the next period. This effect is robust under alternative definitions of geographic proximity and across the two most popular measures of local hot spots of data—the G_i^* *statistic and the Local Moran's I. These findings have important implications for the continuing fight against transnational terrorism.*

Keywords geography of terrorism, hot spot, spatial statistics, transnational terrorism

Introduction

The September 11, 2001 terrorist attacks rekindled wide interest in the patterns of transnational terrorism. Terrorist incidents often appear to concentrate in particular geographic regions and yet are relatively rare in others. Meanwhile, terrorist networks such as the Al Qaeda are more active in certain parts of the world and are frequently observed as having spread their activities across national borders. The literature on the geography of transnational terrorism is growing, but remains small. Also, extant studies of the geography of terrorism typically adopt a focus on such aggregate regional units as Europe and the Middle East. While these studies demonstrate important patterns in the geography of terrorism, their focus on aggregate geographic regions has limitations, as discussed later in detail. In

Address correspondence to Alex Braithwaite, Department of Political Science, University College London, 29/30 Tavistock Square, London, WC1H 9QU, UK. E-mail: a.braithwaite@ucl.ac.uk

this paper, we contribute to the growing literature on the geography of terrorism by studying hot spots of transnational terrorist incidents at the country level. We use local spatial statistics to identify which countries are located within terrorism hot spot neighborhoods, and we estimate empirically the impact of being part of such a hot spot on a country's future experience of terrorist attacks.

We argue that identifying country-level terrorism hot spots and assessing their impact upon future attacks have important implications. The identification of whether or not an individual country is part of a terrorism hot spot provides a more refined understanding of the geographic distribution of terrorism than the regional approach in the literature. In addition, a precise technical identification of the hot spot neighborhood enables analysts to estimate consistently and rigorously the size of its impact upon future attacks at the country level. Consequently, policymakers may better anticipate the effectiveness of their counterterrorist measures that target the hot spot countries and offer a social scientific rationale for their policies. Different policymakers and governments may also use such empirical knowledge to help build consensus as to where they should focus their concerted, collective efforts in the global fight against terrorism. Accordingly, scarce resources can be more effectively allocated to combat transnational terrorism.

The rest of the paper proceeds as follows. The following section reviews the literature on the geography of terrorism. We then describe the empirical patterns of transnational terrorist incidents from 1975 to 1997, explain the G_i^* statistic for spatial analysis, and identify countries located within terrorism hot-spot neighborhoods during this period. The section after this studies how being part of a hot-spot affects future terrorist attacks in the country and empirically estimates the size of that impact. The final section summarizes our findings and discusses their theoretical and policy implications.

Literature on the Geography of Terrorism

In the terrorism literature, only a few studies have analyzed the geography of terrorist activities.[1] In a pioneering study, Midlarsky et al. (1980) investigate the diffusion and contagion of terrorist tactics and events. They argue that the global temporal and spatial distribution of terrorist incidents can follow four possible patterns: randomness, heterogeneity, contagion, and reinforcement. Terrorist events may be distributed randomly in space and time. Otherwise, the nonrandom distribution may follow one or more of the remaining three types. Heterogeneity implies that the propensities of different countries to experience terrorism are disparate across space but constant over time. Reinforcement refers to the idea that the occurrence of a terrorist incident in one country increases the probability that the same country will experience terrorism in the future. Contagion means that the occurrence of a terrorist incident in one country increases the probability of a neighboring country experiencing an incident, resulting in an increasing number of countries that transition from experiencing no terrorism to experiencing some number of incidents in a later period. Focusing on explaining contagion, Midlarsky et al. (1980) propose a theory of hierarchies. Countries with diplomatic prominence are posited to be the first to experience terrorism, which subsequently spreads like a contagious disease to less prominent countries through a process of imitation. Using Poisson and negative binomial probability models, they find evidence of contagion between Latin America and Western Europe in the period from 1973 to 1974. They are puzzled, however, by the finding of an inverse hierarchical order. That

[1] In contrast, scholars have developed a more comprehensive understanding of the temporal regularities in transnational terrorist activities. See, e.g., Hamilton & Hamilton (1983), Enders & Sandler (1993, 1999, 2000, 2002).

is, radical groups in Western Europe appear to have imitated the behaviors of terrorists in Latin America, and not vice versa, as they initially hypothesize.

In their critique of Midlarsky et al., Heyman and Mickolus (1980) argue that this hierarchical theory should be applied to the relationship between terrorist groups rather than that between nation states. Accordingly, they theorize that the use of terrorism spreads from well-developed terror groups to more nascent ones, rather than from well-developed regions to less-developed ones. They argue specifically that during the period studied by Midlarsky et al. (1980), terror groups in Latin America were, in fact, typically more developed and better known than their West European counterparts, suggesting a hierarchical contagion pattern of terrorist tactics and practices spreading from Latin America to Western Europe. Heyman and Mickolus (1980) further point out that contagion is not the only form in which terrorism spreads geographically across borders. Other noncontagious diffusion processes may include cooperation between terrorist groups in terms of intelligence, training, funds, and support, as well as the transference and transportation of terrorist activities across borders in search of weaker victims and/or greater impact. They show that both the contagion and transportation mechanisms are important explanations of the geographic spread of transnational terrorism.

