cmps

Article: New Data Set or Data Collection

Conflict Management and Peace Science
1–32

DOI: 10.1177/0738894218789356
journals.sagepub.com/home/cmp
SAGE

The local geography of transnational terrorism

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Abstract
Why are some locations more attractive targets for transnational terrorism than others? Remarkably little is known about the local-level conditions and attributes that determine precisely where *transnational* terror attacks occur within targeted countries. To date, quantitative terrorism research identifies country- or region-level correlates of terrorism, neglecting possible local factors. In this study, we posit five local-level factors that increase the likelihood of a terror attack: security of a target, accessibility, symbolism, material harm, and exclusion. Using a variety of estimation strategies, including multilevel, negative binomial, and propensity score matching models, we regress new sub-national geographically coded transnational terrorism data on various sub-national measures that might theoretically increase the likelihood of a terror attack. The results demonstrate that although country- and region-level factors matter, numerous local-level conditions, including where civil violence occurs, sub-national economic activity, and proximity to capitals and urban areas, are equally, if not more, important. The results help to substantiate the analytical benefits of adopting the sub-national level of analysis in the study of transnational terrorism.

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Keywords
Geocoding, matching, multilevel modeling, transnational terrorism

On September 21, 2013, Al Shabab operatives attacked the Westgate shopping center in Nairobi, Kenya, killing over 65 individuals and injuring more than 200 others. Al Shabab targeted Kenya because the Kenyan government supported the fight against Islamist insurgents in Somalia. But they did not just choose any random location within Kenya. Instead, they chose a specific location in Nairobi that conferred a number of strategic advantages. Shopping centers in Nairobi, including the Westgate center, had previously been considered secure locations. Considerable numbers of consumers, including many Westerners, frequent shopping centers like Westgate. Indeed, such malls reflect the heartbeat of an economically vibrant, populous capital city. For all these reasons, the Westgate shopping center represented an attractive target for a terror attack.

The kinds of locations targeted by notable terrorist attacks—what Arce and Sandler (2010) refer to as "terrorist spectaculars"—rarely surprise us, even if their outcomes do shock. Recent attacks in Brussels (May 2014), Paris (November 2015), and Dhaka (July 2016), as well as terror attacks against foreign nationals in Kabul, Afghanistan (January 2018), share much in common with the traits observed in the Nairobi attack—they targeted densely populated urban centers, areas of significant economic activity, and iconic sites. Yet most transnational terrorist attacks are not on the scale of the spectacular.[1] Relatively little is known systematically about the location of the bulk of transnational terrorist attacks. Attacks occur in all regions and a majority of countries globally; however, intuition tells us that not all locations within each country are equally likely to experience attacks. Accordingly, our exploratory study seeks to identify which types of locations are more attractive than others.

A recent research program in the civil war and political violence literatures has stressed the benefits of disaggregating conflict data to the sub-national level (Aas Rustad et al., 2011; Gleditsch et al., 2014; Verwimp et al., 2009). This literature has largely proceeded by adopting arguments at the sub-national level that previously were used at the cross-national level. Yet if the results found at the sub-national level simply replicate those at the cross-national levels, then the value-added of the sub-national approach is not clear. Therefore, we point to three factors that establish the benefits of examining transnational attacks at the sub-national level. First, we point out that there are several variables that can only be measured at the sub-national level, including distance to capital and distance to border. Secondly, we use variables that help to clarify on-going debates in the literature on civil war and terrorism: for example, we find that urban areas are associated with transnational terror attacks (Beall, 2006; Savitch and Ardashev, 2001), while civil war has largely been seen as a rural phenomenon (Kalyvas, 2006). Thus, we contribute to identifying the differences between these forms of violence. Thirdly, we combine the sub-national and cross-national levels of analysis in a multilevel model to capture the country-level factors that influence the sub-national location of terror attacks.

Extant research highlights country- and region-level covariates of transnational terrorism (Enders and Sandler, 2006; Li, 2005; Piazza, 2008), identifies cross-national clusters of terrorism in space and time (Braithwaite and Li, 2007; Johnson et al., 2011), and demonstrates that transnational terrorism displays substitution—or spatial displacement—effects (Enders and Sandler, 2006).[2] Remarkably little is known, however, about the local-level conditions and attributes that determine more precisely *where* transnational terrorism occurs within targeted countries.

To address the local-level dimensions of transnational terrorism, we coded the geographic coordinates of (geo-coded) the most recent version of the International Terrorism: Attributes of Terrorist Events (ITERATE) dataset (Mickolus et al., 2015) and merged those data with the lattice-based, PRIO-GRID dataset (Tollefsen et al., 2012).[3]

We claim that individual locations can be characterized via five sub-national factors that directly affect the likelihood that they will host terrorist attacks. We argue that *security* of a target affects the likelihood of a terror attack. In particular, we claim that ongoing civil conflict decreases the security of targets, and so conflict is a key driver of the likelihood of transnational terror attacks occurring locally. We also argue that *accessibility* shapes the likelihood of a terror attack, and so targets near to international borders or located in an urban area are more likely to be attacked than targets farther from borders and urban areas. The symbolism of a target also matters, and so we expect terror groups to attack locations closer to the national capital. The *material harm* that results from targeting a given location will make it more attractive, while *exclusion* can increase grievances and so make a terror attack more likely. In making these arguments, we build on the robust literature that shows how civil war affects the occurrence of domestic terrorism (Findley and Young, 2012; Nemeth et al., 2014), but which has not yet considered the effect of (ostensibly domestic) civil war on transnational terrorism.

In order to test these local-level expectations, we regress our geo-coded transnational terrorism data on a set of covariates that measure sub-national factors that according to our hypotheses affect the propensity of experiencing a terror attack. Each of these covariates is measured at the local (0.5 decimal degree $\times$ 0.5 decimal degree grid cell) level according to PRIO-GRID (Tollefsen et al., 2012). PRIO-GRID contains the most reliable data at a global scale for our independent and control variables. These sub-national variables include measures of mountainous terrain, forest coverage, distance to international borders, level of civil conflict, distance to capital cities, local economic activity, and population density. A central goal of the study is to demonstrate that local-level factors play an important role in explaining transnational terrorism. We expect that country- and region-level factors should matter nonetheless, as the case of Kenya illustrates well. Therefore, to supplement our basic analyses, we estimate comprehensive multilevel models that allow us to draw stronger conclusions about the role of local-level determinants alongside more traditional country-level explanatory and control factors.

The PRIO-GRID incorporates in excess of 64,000 cell locations globally. In addition, our analyses include data covering a 46 year period (1968–2013). Given that there are a total of $\sim$14,000 transnational terrorist events over this time period, the local observation of terrorism turns out to be a very rare event. Accordingly, we employ three techniques designed to take account of this rarity. First, we dichotomize the outcome variable—differentiating between grid location-years in which there is no terrorism and those in which there is at least one terrorist attack. We then employ Rare Events Logit (King and Zeng, 2001a, b) and negative binomial models to assess patterns in this form. Second, we incorporate propensity score techniques to match grid locations in time that share a great many characteristics in common. We then estimate the effects of various local-level "treatments" on the likelihood of experiencing terrorism within a reduced set of highly similar observations. Third, we use multilevel models to capture both local-level as well as state-level variables that shape the location of terror attacks. Finally, we include a large battery of robustness checks in the

Online Appendix, including an Arrellano–Bond dynamic panel model to account for potential endogeneity.

Across each of our models, the analyses confirm that security, accessibility, symbolism, material harm, and exclusion all shape the likelihood of a terror attack. In particular, attacks are most likely at locations which have experienced recent civil violence, are proximate to the capital city and other urban areas, have larger populations, have higher levels of economic activity, and have greater levels of ethnic exclusion. In other words, nearly all of the local-level results are as expected. Of the country-level variables, state repression is positively associated with terrorism and capabilities and capacity are negatively associated with terrorism, but democracy is only negatively associated with terrorism in two of the three specifications. Furthermore, the influence of state capacity as a deterrent decays as distance from the capital increases. The country-level results for military capability are opposite what the literature would lead us to expect and the largely null results for democracy run contrary to many of the arguments and findings in the literature on transnational terrorism.

Thus, the story that emerges is that local factors matter considerably in determining *where* transnational terrorist attacks occur. While of an exploratory nature, the study contributes to the terrorism literature by providing the first examination of local-level determinants of transnational terrorism and showing why scholarship in this area that accounts only for country- and region-level factors provides at best incomplete explanations for the targeting of transnational attacks.

Causes of transnational terrorism

Transnational terrorism has been the focus of substantial scholarly research for several decades (Enders and Sandler, 2006), and the research agenda has only intensified in recent years with an emphasis on quantifying the correlates of this form of terrorism.[4] Nearly all of this research identifies possible country- or region-level causes and consequences, with often rather varied conclusions.[5] With respect to economic productivity, transnational terrorists have been shown to target economically successful countries (Krieger and Meierrieks, 2011; Krueger and Laitin, 2012) or those with with low levels of economic openness (Drakos and Gofas, 2006). It also appears that higher levels of foreign direct investment and trade may decrease transnational terror within recipient countries (Li and Schaub, 2004). In terms of political regime types, transnational attacks are most likely to occur in politically open but unstable countries (Krieger and Meierrieks, 2011). Within democracies, however, democratic participation decreases the likelihood of experiencing transnational terrorism, whereas greater constraints on governments are associated with increases in transnational terrorism. Furthermore, democracies with proportional representation systems experience fewer attacks than those with majoritarian and mixed systems (Li, 2005). Research also demonstrates that attacks are more numerous in countries with greater total populations (Krieger and Meierrieks, 2011) and those with demographic stress (Drakos and Gofas, 2006).

Despite the country- and region-level foci, existing studies only occasionally discuss geography. Midlarsky et al. (1980) investigate the diffusion and contagion of terrorist tactics and events, concluding that the most striking pattern observed is one of contagion from Latin America to Europe. In a response article, Heyman and Mickolus (1980) argue that this pattern actually results from a process of mimicry, with Latin American terrorist groups leading the way and being copied by groups emerging at a later stage in Europe. In a similar consideration of possible displacement effects, Enders and Sandler (2006) show a significant transference of terrorist incidents from North America and West Europe to the Middle East and Asia following the adoption of dramatic new counter-terrorism measures in the US and the UK. Adopting an explicit geographic information systems approach to the analysis of regional clustering of events, Braithwaite and Li (2007) identify *country-level* hot spots of transnational terrorist attacks and demonstrate that the hotspots play a crucial role in subsequent patterns of diffusion in space and time.

These studies have offered insights into the diffusion and contagion of terrorist activities and have contributed to the successful identification and forecasting of regional patterns of heterogeneity and dependence in the distribution of terrorist incidents. However, analysis that aggregates data at the country or region-level misses much of the important geographic variation in terrorist attacks. In response, our study follows the suggestion of John Agnew (1994) to "escape the territorial trap". As not all states share an equal likelihood of hosting attacks, this insight suggests that not all sub-state spatial units within any given state are equally likely to host attacks that target the state. Moreover, sub-state variation could provide greater insights into the distribution of transnational terrorist events than even country- or region-level variation.

There is a precedent for the use of more fine-grained location data in the study of a range of related topics. In the study of civil war, a literature has developed that addresses how local geography affects the likelihood of civil war onset (e.g. Buhaug and Rød, 2006; Raleigh and Hegre, 2009), duration (Buhaug and Lujala, 2005), and rebel capability (Buhaug et al., 2009). Studies of social conflict using georeferenced conflict data, for example, have shown that cell phone coverage (Pierskalla et al., 2013) and environmental factors such as rainfall levels (Hendrix and Salehyan, 2012) and weather conditions (Carter and Veale, 2013) all increase the propensity of conflict at the local level.

Despite the progress made in understanding the effects of local geography on civil war generally, the geographic dimensions of terrorism remain, overall, a remarkably understudied topic of research (Bahgat and Medina, 2013). Bapat (2007) argues that terrorist groups tend to locate themselves in countries that are stronger than their intended target countries because they are attempting to minimize the prospects for retaliation by the targeted country. Building upon this work, Gaibulloev (2015) examines the factors that influence groups' decisions regarding where to base their operations. He demonstrates that groups are most likely to select base countries with higher numbers of pre-existing groups, especially those countries with pre-existing groups that share their ideology. Furthermore, it is apparent that groups base themselves in fragile countries and that are relatively proximate to the venues of their planned attacks.

With respect to the analysis of the locations of the attacks themselves, the majority of published studies have been limited in geographic scope to analyses of attacks in particular countries, for example, Israel (Berrebi and Lakdawalla, 2007), Spain (LaFree et al., 2012), the US (Cothren et al., 2008; Webb and Cutter, 2009), and Iraq (Braithwaite and Johnson, 2012).[6]

Research using "changepoint" regression models has shown that transnational terrorist attacks are increasingly aimed at *soft* or un-hardened locations within target countries, such as private actors, rather than property or public infrastructure (Brandt and Sandler, 2010; Santifort et al., 2013).[7] Much less is known, however, about the process of geographic target selection—and, specifically, about the factors that determine *where* within the borders of independent states transnational terrorist attacks are likely to occur. To our knowledge, Findley and Young (2012) and Nemeth et al. (2014) are the only other global, sub-national, geo-coded studies, both of which focus primarily on domestic terrorism, are limited in temporal scope, and do not consider local and country-level factors simultaneously. Yet considering local- and country-level factors in the same models allows for the exploration of whether or not relationships established at the country level are also found at the local level, and if not, how those relationships differ. In sum, the transnational terrorism literature suffers from a dearth of fine-grained data on the location of terrorist activities on a broadly cross-national basis. This is precisely the lacuna we hope to address in this paper by considering the dimensions of the targeting of transnational attacks using newly coded geographic data.

Determinants of terrorism

We begin by employing a fairly well accepted definition: "[t]errorism is the premeditated use or threat to use violence by individuals or sub-national groups in order to obtain a political or social objective through intimidation of a large audience beyond that of the immediate victims" (Enders and Sandler, 2006: 3).[8] We are especially interested in transnational events—those in which at least two of the nationalities of the perpetrators, victims, or host state differ. Non-state actors often consider terrorism a last resort, because they are typically actors that are located on the "wrong" side of a considerable power asymmetry in their relations with the government that they are challenging. The primary means by which terrorists compensate for this asymmetry is by using violence in a manner that maximizes media coverage and public discussion of their attacks.