Li and Schaub (2004) employ a negative binomial model to analyze how economic globalization affects transnational terrorist incidents within 112 countries from 1975 to 1997. Based on the premise that transnational terrorist incidents are unevenly distributed geographically, they include variables in their empirical models that enable them to control for regional variations. Specifically, their models compare the number of terrorist incidents in Europe, Africa, Asia, and America, relative to a reference region—the Middle East. They find that the Middle East has the highest concentration of transnational terrorist incidents, with Europe ranked second. Africa, Asia, and the Americas experience significantly fewer transnational terrorist incidents, approximately 69%, 65%, and 33%, respectively, compared with the Middle East.

More recently, Enders & Sandler (2006) study the distribution of transnational terrorism among countries by income class and geography, with a focus upon comparing patterns from the periods before and after 9/11. They find no evidence of an income-based, post-9/11 transfer of attacks to low-income countries. Contrary to common intuition, efforts by wealthy states to counter terrorism do not appear to have resulted in the transference of these acts to poorer (presumably less capable) states. But they do demonstrate that the post-9/11 period has witnessed a significant transference of terrorist incidents from North America and West Europe to the Middle East and Asia following the adoption of dramatic new counterterrorism measures in the United States and the United Kingdom.

While previous studies offer insights into the diffusion and contagion of terrorist activities and identify regional patterns of heterogeneity and transference in the distribution of terrorist incidents, emphasis on regional units that are aggregates of nation-states results in geographic analyses that are less refined than the country-level spatial analysis. Thus, extant studies of the geography of terrorism suffer from several weaknesses. First, focusing on regional units, these studies implicitly assume that all states in the same region are equally likely to become venues of terrorist attacks, ignoring within-region and between-state variations in levels of terrorism. Furthermore, as we will demonstrate, the locations of terrorism hot spots do not coincide perfectly with conventional boundaries of regional units. Hence, extant studies can neither identify accurately which countries are (or are not) part of terrorism hot spots, nor can they estimate precisely the impact that these hot spots have upon terrorist attacks in the subsequent period. Finally, focusing on regional units does not help one better understand the country-level origins of terrorism hot spots and the subsequent spread of terrorism.

Identifying Hot Spots of Transnational Terrorist Incidents

Recent advances in spatial analysis facilitate the precise identification of hot spots of political phenomena. These new spatial analysis techniques have been commonly applied to account for the regional concentration of international conflict (Anselin & O'Loughlin, 1990, 1991; Kirby & Ward, 1987; Ward & Gleditsch, 2002) and democratic political regimes (O'Loughlin et al. 1998), as well as to explain the co-evolution of the two (Gleditsch & Ward, 2000; Gleditsch, 2002). But these new methods have never been applied to the study of terrorist violence, a task we undertake in this analysis.

Following previous research (e.g., Enders & Sandler, 1999, 2002), we define terrorism as the premeditated or threatened use of extra-normal violence or force to obtain a political, religious, or ideological objective through the intimidation of a large audience. Terrorist incidents are considered transnational if they occur in one country and involve victims, perpetrators, targets, or the institutions of another country. Before we move onto the spatial analysis, we first set the stage with the descriptive patterns of transnational terrorist incidents over time. Based on the ITERATE (International Terrorism: Attributes of Terrorist Events) database (Mickolus, 1982; Mickolus et al., 1989; Mickolus et al., 1993; Mickolus et al., 2002), our terrorism data measure the number of transnational terrorist events that occur in a country in a given year. For the sake of analysis, we employ a subset of the ITERATE dataset, covering 143 countries for the years 1975 to 1997. Table 1 summarizes the terrorism data in terms of annual global averages, standard deviations, and ranges. From this table, one can "eye-ball" temporal changes in the aggregate data and in the distribution of events over time.

TABLE 1 Annual descriptive statistics for transnational terrorist incidents

Year	Mean	Standard Deviation	Minimum	Maximum
1975	2.33	8.03	0	70
1976	3.08	8.56	0	56
1977	2.26	6.25	0	48
1978	1.88	4.73	0	37
1979	2.25	5.75	0	40
1980	3.53	9.35	0	67
1981	3.18	8.12	0	55
1982	2.90	8.00	0	49
1983	2.94	7.55	0	70
1984	3.24	8.43	0	79
1985	3.58	9.10	0	82
1986	3.69	10.16	0	96
1987	3.40	9.42	0	73
1988	2.83	5.96	0	42
1989	2.43	4.70	0	31
1990	2.53	5.66	0	49
1991	3.97	10.23	0	87
1992	2.42	5.47	0	38
1993	3.74	16.06	0	180
1994	2.55	5.58	0	41
1995	2.03	3.56	0	28
1996	1.44	2.73	0	21
1997	1.23	3.22	0	23

Table 1 demonstrates several interesting patterns. First, the average number of incidents per country per year remains relatively constant between 2 and 4. The only large deviation is the sharp decline in 1996 and 1997, down to 1.44 and 1.23, respectively. Second, the standard deviation (SD) in the number of events is invariably larger than the mean, suggesting overdispersion in the count data. Third, the SD in the number of attacks ranges between 2.73 and 16.06, suggesting that the spatial distribution of events is likely to be heterogeneous over time.[2]