Sub-national factors

Locations differ in the extent to which they are home to assets of value to the terrorists, the targets, or the audience. On the one hand, this means that such locations are likely to attract greater levels of public attention when attacked. This is crucial, because, as noted above, we assume that terrorists must overcome a considerable resource disadvantage *vis-á-vis* the government that they challenge. One key way of doing that is to mobilize support by getting the group's message out to as wide a population as possible, which is also likely to provoke a fearful response within the widest possible audience. This strategy might, for instance, involve terrorists looking to damage symbolic assets that represent a tyrannical government against which they perceive themselves as struggling. This could also include assets that are likely to be held dear by citizens. These attacks can enable the terror groups to coerce the targeted state to concede to their policy demands as well as damage the capacity of the state to respond.[9]

Conceptually, we argue that the degree to which sub-national factors enable transnational terror attacks to coerce and damage the targeted state is most credibly thought of as the product of at least five components. The first concerns the *security* of the target.[10] Factors such as the presence of military and police personnel, barriers to entry, and technology that detects the movement of individuals near the perimeter of the target (surveillance equipment, etc.) all serve to increase the security of the target.[11] However, ongoing civil conflict in a country may reduce and degrade the security infrastructure of a country, allowing for attacks on targets that may otherwise be less vulnerable.[12] Civil conflict may attract foreign actors to the country, such as international aid organizations, that can serve as targets for attacks by terror groups. We thus expect that:

H1: Ongoing civil conflict in an area increases the likelihood of a transnational terrorist terrorist occurring relative to areas without civil conflict.

Secondly, because we are interested in the determinants of transnational attacks, factors which make a location more *accessible* for foreign groups to attack should be associated with sub-national targeting. Therefore, we expect that the closer an area is to an international border, the more terror groups have *access* to it, and the more likely it is to be attacked. The attacks captured here could include both terrorists crossing international borders and terror groups targeting people who cross borders, including tourists, refugees, and merchants ferrying goods across borders.

H2: Proximity to an international border increases the likelihood of a transnational terrorist attack.

Furthermore, the level of urbanization also shapes the *accessibility* of the sub-national location.[13] Targets that are located in isolated, difficult-to-reach areas are less accessible, and thus less vulnerable, than targets in urban ones. Thus, we expect urbanized areas to experience more transnational terror events than less urbanized ones.[14] We thus expect that:

H3: The closer a location is to an urban area, the higher the likelihood of a transnational terrorist attack.

Next, the *symbolism* of a target, whether cultural, political, or social, can enhance how valuable a target is.[15] Attacking a symbolic target, such as those located in or near the national capital, enhances the significance of the attack beyond its immediate, direct effects.[16] Furthermore, capitals will include foreign targets that domestic perpetrators can attack, including embassies, offices of international aid organizations, and commercial venues frequented by foreign nationals such as restaurants, hotels, and malls.

H4: The closer a location is to the capital, the higher the likelihood of a transnational terrorist attack.

The sub-national nature of our data allows us to explore a fifth hypothesis, that civil conflict concentrates attacks in specific geographic areas. If transnational attacks are indeed motivated by the access and symbolism associated with international borders and state capitals, respectively, civil conflict should lead to attacks which are more concentrated in these areas. For example, civil conflict may draw more international aid organizations into a country, providing more opportunities to target foreign actors in capital cities and at international borders as they travel into the country. We therefore explore the two following hypotheses through the inclusion of interaction terms.

H5a: The closer a location is to an international border, the greater the impact of civil conflict on transnational terrorist attacks.
H5b: The closer a location is to the capital, the greater the impact of civil conflict on transnational terrorist attacks.

Additionally, the *material harm* that can result from attacking a target increases its value for terror groups. For example, one terrorist manual called for "blasting and destroying the embassies and attacking the vital economic centers" as well as destroying the "bridges leading into and out of cities" (Anonymous, 2003: 12). Thus, we expect that more economically productive and highly populated areas should be more valuable as targets for terrorist attacks, leading to the following hypotheses:

H6: The greater the size of the local population in an area is, the higher the likelihood of a transnational terrorist attack relative to areas with lower levels of local population.
H7: The higher the economic productivity of a location is, the higher the likelihood of a transnational terrorist attack.

Finally, because *exclusion* owing to marginalization of ethnic groups is a major motivation for transnational attacks, we expect that the greater the number of excluded ethnic groups in an area is, the more likely it is to be targeted.[17] The logic is that the exclusion of ethnic groups creates grievances that may motivate the use of terror attacks as a way of drawing attention to their plight and putting pressure on the government to address those grievances (Choi and Piazza, 2016). However, there may be a non-linear relationship between the number of excluded groups and the number of attacks. Building from the literature on civil wars and ethnic conflict (Hegre and Sambanis, 2006), the intuition is that the relationship between ethnic exclusion and propensity for conflict may follow an inverted-U, such that propensity for conflict is in the middle range of levels of ethnic diversity, rather than the lowest or highest levels. To account for this possibility we include the following hypothesis:

H8: The greater the number of excluded ethnic groups in a location is, the higher the likelihood of a transnational terrorist attack. However, the rate of this increase diminishes as the number of excluded ethnic groups grows.

Country-level determinants

Our hope is to draw greater attention to local determinants of transnational terrorism behavior by considering how terrorist groups choose targets based on the geographic distribution of factors within target countries. And yet, we do not contend that country-level factors are irrelevant. Indeed, we argue that a satisfactory explanation for transnational terrorism needs to account for both local- and country-level factors. At the country level, we expect that state repression should increase terrorism, power asymmetries (between the government and their opponents) should increase terrorism, greater state capacity should decrease terrorism, ethnic fractionalization should increase the incidence of terrorism, and democracy should be associated with less terrorism. None of these arguments is novel; at least some evidence for each of these expectations can be found in the larger literature as discussed in the literature review (for example, many of these claims are made by Chenoweth, 2013). Our hope is that an examination of these factors in conjunction with the sub-national factors mentioned above provides the best means of complementing a local explanation to produce a more comprehensive explanation of the targeting of transnational attacks.

Modeling the geography of terrorist attack locations

In order to test the validity of the various hypotheses outlined in the prior section, we designed a series of multivariate models to capture cell- and country-level drivers of the location of transnational terrorist events. First, we detail the process followed to measure the location of terrorist attacks. We then outline the operationalization of each of the parameters included in our various specifications. We then identify the estimation techniques employed during testing. These techniques are designed primarily to facilitate analysis of rare events and count data.

Measuring terrorist attack location

To examine sub-national variation, we geographically coded the known locations of all events in the ITERATE dataset. Each of the over 14,000 transnational terrorist events from the ITERATE database has thus been assigned a pair of latitude and longitude coordinates and then joined (using ArcGIS v10.0) with their corresponding grid cell location from the PRIO-GRID dataset. As a result of the merge, we have both a count and a binary indicator of terrorist attack locations. In the first instance, we have a simple count (0 or positive integer) of the total number of attacks within each cell in each year. In the second instance, the binary variable is assigned a value of "1" if at least one terrorist attack occurs within the cell in a given year and "0" otherwise.

Geo-coding the terrorism events

The ITERATE project provides detailed data on the characteristics of transnational terrorist groups, their activities that have international impact, and the environment in which they operate (Mickolus et al., 2015). We have geo-coded all events from 1968 to 2013, but for analysis purposes we are constrained by the data in PRIO-GRID (as discussed below) such that the empirical analysis reported in the paper covers 1968–2013.[18]

Geo-coding methodology

This project uses a modified version of the UCDP/AidData geo-coding methodology originally based on Sundberg et al. (2010) to assign sub-national geographic information, where possible, to ITERATE terrorism event entries based on information provided in event descriptions.[19] Among the information coded, we include latitude and longitude coordinates, location name and ID, administrative boundary information, and a precision code.

Sources vary with respect to the precision of information about locations of attacks that are reported in ITERATE. Sometimes the exact location is named and in other instances the general area is reported; therefore, we identify coordinates for information at four main levels, ranging from point locations, through two administrative divisions, to the country level. Seven precision categories are connected to the coordinates in order for researchers to select subsets of the dataset that contain different levels of precision. If the event description only gives information on the administrative division, and not the exact location, then the centroid point of the administrative division is entered into the latitude and longitude columns. If there is no direct mention of any location in the event description, the country coordinates are coded with precision "7", which indicates that the location is unknown.

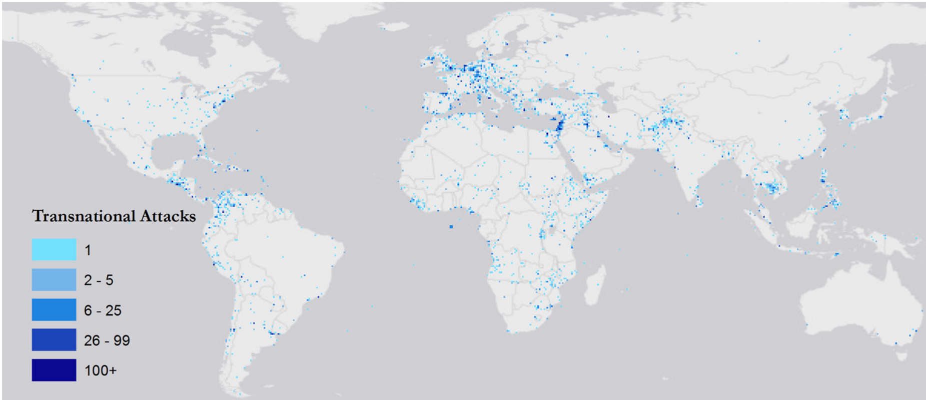

Figure 1. Global locations of transnational terrorism, 1968–2013.

In order to obtain the latitude and longitude coordinates of geographic locations mentioned in the documentation, a geographic gazetteer is necessary. This project has relied primarily upon www.geonames.org, which provides not only the latitude and longitude of a location, but also the administrative division under which it is governed (province, district, central government, etc.) and a geographic identifier that is unique to each location. More details about precision codes appear in the Supplementary Material (available at the *CMPS* website). The majority of terrorist event observations are coded at the precision code 1 level (76.8%) and 90% of the events can be geo-coded at precision codes 1–5.[20] Thus, the majority of the observations of terror attacks in the dataset are coded with a relatively high degree of precision as to where the attack occurred. We include all observations except the 7s (for which information is unavailable) in the statistical models that follow. Figure 1 displays the global distribution of terrorism events based on our coding of the ITERATE data, and the Supplementary Material contains maps of selected individual countries to provide a closer look.[21]

Measuring sub-national factors

All of the location-level data used to operationalize our key explanatory variables are drawn from the PRIO-GRID dataset (Tollefsen et al., 2012). We use the PRIO-GRID cell-year as the unit of analysis, instead of alternative sub-national units of analysis such as municipalities or administrative units, because PRIO-GRID offers the most comprehensive global coverage for our covariates. We detail their operationalization and list, where appropriate, details of the original source data.[22]

Civil conflict. This covariate is a dummy variable representing the presence or absence of ongoing intrastate or internationalized intrastate conflict events within the cell. These data reflect the conflicts in the UCDP conflict dataset (Harbom and Wallensteen, 2010) and are based on the updated version 3 of the conflict site coding (Dittrich Hallberg, 2012) for the time period 1989–2008 and version 2 of the conflict site coding (Raleigh et al., 2006) originally developed by Buhaug and Gates (2002) for the time period 1968–1988.[23]

Distance to international border. This data draws on the same cShapes data to compute the spherical distance from the cell centroid to the border of the nearest neighboring country (Weidmann et al., 2010). In order to explore how distance to international border influences the relationship between civil conflict and transnational terrorism we include an interaction between civil conflict and distance to international border in our estimation.

Distance to state capital. These data provide the distance from the cell to the national capital in the corresponding country using the cShapes dataset and are scaled in hundreds of kilometers (Weidmann et al., 2010). In order to explore how distance to state capital influences the relationship between civil conflict and transnational attacks, we include an interaction term between civil conflict and distance to state capital in our estimation.

Urban. This variable, drawn from Nelson (2008), shows the estimated travel time in 100 minute units to a city with a population of greater than 50,000 within the cell. We multiply the distance by negative one so that the variable reflects proximity to an urban area.

Population. These data measure the total population of each cell for 1970, 1980, 1990, 2000, and 2005 based on the History Database of the Global Environment (Goldewijk et al., 2011). The missing years were filled by log-scale interpolation for years between 1970 and 2005 without data and log-scale extrapolation for years prior to 1970 and after 2005. Population is divided by 1000 to facilitate interpretation.

Economic productivity. These data represent the gross cell product in 1990 USD in each cell corrected for the purchasing power parity. The variable is drawn from the G-Econ dataset (Nordhaus, 2006). To facilitate interpretation, gross cell product is divided by 1000 US dollars.

Number of excluded ethnic groups. This variable counts the number of excluded groups as defined in the GeoEPR data. This includes all local discriminated or powerless groups (Vogt et al., 2015). To account for possible non-linearities we include the first and second order terms: the number of excluded ethnic groups and the number of excluded ethnic groups squared.

Sub-national control variables

Spatial lag. To control for the potential for attacks to follow patterns of either spatial autocorrelation or substitution, we include a spatial lag of attacks in queen-style contiguity neighbors. This is typically the four cardinally adjacent cells and the four diagonally adjacent cells. The spatial lags are included in all of the models.

Infant mortality rate. Because baseline levels of grievance may be a significant driver of terrorism, we control for the infant mortality rate. These data based on the SEDAC Global

Poverty Mapping project (Storeygard et al., 2008) represent the number of children per 1,000,000 that die before reaching their first birthday. These data were only available for the year 2000, and so data for that year were entered for all remaining years.

Precipitation. To account for baseline climate affects we control for the local level of precipitation. These data provide yearly total precipitation in each cell scaled in meters, based on meteorological data gathered by the University of Delaware (National Oceanic and Atmospheric Association, 2011).

Total land area in grid cell. The land area is not the same in each cell owing to coastlines, which may affect the baseline likelihood of an attack. Therefore, we include the amount of land area in each location as a control variable. This covariate represents the area of land within the grid cell (Tollefsen et al., 2012) scaled as 100 square kilometer units.

Nighttime light emission. The cells vary widely in their levels of electrification, which can crucially influence development and state capacity. Therefore we include nighttime light emission data from the Satellite Nighttime Lights Time Series Version 4 (Elvidge et al., 2014) calibrated to account for intersatellite differences and internannual sensor decay in order to accommodate time series analysis. The time series is available from 1992 to 2012. Therefore, we include models for 1992–2012, which includes this variable and models on the full sample excluding the variable.

Lagged terrorist attacks in cell. To account for temporal effects, we include one and two year lags of transnational attacks. This helps account for the temporal autocorrelation of transnational attacks at the cell level.

Country level variables

Regime type. We used several measures of regime type including the Vanhanen Index of Democratization (Vanhanen and Lundell, 2014), Freedom House Imputed Polity Index (Hedenius and Teorell, 2005), and the Revised Combined Polity Score (Marshall et al., 2013).