What are spatial statistics? And which spatial statistic shall we use to identify terrorism hot spots? Before we address these questions, we need to define our conception of a terrorism hot spot. Imagine that the international system consists of a number of countries. According to an a priori criterion of geographic proximity, to be explained in detail later, geographically proximate countries constitute "a neighborhood." The neighborhood represents an aggregation of states that is more flexible and more disaggregated than the regional units previous studies of the geography of terrorism focus on (e.g., in the distinction between Europe and the Middle East). Thus, many such neighborhoods exist in the international system. A terrorism hot spot is defined as a neighborhood of countries that experiences a larger number of terrorist incidents than one would expect of an average neighborhood in the international system according to a random process. For illustrative purposes, imagine the smallest possible neighborhood as one of just two countries (e.g., Canada's neighborhood comprises just itself and the U.S.). Under what conditions will this neighborhood, consisting of Canada, denoted as country i, and its neighbor, the U.S., denoted as country j, be considered a hot spot of terrorism? Based on the definition above, it follows that the neighborhood is a terrorism hot spot when the total number of terrorist incidents across i and j is greater than the expected number of incidents (i.e., the average number) for such a neighborhood. Canada is considered to be located in a terrorism hot spot in years in which the combined level of terrorism of the U.S. and Canada exceeds the expected number of attacks for a neighborhood of this size in the system. Therefore, such clustering is possible under three scenarios from the perspective of individual members in the neighborhood. First, both state i and its neighbor j experience large numbers of terrorist incidents such that their total count exceeds the expected count for the neighborhood. Second, state i has a low or moderate number of incidents, but its neighbor j has such a high number that their total count exceeds the expected count for the neighborhood. Third, while its neighbor j experiences a low or moderate number of incidents, state i has such a large count that their total count exceeds the expected count for the neighborhood. Regardless of the variations in the number of incidents between i and j, the neighborhood is a terrorism hot spot such that each individual member is part of that hot spot.

Spatial association statistics examine whether the number of events within an area (for example, the number of terrorist attacks within a country) is similar to the count of events in neighboring areas. A number of global statistics (including Moran's I, Geary's C, and Ord and Getis's G) focus on whether or not there are signs of global spatial nonstationarity in the data by exploring spatial autocorrelation between observations and the similarity of values among neighboring countries. These global measures, however, do not tell us about the precise location of any hot spot neighborhood that may be responsible for this observed spatial nonstationarity. In order to identify spatial clusters or hot spots, localized spatial statistics should be used instead of global spatial statistics (see, e.g., Anselin, 1995; O'Loughlin, 2002).

A number of localized spatial statistics (such as local Moran's I, local Geary's C, and Getis and Ord's Gi and G_i^*) can help identify various types of clusters including hot spots

[2]These descriptive patterns are consistent with the findings of Midlarsky et al. (1980).

in data (Chainey & Ratcliffe, 2005: 163–164).[3] In practice, for the task of identifying local hot spots of events, the G_i^* statistic is favored over the alternatives—Moran's I[4], Geary's C[5], and G_i[6] (see, e.g., O'Loughlin, 2002; Gleditsch, 2002). The G_i^* statistic has been widely used in a number of research areas to detect hot spots—local "pockets" of dependence in data—that global statistics of spatial dependence fail to identify. For example, the G_i^* statistic is applied to analyze spatial clustering in patterns of voting in Weimar Germany (O'Loughlin, 2002), co-evolving zones of war and democracy (Gleditsch, 2002), and the clustering of incidents of criminal activity (Craglia et al., 2000).[7] The G_i^* statistic is preferred over alternatives in identifying hot spots for several reasons. First, the statistic approximates

[3]Separate from the goal of identifying specific pockets, clusters, or hot spots, scholars also use spatial statistics to diagnose the source of spatial dependence in one's data. Anselin (1995) and Anselin & Bao (1997), for instance, discuss the process of identifying dependence between observations of the dependent variable (spatial lag) and dependence between error terms (spatial error) in correcting for dependence in one's statistical models. Rather than to diagnose and correct for spatial dependence, the focus of our analysis is to identify and locate individual countries located within terrorism hot spot neighborhoods.

[4]Local Moran's I is based upon covariance between observations at neighboring locations and is designed to distinguish among "high-high," "low-low," "high-low," and "low-high" clusters of observations. For instance, in a two-country neighborhood, if country *i* and its neighbor *j* each experience levels of terrorism significantly higher than the expected value for an average country, the local Moran's *I* will identify a "high-high" cluster. If country *i* experiences a level of terrorism significantly lower than the expected value for an average country, while its neighbor *j* experiences a higher level of terrorism than this same expected value, this statistic would identify a "low-high" cluster, and so on. The disadvantage of this statistic is that it emphasizes the level of events of each individual member of a neighborhood, rather than the combined level of events for the neighborhood as a whole. If, say, country *i* experiences a level of terrorism close to the expected level for an average country (i.e., not statistically distinguishable from this expected level), while country *j* experiences a level of terrorism in excess of the expected value, no cluster will be identified for country *i*, regardless of *j*'s experience and that of the neighborhood. As such, the local Moran's I measure is able to identify country *i* as being located within a cluster only when its own experience of terrorism is statistically distinguishable from the mean expected value. This inflexibility is inconsistent with our own neighborhood-level conceptualization of hot spots, in which it is the aggregate experience of terrorism in country *i*'s neighborhood that determines whether or not country *i* is considered to be located within a hot spot. For a more detailed overview of the local Moran's I statistic see Anselin (1995).

[5]The local Geary's C statistic is based upon measuring differences in values between neighboring locations. Hence, it identifies clusters of similarly valued counts of events, without clearly indicating whether or not these similar values are jointly low, jointly medium, or jointly high, compared to the expected value for an average country. While it identifies clusters of similar values, the statistic does not specifically identify the kind of terrorism hot spot we have in mind. As such, it is not appropriate for the purpose of our analysis.

[6]In identifying local clusters or hot spots of events, the G_i statistic (Getis & Ord, 1992) excludes information about events occurring in country *i* when computing whether or not country *i* is located within a local hot spot neighborhood. In choosing to employ this statistic, therefore, one has to assume implicitly that the number of terrorist incidents in country *i* is independent of or does not contribute to terrorism in the other countries in the neighborhood. These two assumptions are problematic for computing hot spots of terrorist incidents for two reasons. First, one could hardly predict *ex ante* whether the level of terrorism from any given country in a neighborhood is inconsequential or irrelevant. Second, since a hot spot refers to a hot spot neighborhood, terrorist activities in *all* countries within the geographic neighborhood are relevant to the neighborhood as a whole. Hence, the G_i^* statistic is typically preferred over the G_i statistic in many studies of spatial clustering (see, e.g., O'Loughlin, 2002, Gleditsch, 2002), because it explicitly takes into account the levels of terrorism in country *i* as well as within the neighbor *j*.

[7]A number of additional measures of "hot spots" have been developed recently, primarily outside of political science (Brimicombe, 2004; O'Loughlin, 2002). They offer opportunities to examine directional spatial dependence, among other trends, but do not offer the intuitive appeal or technical ease of the G_i^* statistic. Future research should explore the application of these new measures to the study of terrorism.

the typical definition of a hot spot, identifying areas where local averages are significantly higher than global averages (Chainey & Ratcliffe, 2005, 164). Second, unlike the local Moran's I, G_i^* does not require that in a geographic neighborhood, *both* state i and its neighbors j experience levels of terrorism that are statistically distinguishable from (either higher or lower than) the expected experience of terrorism of an average country. Third, G_i^* is able to identify states that are located within neighborhoods experiencing *high* levels of terrorism, even if country i's own experience of terrorism is not different from the global mean. For these reasons, we employ the G_i^* statistic to identify hot spots of transnational terrorist incidents.

How is the G_i^* statistic constructed technically? Technically, G_i^* offers a country-by-country measure of spatial association, identifying cases of hot spots via the high combined number of terrorist attacks of all countries in the neighborhood. The indicator intuitively reflects the spatial clustering of terrorist incidents. It also allows us to identify whether or not a country is part of a terrorism hot spot.[8] Following Ord & Getis (1995) and O'Loughlin et al. (1998), the G_i^* statistic is specified as:

$$G_i^* = \frac{\Sigma_j w_{ij} x_j - \sum_i (w_{ij} + w_{ii})\bar{x}}{\hat{\sigma}_x \sqrt{n \sum_j w_{ij}^2 - \sum_i w_{ij}^2 / (n-1)}}$$

where w_{ij}[9] denotes element i,j in a binary contiguity matrix, x_j is an observation at location j, and $\bar{x}$ and $\hat{\sigma}_x^2$ denote the sample mean and variance. The G_i^* can be compared to the standard normal distribution and indicates the extent to which high valued observations of an event are clustered around a particular country, i. A positive and statistically significant

[8]Gleditsch (2002) notes that G_i^* scores for localized clustering are somewhat dependent upon the total number of neighbors/contiguous countries. He argues that countries with greater numbers of neighbors are more likely to face a greater number of external threats. Getis & Ord (1992:193) point out, however, that 'as data points become more clustered in the vicinity of point i, the expectation of G_i^* rises, neutralizing the effect of the dense cluster of j values that exists if a state has an unusually high number of neighbors.' Still, another implication is that we are less likely to find significant values for countries that have very few neighbors than for those that have multiple neighbors. The consequence is that it poses a tougher test for us to find significant evidence on the impact of terrorist hot spots. This critique also relates indirectly to the fact that the G_i^* statistic is most efficient when employed to analyze data aggregated within polygons of approximately equal area. Clearly this is not the case in terms of countries within the international system. As things stand, however, the authors are unaware of any preferable alternatives that would help overcome this critique.

[9]We employ three alternative measures of contiguity/proximity in defining the spatial weights matrix, w_{ij}: first-order land contiguity, land and sea contiguity, and contiguity of boundaries separated by not more than 950 km. Each of these is frequently employed in quantitative studies of international conflict. The measure of direct or "first-order" contiguity identifies two states as being neighbors if they share a land border with one another. According to this operationalization, the U.S. currently "neighbors" two countries—Canada and Mexico. For this, we use the Correlates of War measure of direct contiguity (Stinnett et al., 2002). O'Loughlin et al. (1998, 554) identify contiguity as the preferred metric for the study of interaction and diffusion in the IR literature (Most & Starr, 1980; Kirby & Ward, 1987; Siverson & Starr, 1991.) The second measure of contiguity includes both land borders and borders that are separated by not more than 150 km of water. This measure also is commonly employed in conflict studies to measure contiguity (see, Bennett & Stam, 2004). Using this operationalization, we would identify Canada, Mexico, the Bahamas, Cuba, and Russia as neighbors of the U.S. The third measure of proximity we employ is based on Gleditsch & Ward's (2001) minimum distance dataset that allows us to identify neighbors as states whose territories are within 950 km of one another. In this instance, Canada, Mexico, the Bahamas, Jamaica, Cuba, and Russia are coded as neighbors of the U.S. In line with the COW coding rules, our contiguity measures most closely approximate those of the queen definition of contiguity—meaning that any length of shared border is sufficient to indicate contiguity.

value for the G_i^* statistic at a particular location implies spatial clustering of high values around that location (Ord & Getis, 1995).