Capability and capacity. To measure state capability and capacity we used the CINC score from the Correlates of War Project (Singer et al., 1972), as well as the two-factor measure of military capacity and bureaucratic capacity developed by Hendrix and Young (2014). To provide a better spatial measure of capacity, we interact these measures of military and bureaucratic capacity with distance to state capital.

Political terror. To operationalize government use of repression, we draw upon the Political Terror Scale published by Amnesty International. The Political Terror Scale provides a measure of state-sanctioned killings, torture, disappearances, and political imprisonment at the country level (Gibney et al., 2013).

Choice of estimators

The PRIO-GRID dataset (Tollefsen et al., 2012) partitions global territories into 64,804 equally sized (0.5×0.5 degree) grid cells. We use observations from PRIO-GRID for 1968–2013, which means that the primary unit of analysis is the cell-year. To consider both local- and country-level factors together, we complement the standard time-series cross-section models with multilevel models that bring together cell-year and country-year information into the same analysis. Because the cell level measure of civil conflict is only available until 2008 but we have geo-coded terrorism data through 2013, we also estimate each model on the full temporal span of the data by excluding civil conflict.

The data structure comprises a large number of observations and, in this data structure, terrorist events are rare. While terrorism is widespread and occurs fairly often *somewhere* in the world at a given time, it is highly unlikely to occur at the bulk of our grid cell locations. To address the rarity of events, we employ several estimation strategies. First, we collapse terrorist attack counts into a binary variable indicating that an attack either happened or did not. Using the dichotomized variable, we employ Rare Events Logit (King and Zeng, 2001b) using the full sample. Second, to preserve information about the count of attacks, we use a negative binomial model on the full sample. The results from estimating these models are presented in Tables 1 and 2, respectively. In the Supplementary Material, we also estimate zero-inflated negative binomial models as a robustness check on the negative binomial results.[24]

Additionally, we use propensity score matching to reduce the number of observations and improve comparability. In the matching models, we match one to one on propensity for civil violence and compare a reduced set of observations that are otherwise similar on all other observable dimensions related to civil conflict. The model diagnostics for this matching are presented in Online Appendix Figure A1 and indicate that our matched sample improved balance between the matched and unmatched sample on all covariates. With the matched sample, we conduct Rare Events Logit and Negative Binomial models. These results are presented in Table 4. In addition, we estimate the multilevel model on the matched sample, the results of which are presented in Online Appendix Table A5.

Finally, we consider a wide range of model specifications in the Supplementary Material for this article. In addition to the ZINB (Online Online Appendix Tables AA3 and A4) and matched multilevel models (Online Appendix Table A5), we include models with cell, year and country fixed effects (Online Appendix Table A6). We also estimate all of the models in the main text of the paper while excluding attacks at precision code 6 to ensure that the country centroid coordinates are not unduly affecting the results (Online Appendix Tables A7–A10) and only including attacks with more than six fatalities (Online Appendix Table A11). We include models disaggregated into temporal splits by decade (Online Appendix Tables A12–A15), and include a model with civil wars separated in internationalized and non-internationalized civil wars (Online Appendix Table A16). Additionally, we estimate models in which the perpetrators and victims of attacks are disaggregated by whether they were foreign or domestic (Online Appendix Tables A17–A20). Because attacks may involve a mix of both foreign and domestic perpetrators we consider this in the inclusive sense (e.g. attacks in which any of the perpetrators were foreign) and the exclusive sense (e.g. attacks with only foreign perpetrators). We also pair the perpetrator and victim nationality types to investigate attacks on foreign victims by local perpetrators and attacks by foreign perpetrators on local victims separately. In addition, we disaggregate by attack modes (Online Appendix Tables

Table 1. Cell-year level Rare Events Logit

	Rare Events Logit 1968–2008	Rare Events Logit 1968–2013	Rare Events Logit 1992–2008	Rare Events Logit 1992–2012
Civil Conflict in Cell	1.310***		1.629***	
	(0.110)		(0.148)	
Distance to International Border	−0.135***	−0.124***	−0.145***	−0.129***
	(0.0175)	(0.0141)	(0.0250)	(0.0189)
Civil Conflict × Distance to Border	−0.0164		−0.0478	
	(0.0332)		(0.0437)	
Distance to Capital	−0.0604***	−0.0703***	−0.0941***	−0.109***
	(0.00826)	(0.00809)	(0.0126)	(0.0118)
Civil Conflict × Distance to Capital	−0.0584***		−0.0778***	
	(0.0175)		(0.0224)	
Urban	0.158***	0.168***	0.115***	0.123***
	(0.0290)	(0.0282)	(0.0268)	(0.0285)
Population	0.235***	0.00777***	0.163***	0.0727**
	(0.0311)	(0.00125)	(0.0314)	(0.0260)
Economic Activity (logged)	0.665***	0.792***	0.0596	0.135
	(0.0430)	(0.0370)	(0.0822)	(0.0722)
Excluded Ethnic Groups	0.360***	0.405***	0.284*	0.326**
	(0.0928)	(0.0814)	(0.125)	(0.107)
Excluded Ethnic Groups Squared	−0.0710	−0.0744*	−0.0398	−0.0392
	(0.0379)	(0.0333)	(0.0582)	(0.0474)
Infant Mortality Rate	0.0118	0.0684***	0.0626***	0.124***
	(0.00975)	(0.00920)	(0.0109)	(0.0101)
Precipitation	0.541***	0.700***	0.712***	0.590**
	(0.156)	(0.164)	(0.171)	(0.200)
Land Area	−0.00952	−0.00315	−0.0225***	−0.0185**
	(0.00513)	(0.00507)	(0.00681)	(0.00645)
Spatial Lag	0.574***	0.672***	0.998***	1.303***
	(0.0596)	(0.0580)	(0.215)	(0.235)
Transnational Attacks (Lagged One Year)	2.670***	2.924***	2.570***	2.727***
	(0.0792)	(0.0733)	(0.110)	(0.108)
Transnational Attacks (Lagged Two Years)	2.336***	2.585***	1.876***	2.089***
	(0.0874)	(0.0770)	(0.125)	(0.114)
Nighttime Lights			3.486***	3.620***
			(0.370)	(0.340)
Constant	−5.531***	−5.791***	−5.674***	−5.823***
	(0.148)	(0.142)	(0.200)	(0.191)
Observations	1,674,853	1,894,453	737,008	912,499

Clustered standard errors in parentheses
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

A21–A26) to consider how modes of attack have changed over time and by attacks with only the most precise codes related to an exact location (Online Appendix Tables A27–A28). We include five case studies to illustrate the hypotheses (Online Appendix Tables A29–A39).