A terrorism hot-spot neighborhood is indicated by a positive and statistically significant G_i^* statistic. This statistic details the differences between summed numbers of terrorist incidents at all contiguous pairs of countries and the mean value of these numbers, as a proportion of the global variability in the numbers of terrorist incidents. As such, G_i^* measures the concentration, or the lack thereof, of the sum of the numbers of terrorist incidents spatially. If, for example, large numbers of terrorist incidents occur in the neighborhood consisting of country i and its neighbors j, it follows that the value of G_i^* is high. Because this statistic approximates a standard normal distribution as the sample size increases (Ord & Getis, 1995), one can identify rigorously whether a country is located in a terrorism hot-spot using a statistical significance test.

To identify precisely which countries are located in terrorism hot-spots in given years, we compute the G_i^* statistic using three year aggregates (as sliding windows) of the numbers of terrorist incidents in each country, producing G_i^* values for all 143 countries for each of the 23 years in the study. Those states that return statistically significant G_i^* scores (p value < 0.05) in each year are considered to be located in transnational terrorism hot spots during that year. We calculate the G_i^* statistic using three alternative operationalizations of the W_{ij} matrix: (1) direct land contiguity, (2) contiguity defined by shared land boundaries or those separated by not more than 150 km of sea, and (3) a minimum distance between countries of not more than 950 km. A complete list of countries identified by the G_i^* as being located within a terrorism hot-spot is presented in the Appendix.[10] This list demonstrates that terrorism hot spots are observed for 319, 394, and 607 country years for the three measures of geographic proximity (direct land contiguity, land and sea contiguity, and 950 km minimum distance), respectively.

Assessing the Impact of Terrorism Hot Spots on Future Attacks

In this section, we assess empirically the impact of being located within the terrorism hot spot on a country's future level of terrorist attacks. Specifically, we address two questions. If a country is part of a terrorism hot-spot, does that experience increase the number of terrorist attacks within the country in the subsequent period? If so, what is the size of that observed impact?

Before we embark on the empirical analysis, it is important to identify the theoretical reasons for why we might expect that terrorism hot-spots cause more terrorist attacks in subsequent years. Building on the work of Midlarsky et al. (1980) and Heyman and Mickolus (1980), we argue that a number of reasons account for why terrorism hot spots result in increases in future terrorist incidents. First, terrorist groups imitate and influence each other; copycat attacks are frequent. Terrorist groups located in hot-spot neighborhoods have more opportunities to observe and imitate each other. They are exposed to the influence of terrorist events more frequently than terrorist groups outside of hot-spot neighborhoods. This may lead to spiraling numbers of attacks in hot-spot countries. Second, terrorists transport and relocate to other locations by moving across borders and, as such, geographic proximity facilitates transportation and relocation across borders of countries located within the same hot-spot neighborhood. Even within a rapidly globalizing international community, transport and relocation remain much less costly between geographically contiguous countries than between geographically distant ones. This is particularly the case in economically

[10]The complete annual list of hot spot countries is not reported here due to space limitation, but is available online at http://www.personal.psu.edu/qx14/research_papers/geoterrorism_cmps_final_appendix.pdf.

poorer, developing countries. While terrorist networks spread and communications have become global, allowing actors to remotely control attacks, it remains difficult to plan activities targeting Western Europe or the U.S. from places like Afghanistan without local cells in the target countries. Third, terrorist groups in hot-spot countries may have less difficulty obtaining logistical and tactical cooperation from other groups in neighboring countries within the same hot-spot neighborhood. This improves their effectiveness and potentially reduces the risks associated with their terrorist activities. Finally, hot-spot countries are likely to become relocation destinations for terrorist groups from outside of the original hot-spot neighborhood. This is the case because hot-spot countries are likely to have (1) many valuable, newsworthy targets, and/or (2) porous borders that are easy to infiltrate illegally, and/or (3) weak police forces and institutions of government. Hot-spot countries thus become such attractive target destinations that foreign terrorist groups relocate, importing their activities into the hot-spot neighborhood. For these theoretical reasons, therefore, we should expect that, all else being equal, if a country is located within a hot-spot neighborhood, it is likely to experience more future terrorist incidents than another country that does not currently belong to such a neighborhood.