As an additional step towards addressing endogeneity, we use a dynamic-panel general method of moments approach developed by Arrelleno and Bond (1991) and Blundell and

Table 2. Cell-year level negative binomial regression

	Negative Binomial 1968–2008	Negative Binomial 1968–2013	Negative Binomial 1992–2008	Negative Binomial 1992–2012
Civil Conflict in Cell	1.537***		1.590***	
	(0.136)		(0.199)	
Distance to International Border	−0.120***	−0.119***	−0.0893*	−0.100***
	(0.0243)	(0.0197)	(0.0358)	(0.0249)
Civil Conflict × Distance to Border	−0.0269		−0.0770	
	(0.0435)		(0.0624)	
Distance to Capital	−0.0658***	−0.0733***	−0.0841***	−0.0961***
	(0.00875)	(0.00847)	(0.0128)	(0.0116)
Civil Conflict × Distance to Capital	−0.0772***		−0.0662**	
	(0.0197)		(0.0251)	
Urban	0.129***	0.139***	0.0959***	0.0916***
	(0.0224)	(0.0220)	(0.0225)	(0.0225)
Population	0.601***	0.390***	0.421***	0.392***
	(0.0577)	(0.0619)	(0.0645)	(0.0550)
Economic Activity (logged)	0.710***	0.784***	−0.0400	0.00856
	(0.0562)	(0.0602)	(0.0937)	(0.0866)
Excluded Ethnic Groups	0.483***	0.505***	0.375**	0.394**
	(0.116)	(0.106)	(0.129)	(0.121)
Excluded Ethnic Groups Squared	−0.107*	−0.112**	−0.0505	−0.0578
	(0.0457)	(0.0430)	(0.0512)	(0.0507)
Infant Mortality Rate	0.00685	0.0634***	0.0679***	0.116***
	(0.0115)	(0.0107)	(0.0127)	(0.0113)
Precipitation	0.522**	0.684***	0.659**	0.484*
	(0.183)	(0.194)	(0.216)	(0.243)
Land Area	−0.0132*	−0.00845	−0.0218*	−0.0195*
	(0.00575)	(0.00580)	(0.00896)	(0.00836)
Spatial Lag	1.670***	2.344***	4.596***	5.770***
	(0.252)	(0.302)	(0.873)	(0.767)
Transnational Attacks (Lagged One Year)	1.352***	1.549***	1.664***	1.846***
	(0.153)	(0.145)	(0.282)	(0.211)
Transnational Attacks (Lagged Two Years)	1.023***	1.232***	0.817***	1.031***
	(0.176)	(0.200)	(0.137)	(0.148)
Nighttime Lights			4.080***	3.977***
			(0.455)	(0.424)
Constant	−5.466***	−5.642***	−5.979***	−6.001***
	(0.182)	(0.178)	(0.294)	(0.252)
$\ln(\alpha)$	2.913***	3.104***	2.937***	3.077***
	(0.0914)	(0.0883)	(0.140)	(0.113)
Observations	1,674,853	1,894,453	737,008	912,499

Clustered standard errors in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Bond (1998) as a means for producing consistent estimates with endogenous regressors. This estimator differences time invariant fixed effects, therefore removing them, and instruments the lagged variables in order to reduce bias owing to unobserved panel-specific effects. The results of the Arellano–Bond dynamic panel model are given in Online Appendix Table A40.

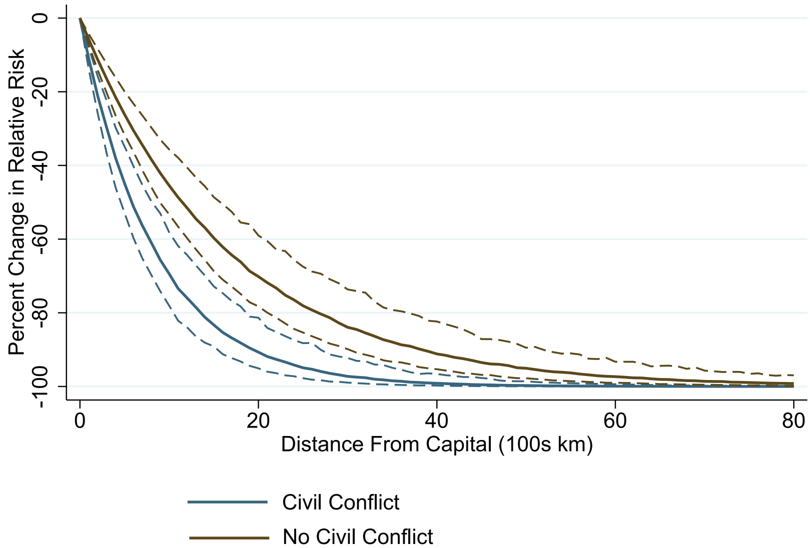

Figure 2. Marginal effect of capital distance: percentage change in risk relative to capital.

Results: location, location, location

Overall, the results provide support for nearly all of the hypotheses outlined earlier. The results of the Rare Events Logit models are presented in Table 1 and Negative Binomial Models are presented in Table 2. First, we find that transnational terrorist attacks are significantly more likely to occur at cell locations with recent experience of civil conflict events. This finding holds across multiple model specifications. This supports our first hypothesis, that terrorists are likely to target areas in which civil conflict is occurring. This is an interesting and important finding as it suggests that ostensibly domestic civil conflict events have highly important implications for transnational and global security interests. This finding also aligns with a growing body of research that highlights the commonalities between civil war and terrorist violence.

The coefficient on distance to international border is negative and significant across each of the Rare Events Logit and Negative Binomial specifications. It is apparent that locations proximate to international borders are more likely to be targeted with transnational attacks. This makes a great deal of sense from a purely practical perspective. Those transnational attacks that involve foreign perpetrators, for instance, will find it easier to penetrate shorter distances into the country. It might also be the case that areas proximate to the border are often more populous and contain greater numbers of valuable assets. Similarly, the coefficient for urban areas is positive and significant. As anticipated in our third hypothesis, those locations within or closer to urban areas are more likely to be targeted by transnational terrorists. This finding supports the notion that such locations are more likely to contain easily accessible targets. To target more rural areas would be counterproductive if the terrorists are looking to increase attention and publicity regarding their causes.

There is also an observed negative effect of distance to the capital which is statistically significant across each of the Rare Events and Negative Binomial specifications. Figure 2

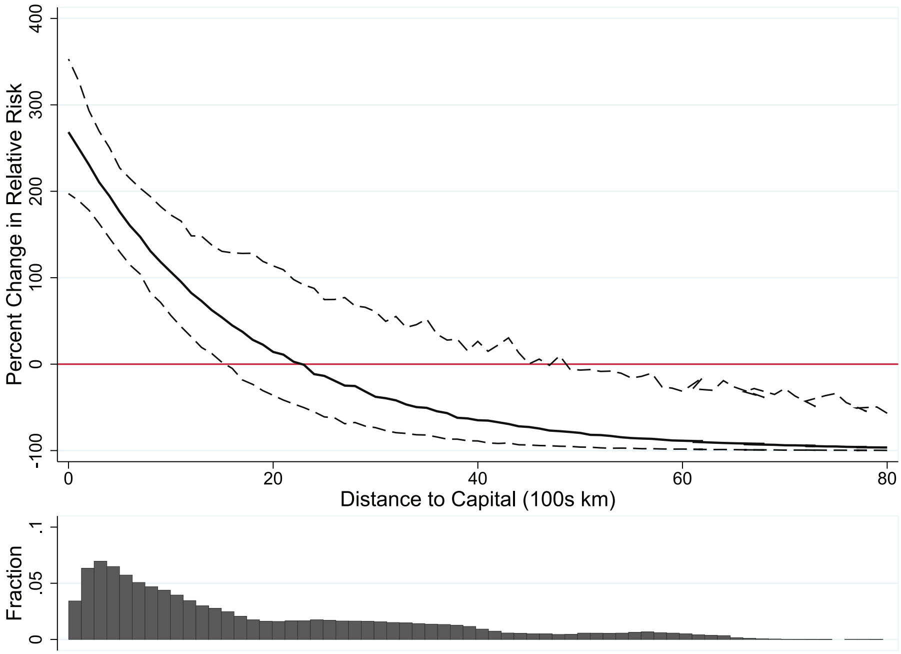

Figure 3. Marginal effect of civil conflict: percentage change in risk relative to no conflict.

presents the marginal effect of moving away from the capital in terms of percentage change in relative risk.[25] Figure 2 shows that the risk of an attack diminishes the further an area is from the capital, but that this effect is significantly stronger for areas experiencing civil conflict than it is for areas without civil conflict. This finding aligns with anecdotal evidence from recent attacks against Brussels, Paris, and Dhaka, for example. Clearly, terrorists often target capital cities, because of their value and the likelihood of producing a massive media response.