We evaluate the above hypothesis empirically using a pooled time series cross-sectional design. The unit of analysis is the country year. The sample includes 112 countries from 1975 to 1997, excluding those that never experience any terrorist event at all. This design is consistent with that employed in Li & Schaub (2004). The sample size is smaller than that for hot spot identification in the previous section due to data availability for several important control variables employed in the statistical models below. The dependent variable is the annual number of transnational terrorist events that occur in a country. The key independent variable is the hot spot dummy variable, which is coded 1 if a country is part of a hot spot neighborhood in a given year according to the G_i^* statistic and 0 otherwise. The hot-spot variable is lagged one year behind the dependent variable to capture the idea that we are looking at how being part of a hot-spot neighborhood in the current period affects future terrorist attacks within a country in the next period. Because we have three different measures of geographic proximity, the hot-spot dummy based on the G_i^* statistic has three variants: one based on land contiguity, a second based on land and sea contiguity, and a third based on a minimum distance of 950 km between two countries' territories. We expect the hot-spot dummy to affect future terrorist incidents positively. We examine empirically whether the effect holds among the three variants of geographic proximity.[11]

We control for a variety of possible confounding causes of transnational terrorist incidents, following Li & Schaub (2004) and Li (2005). These include indicators of trade openness, economic development, country size, level of democracy, government capability, military conflict involvement, past terrorist incidents, and regional locations. For the sake of brevity, details about the operationalizations of these variables are presented in Table 2.

[11]One may wonder if the analysis borders on being tautological, because a country in a hot spot must by definition experience higher levels of terrorism than those outside of such hot spots. This is not the case for several reasons. First, as discussed in detail in the previous section, a country may be part of a hot-spot neighborhood even if it does not itself experience a large number of terrorist incidents. In such instances, countries are considered vulnerable on the basis of their neighbors' considerable experiences of terrorist incidents. Second, because we are interested in the impact of the hot spot on future terrorist attacks, the dependent variable is lagged temporally behind the hot-spot independent variable. Third, we also control for the effect of the country's own history of terrorism by including a lagged version of the dependent variable as an independent variable in our models, as explained in detail below. This further ensures that the hot-spot variable captures the impact of the experiences of the entire hot-spot neighborhood on a country, rather than only the country's own past terrorism experiences.

TABLE 2 List of control variables

Control Variables	Definition
Trade	Total trade of a country as a percentage of GDP
Economic Development	Real GDP per capita, adjusted for purchasing power parity (PPP), logged
Partners' Development	Logged yearly GDP per capita (PPP) average of the largest eight destination countries of a country's exports
Size	Total population, logged
Democracy	Level of democracy in a country from POLITY IV
Government Capability	Logged annual composite percentage index of a state's share of the world's total population, GDP per capita, GDP per unit of energy, military manpower and military expenditures
Past Incidents	Annual number of terrorist incidents that occur in a country in the previous year
Conflict	one if a state is engaged in interstate military conflict or war and zero otherwise

GDP = gross domestic product.

A few issues on the control variables require additional clarification because they are pertinent to the validity of our spatial analysis. First, the past incident variable, measured by the lagged dependent variable, captures the reinforcement effect—the effect of a country's past experience with terrorism on the probability of its experiencing future events. The inclusion of this variable allows us to control for a country's past experience of terrorism while assessing the impact of the local hot spot upon the country's future experience of terrorism. The lagged dependent variable also helps control for other possible omitted variables. Because the lagged dependent variable often absorbs variations in the dependent variable that could otherwise be explained by other independent variables, this should make it harder for us to find statistically significant results.

Second, the five regional dummy variables (Europe, Middle East, Africa, Asia, and America), with four included in the model and the Middle East excluded as the reference category, provide one way to capture a temporally stable but spatially heterogeneous distribution of terrorist activities.

Third, many of the independent variables included in our analyses are themselves potentially influenced by terrorist attacks. This is potentially true of indicators of national economic conditions (e.g., Blomberg et al., 2004), investments (e.g., Abadie & Gardeazabal, 2003), and democratic institutions (e.g., Li, 2005). To control for the possibility of reverse causality in the relationships between our variables, we lag all independent variables one year behind the dependent variable. While this practice may not perfectly resolve the potential problems of endogeneity that affect studies of this ilk, it does represent the conventional approach in this field. As long as the weak exogeneity assumption is satisfied, lagging the independent variables removes the correlation between the independent variables and the model's error term.[12]

[12]Other scholars (see, e.g., Alberto, 2004; Miguel et al., 2004) have sought to solve the problem by using the instrumental variable approach. Lagging the independent variables, though a crude tactic, essentially follows the same logic as the instrumental variable approach. Since the endogeneity of the control variables is not the focus of this paper, however, we leave the search for a better solution to this problem to future research.

Finally, it may be of concern to some readers that our statistical analyses may have omitted an important variable because we are unable to control for governments' counterterrorism expenditures. Logically, one might anticipate that national governments of countries located in hot spots expect to experience more terrorist attacks in the future and choose, accordingly, to increase their counterterrorism spending. These counterterrorism efforts also correlate with economic variables. It is worth noting that a confounding effect such as this is well controlled for in the current analysis. While no systematic data are available to directly measure each country's counterterrorism spending, the inclusion of the lagged dependent variable helps to control for the effect of potentially relevant but omitted variables. In addition, the government capability variable is a function of and thus controls for the effect of counterterrorism spending.[13]

In terms of statistical estimation, because our dependent variable is an event count, we select a negative binomial regression (Negbin I) (Long, 1997; Cameron & Trivedi, 1986). We also estimate robust standard errors clustered on the country, as they are robust to both heteroskedasticity and to a general type of serial correlation within any cross-sectional unit (Rogers, 1993; Williams, 2000).