The interaction term for distance to international border and civil conflict was negative as predicted by Hypothesis 5a in the Rare Events Logit and Negative Binomial models, but failed to achieve statistical significance. However, the interaction term for distance to capital and civil conflict was negative and statistically significant in each of the models, suggesting that transnational attacks during civil conflict are especially concentrated around state capitals. We explore the implications of this interaction in Figure 3, which presents the marginal effects of civil conflict on the relative risk of transnational attack for varying values of distance to capital. This figure shows that the risk of an attack significantly increases owing to civil conflict for areas within approximately 1800 km of the capital. Terrorism driven by civil conflict seems to be mostly concentrated in areas around the capital of a state, and the heightened risk of attack owing to civil conflict appears to be attenuated the further an area is from a state capital.

We find that local areas that are more populous are also significantly more likely to host attacks. This supports our sixth test hypothesis. The coefficient for economic activity is also positive across each model specification, although it is not statistically significant in three of

Table 3. Marginal effects at means: percentage change in relative risk

Variable	Percentage change in relative risk[a]	Confidence interval
Urban	3,117.3%	[825.2%, 11,211.2%]
Population	5.7%	[4.2%, 7.2%]
Economic Activity	64.8%	[54.8%, 75.7%]
Infant Mortality Rate	13.1%	[-5.9%, 37.4%]
Precipitation	23.5%	[9.5%, 39.8%]
Attack in Neighboring Cell	7.4%	[5.8%, 9.1%]
Attack One Year Prior	1,342.3%	[1,131.4%, 1,589.3%]
Attack Two Years Prior	933.5%	[774.8%, 1,140%]

[a]Marginal effect at means of change from 10th percentile to 90th percentile. Marginal effect of one additional attack presented for spatial and temporal lags.

the 1992–2012 models which incorporate nighttime lights. This may be due to the high and statistically significant correlation between economic activity and nighttime lights (0.7552, $p < 0.001$). These results provide mixed support for our seventh test hypothesis, that higher levels of economic activity make locations more likely to be targeted. Once again, it is likely that this reflects the terrorist's assessment that locations with greater productivity represent more valuable targets for garnering public attention and potentially hurting their opponents.

We include the marginal effects at means of urban population, economic activity, infant mortality rate, and precipitation in terms of percentage change in relative risk at the 90th percentile vs the 10th percentile in Table 3. These results show that the effect of the urban variable is quite substantial, as attacks are over 30 times more likely to occur in areas at the 90th percentile vs the 10th percentile. In contrast, the effect of a similar change in population, economic activity, infant mortality or precipitation only results in a 5.7, 64.8, 13.1 and 24.1% increase, respectively.

Finally, we uncover support for our eighth test hypothesis. Local areas that host greater numbers of excluded groups are associated with a higher likelihood of being targeted; however, this result is non-linear—it returns a negative and significant coefficient on the number of excluded ethnic groups squared. To help interpret the non-linear effect of excluded ethnic groups, Figure 4 presents the marginal effects at means of the number of excluded groups on the percentage change in relative risk. Figure 4 shows that as the number of excluded ethnic groups increases, the risk of an attack increases; however the relationship is slightly non-linear. As the number of excluded groups increases, the impact of an additional group on the risk of attack is slightly diminished.

The spatial lag variable is significant in each of the models, suggesting that terror attacks occurring in adjoining cells are associated with high levels of terror attacks in the local cell, while the significant coefficients for the temporal lags suggest that attacks in years $t-1$ and $t-2$ are associated with attacks in year t. In other words, it suggests that terror groups return to previously struck locations over at least a two-year period. Table 3 presents the marginal effect of an attack in a nearby cell and in prior years upon the risk of attack. An attack in a neighboring cell has a relatively minor effect upon the risk of attack (7.4%); however, an attack one or two years prior makes an attack about 10 times more likely (1000%).

The results of the zero-inflated negative binomial models are found in Online Appendix Table A3. We find that areas with civil conflict, urban areas, populated areas, more

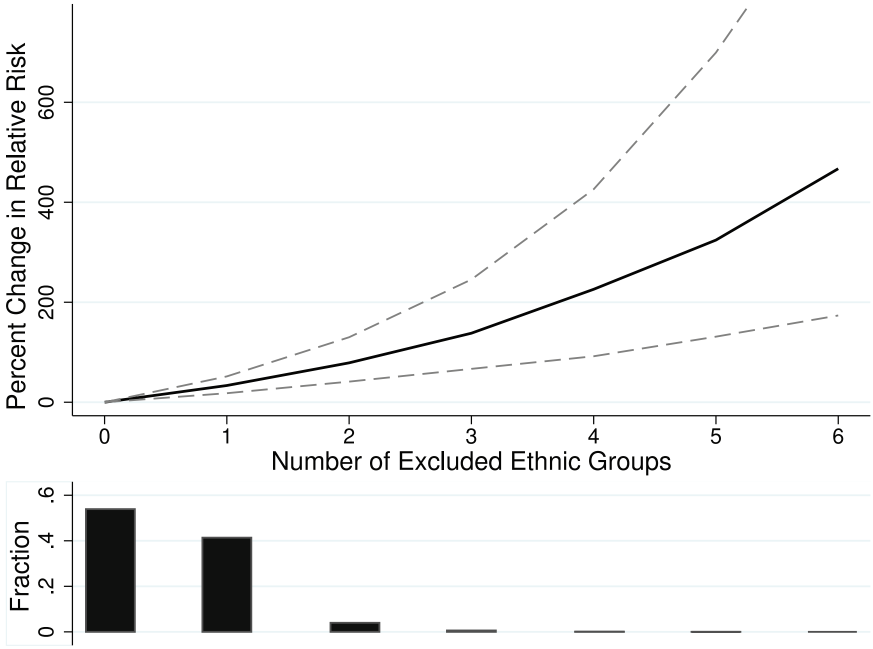

Figure 4. Marginal effect of number of excluded ethnic groups: percentage change in relative risk.

economically active areas, and areas with higher levels of precipitation, and areas in which attacks have occurred in nearby units, are all significantly more likely to be targeted by transnational terrorism at all. These findings align with our expectations. We do, however, observe some intriguing differences from the negative binomial models at the count stage. Most notably, urban areas and precipitation, while more likely to be targeted, are negatively associated with transnational attacks at the count stage. Additionally, proximity to capital and economic activity are associated with more attacks at the count stage, but are not statistically significant at the count stage.[26]

Propensity score matching

As noted above, our sample contains a large number of zero counts of events. Our strategy for dealing with this potential problem involved using propensity score matching to reduce the sample size and create more balanced comparisons. In particular, we matched the sample on the civil conflict variable, meaning that the observations should in expectation be highly similar in all ways related to the propensity for civil conflict except that some experienced civil conflict and others did not. Table 4 presents the results for matched data using a Rare Events Logit model and a Negative Binomial model. The effect of civil conflict is positive and significant in both the Rare Events Logit and Negative Binomial models. The results of the matched models are very similar to the non-matched Rare Events Logit and the Negative Binomial, with the exception that the coefficients for excluded ethnic groups in the model with nighttime emissions and the interaction term for civil conflict and distance to capital are no longer significant.