Table 3 reports the statistical findings for three models, each including a hot-spot variable that is based on the G_i^* statistic defined by one of the three alternative measures of geographic proximity. The results for the control variables are consistent across each of our three models and with those in previous studies (e.g., Li & Schaub, 2004.) Trade openness and military conflict do not have any statistically significant effect on the number of transnational terrorist incidents. Economic development reduces the number of terrorist incidents in a country. Country size, the level of democracy, government capability, and past incidents each have a statistically significant positive effect on the number of terrorist incidents. The significant positive effect of the past incident variable corroborates the reinforcement effect noted in the literature, indicating that higher current levels of attacks encourage more future terrorist events. The regional variables depict plausible patterns in the geographical distribution of terrorist incidents. With the Middle East serving as the reference group, Europe, America, Asia, and Africa all have a negative sign though only the final two return statistically significant coefficients. This shows that the Middle East has the highest concentration of transnational terrorist incidents, with Europe ranking second and America third. Asia and Africa experience significantly fewer transnational terrorist incidents than the Middle East. The regional variables reflect regional heterogeneity in the distribution of terrorism. The fact that our control variables are consistent with relationships identified elsewhere in the literature increases our confidence in the analyses conducted in this paper.

Across the three models in Table 3, the effect of the hot-spot variable is consistently positive and statistically significant. If a country is part of a terrorism hot spot in the current period, the number of transnational terrorist attacks within that country will increase in the next year. This result is consistent with our theoretical expectation. Also, it is worth noting that the impact of the hot-spot neighborhood variable remains robust and significant even when we control for the previous level of terrorism and the regional variations in terrorist incidents (as discussed above). Furthermore, the significant effect of the hot-spot variable is not sensitive to how geographic proximity is defined. That is, whether geographic proximity is measured by land contiguity, land and sea contiguity, or a minimum distance of 950 km

[13]We submit that the government capability variable also suffers a potential endogeneity problem, as counterterrorism spending is chosen strategically in response to expected terrorist behaviors (see, e.g., Bueno de Mesquita, 2005). Albeit imperfect, we employ the conventional solution of lagging the variable behind the dependent variable. Future research may look into a better solution of the problem.

TABLE 3 Effect of terrorism hot spot on future attacks, based on G_i^*, 1975–1997

	(1) Land contiguity	(2) land & sea contiguity	(3) 950 KM minimum distance
Hot Spot$_{t-1}$	0.408**	0.643**	0.383**
	(0.125)	(0.104)	(0.089)
Europe	−0.276	−0.237	−0.264
	(0.205)	(0.166)	(0.199)
Asia	−0.864**	−0.702**	−0.775**
	(0.281)	(0.266)	(0.271)
America	−0.223	−0.158	−0.133
	(0.193)	(0.167)	(0.187)
Africa	−0.966**	−0.871**	−0.852**
	(0.222)	(0.211)	(0.218)
Past Incidents$_{t-1}$	0.015**	0.018**	0.016**
	(0.005)	(0.004)	(0.005)
Trade$_{t-1}$	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)
Economic Development$_{t-1}$	−0.162*	−0.143*	−0.152*
	(0.070)	(0.069)	(0.069)
Size$_{t-1}$	0.260**	0.243**	0.268**
	(0.053)	(0.051)	(0.054)
Democracy$_{t-1}$	0.034**	0.028**	0.033**
	(0.009)	(0.009)	(0.009)
Government Capability$_{t-1}$	0.650**	0.629**	0.665**
	(0.119)	(0.114)	(0.116)
Conflict$_{t-1}$	0.116	0.085	0.091
	(0.126)	(0.123)	(0.129)
Constant	−2.186*	−2.154*	−2.527*
	(1.020)	(0.983)	(1.041)
Observations	2402	2402	2402

Robust standard errors in parentheses.
$^{*}p < 0.05$.
$^{**}p < 0.01$.

does not change the statistically significant impact of currently being located within a hot spot upon a country's future experience of terrorist attacks.

How large in size is the impact of being located within a hot-spot neighborhood? To gauge the substantive impact of the terrorism hot spot, we compute the percentage change in the expected number of terrorist attacks within a country when the hot-spot dummy is changed from a "0" to a "1"—i.e., the difference in expected numbers of attacks between countries that are not located within hot spots and those that are.[14] Relative to its a non–hot-spot counterpart, a hot spot country experiences about 50%, 90%, and 47% more terrorist incidents, based on the land-contiguity, the land and sea contiguity, and the 950 km minimum distance hot-spot measures in models 1, 2, and 3, respectively. While the impact of the hot-spot variable varies depending on which definition of geographic proximity the analyst

[14]The size of effect is computed using the "listcoef" command in Stata, written by Scott Long.

TABLE 4 Effect of terrorism hot spot on future attacks, based on Moran's I and G_i, 1975–1997

	(1) Moran'I Land	(2) Moran'I Land & sea	(3) Moran'I 950 km	(4) G_i Land	(5) G_i Land & sea	(6) G_i 950 km
Hot Spot$_{t-1}$	1.006**	1.047**	0.911**	0.093	0.356**	0.158
	(0.119)	(0.104)	(0.115)	(0.126)	(0.138)	(0.102)
Europe	−0.217	−0.168	−0.210	−0.250	−0.253	−0.260
	(0.143)	(0.137)	(0.144)	(0.216)	(0.196)	(0.214)
Asia	−0.697**	−0.617*	−0.644*	−0.943**	−0.863**	−0.897**
	(0.238)	(0.240)	(0.251)	(0.272)	(0.270)	(0.275)
America	−0.109	−0.046	−0.052	−0.238	−0.204	−0.203
	(0.145)	(0.140)	(0.146)	(0.193)	(0.183)	(0.192)
Africa	−0.914**	−0.858**	−0.847**	−0.992**	−0.938**	−0.946**
	(0.202)	(0.203)	(0.197)	(0.219)	(0.215)	(0.218)
Past Incidents$_{t-1}$	0.012**	0.012**	0.012**	0.017**	0.018**	0.018**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Trade$_{t-1}$	−0.001	−0.001	−0.001	−0.002	−0.002	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Economic	−0.165*	−0.153*	−0.152*	−0.156*	−0.149*	−0.154*
Development$_{t-1}$	(0.066)	(0.066)	(0.065)	(0.072)	(0.070)	(0.071)
Size$_{t-1}$	0.228**	0.224**	0.234**	0.270**	0.263**	0.272**
	(0.049)	(0.049)	(0.050)	(0.054)	(0.054)	(0.054)
Democracy$_{t-1}$	0.027**	0.024**	0.028**	0.036**	0.033**	0.035**
	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)
Government	0.633**	0.632**	0.658**	0.665**	0.657**	0.668**
Capability$_{t-1}$	(0.114)	(0.116)	(0.108)	(0.125)	(0.120)	(0.124)
Conflict$_{t-1}$	0.063	0.096	0.022	0.119	0.124	0.097
	(0.118)	(0.118)	(0.117)	(0.127)	(0.126)	(0.128)
Constant	−1.851*	−1.943*	−2.094*	−2.371*	−2.351*	−2.450*
	(0.914)	(0.895)	(0.932)	(1.036)	(1.027)	(1.032)
Observations	2402	2402	2402	2402	2402	2402

Robust standard errors in parentheses.
$^{*}p < 0.05$.
$^{**}p < 0.01$.

adheres to, it remains really quite large in size across all three different hot-spot variables in Table 3.

The hot-spot variable in Table 3 is based on the G_i^* statistic. One may wonder whether the results in Table 3 would be robust if an alternative local spatial statistic were used to operationalize the hot-spot variable. Table 4 presents the results for two sets of robustness tests, one set based on the local Moran's I and the other the G_i statistic. The Moran's I hot-spot variable also consistently has a positive and statistically significant effect on the number of terrorist attacks across the three different definitions of geographic proximity. In contrast, the set of results for the G_i based hot-spot variable are not statistically robust. The G_i based hot-spot variable has the expected positive sign across all three different definitions of geographic proximity, but the positive effect is statistically different from zero only in the case of land and sea contiguity. These results are not surprising. As we noted in earlier sections, the local Moran's I "high-high" category—as is employed here—is not drastically dissimilar to the hot-spot concept captured by the G_i^* statistic. The G_i statistic is not, however, nearly as useful for the purpose of measuring hot spots specific to country *i*, because as noted, it employs unrealistic assumptions and omits the information about levels of attacks specific to the country in question. Hence, we feel confident concluding that the positive effect of the hot spot on future terrorist attacks is not contingent upon the selection of a specific local spatial statistic, provided that the statistic selected is appropriate for the job.

Conclusion

To combat transnational terrorism, it is important to understand its geography. But the extant literature on the geography of terrorism is fairly thin and typically focuses on the distribution and diffusion of terrorism among aggregate regions such as Europe and the Middle East. In this analysis, we study transnational terrorism hot spots at the country level. With local spatial statistics, we identify countries that are located within neighborhoods that are hot spots of terrorist attacks and assess empirically the impact of these hot spots on the countries' subsequent experiences of terrorist incidents. We find that countries with significant experiences with terrorist incidents are often located within these hot spots, but that not all countries within these hot spots have experienced large numbers of incidents. By means of a pooled time series cross-sectional analysis of 112 countries from 1975 to 1997, we also find that when a country is located within a terrorism hot-spot neighborhood, it is highly likely to experience a large increase in its number of terrorist attacks in the next period. This effect is robust under three alternative definitions of geographic proximity, using either the G_i^* statistic or the local Moran's I to identify hot spots.

Our findings have instrumental value for policymakers in that it offers a specific technique for identifying terrorism hot-spot neighborhoods and countries that are located within them. Our analysis demonstrates that policymakers worried about global terrorism should contemplate prioritizing their policy agenda. They should invest more resources directed at combating terrorist activities in countries located in hot-spot neighborhoods because these represent countries that are highly likely to experience a sharp increase in terrorist attacks in subsequent years. International cooperation in counterterrorism that targets hot-spot countries is therefore likely to be most effective in curtailing the subsequent rise in terrorist activities. A multilateral approach is also likely to be more useful than unilateral policies that target individual states, because unilateral policies are known to merely drive terrorists to new locations (Enders & Sandler, 2006) and, therefore, produce negative international externalities.

Of course, fighting terrorism is a complex task. Though we have identified an avenue through which transnational terrorism could be curtailed, there could be countervailing forces that diminish the effectiveness of the strategy that targets hot spot countries. Some of the most challenging tasks require coordinating effective international collective action and decisively selecting an appropriate type of policy (proactive or defensive) in counterterrorism (see Arce and Sandler, 2005). We believe, however, that identifying neighborhoods of terrorism hot spots and countries that are located within them should increase the likelihood of finding a suitable resolution.

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