Table 4. Matching models: rare events logit and negative binomial

	Rare Events Logit	Rare Events Logit	Negative Binomial	Negative Binomial
Civil Conflict in Cell	0.873***	1.477***	0.978***	1.419***
	(0.144)	(0.192)	(0.169)	(0.225)
Distance to International Border	−0.179***	−0.137**	−0.179***	−0.119*
	(0.0362)	(0.0468)	(0.0410)	(0.0535)
Civil Conflict × Distance to Border	0.0311	−0.0681	0.0401	−0.0624
	(0.0443)	(0.0564)	(0.0532)	(0.0717)
Distance to Capital	−0.138***	−0.118***	−0.158***	−0.0831
	(0.0309)	(0.0349)	(0.0432)	(0.0427)
Civil Conflict × Distance to Capital	−0.00469	−0.0657	−0.00983	−0.0741
	(0.0318)	(0.0363)	(0.0426)	(0.0451)
Urban	0.135***	0.122***	0.118***	0.103***
	(0.0266)	(0.0296)	(0.0271)	(0.0252)
Population	0.215***	0.110***	0.457***	0.263***
	(0.0344)	(0.0332)	(0.0549)	(0.0566)
Economic Activity (logged)	0.486***	0.0906	0.514***	−0.0253
	(0.0725)	(0.119)	(0.102)	(0.170)
Excluded Ethnic Groups	0.257*	0.119	0.328*	0.132
	(0.112)	(0.183)	(0.133)	(0.165)
Excluded Ethnic Groups Squared	−0.0215	−0.00886	−0.0299	0.00553
	(0.0485)	(0.0977)	(0.0545)	(0.0678)
Infant Mortality Rate	−0.00308	0.0403**	−0.00969	0.0423**
	(0.0120)	(0.0144)	(0.0143)	(0.0158)
Precipitation	0.453**	0.685***	0.411*	0.594*
	(0.154)	(0.190)	(0.207)	(0.260)
Land Area	−0.0104	−0.0135	−0.0106	−0.00569
	(0.00687)	(0.00806)	(0.00877)	(0.0112)
Spatial Lag	0.524***	0.810***	1.174***	3.358***
	(0.0642)	(0.168)	(0.204)	(0.452)
1 Year Lagged DV	2.399***	2.403***	0.884***	1.356**
	(0.0961)	(0.137)	(0.221)	(0.435)
2 Year Lagged DV	2.120***	1.705***	0.525***	0.693***
	(0.108)	(0.154)	(0.127)	(0.166)
Nighttime Lights		3.111***		4.535***
		(0.537)		(0.874)
Constant	−4.687***	−5.285***	−4.471***	−5.677***
	(0.251)	(0.325)	(0.344)	(0.410)
ln(α)			2.601***	2.772***
			(0.140)	(0.161)
Observations	244,163	110,386	244,163	110,386

Clustered standard errors in parentheses.
$*p < 0.05$, $**p < 0.01$; $***p < 0.001$.

Multilevel models

To compare the local and country level factors together, we examine whether modeling the multilevel structure influences the inferences of the original models. The results for the multilevel random effect negative binomial models are presented in Table 5 for the full sample.

The results for the multilevel models which include nighttime lights are presented in Table 6. In both, each column includes a different measure of regime type. The left column includes the Vanhanen Index of Democratization. The middle column includes the Freedom House Imputed Polity Index. The right column includes the Revised Combined Polity Score. In each of the multilevel models, civil conflict has a positive and significant effect. The coefficients on distance to borders, cell population, and urban are significant and positive for all of the multilevel models. Economic activity is significant in Table 5, but loses its significance in Table 6 when nighttime lights are included. While the coefficient for distance to capital is negative in each of the multilevel models, neither it nor its interaction with civil conflict achieve statistical significance. The effect of excluded ethnic groups is positive and significant in all but one of the multilevel models, but the squared term for ethnic exclusion is not significant. In sum, nearly all of the results are robust to this modeling choice and demonstrate a set of local covariates that are consistently important for explaining transnational terrorism. For a robustness check, we estimated the multilevel models on the sample matched on propensity for civil conflict (Online Appendix Table A5). The results are substantively similar to those in Table 5, with the exception that the coefficient for excluded ethnic groups is no longer significant.

With respect to variation from prior results, however, we do find that once we account for country-level variables, attacks are *more* likely at greater distances from international boundaries. It is possible that once we account for country-level strategic considerations, borders become less significant targets for foreign perpetrators of terrorist attacks. We also find that the the interaction term for civil conflict and distance to capital as well as the quadratic term on excluded ethnic groups at the cell level is not significant in models which take into account the hierarchical nature of the data. In this instance, it might be that country-level repression and regime types provide structural influences on motivations for violence that mute or subsume one of the effects of the locations of ethnic groups.

Turning to the country level variables, the coefficient on Political Terror Scale is positive and significant for all of the multilevel models, which aligns with our expectations. The coefficients on military capacity and bureaucratic capacity are also negative and significant for each model in Table 5, with the exception of bureaucratic capacity in the first model. However, when nighttime lights are included in Table 6, the coefficient for bureaucratic capacity is actually positive and significant in two of the models. These results suggest that state capacity has a negative effect on transnational terrorism, which is expected, but that increases in state capabilities reduce terrorism, a result that runs contrary to conventional wisdom in the larger literature on transnational terrorism. It may be the case that military capability serves as a deterrent for terrorism rather than an opportunity structure in which terrorism is the primary available means.

To understand how the effect of state capacity on terrorism changes across space within states, we interact military and bureaucratic capacity with distance to capital. The interaction is not significant for bureaucratic capacity or military capacity and distance to capital in the model. None of the coefficients on the regime type variables (Freedom House Imputed Polity Index, Revised Combined Polity Score, and Vanhanen Index of Democratization), with one exception of the Freedom House variable, return statistically significant estimates.[27]

Finally, it is worth noting that the random effect for the country is significant across each of the multilevel models. This suggests that it is necessary to account for the multilevel nature of factors affecting where transnational terrorist attacks are likely to occur.

Table 5. Multilevel Negative Binomial models

	Multilevel Negative Binomial	Multilevel Negative Binomial	Multilevel Negative Binomial
Civil Conflict in Cell	0.923***	0.919***	0.804***
	(0.148)	(0.148)	(0.154)
Distance to International Border	0.0337*	0.0341*	0.0377**
	(0.0136)	(0.0136)	(0.0136)
Civil Conflict × Border Distance	−0.0798*	−0.0800*	−0.0864**
	(0.0322)	(0.0322)	(0.0329)
Distance to Capital	0.00739	0.00751	0.00847
	(0.0135)	(0.0135)	(0.0140)
Civil Conflict × Capital Distance	0.0160	0.0165	0.0309
	(0.0182)	(0.0182)	(0.0192)
Urban	0.155***	0.154***	0.142***
	(0.0136)	(0.0136)	(0.0136)
Population	0.621***	0.623***	0.591***
	(0.0381)	(0.0381)	(0.0372)
Economic Activity (logged)	0.672***	0.671***	0.705***
	(0.0493)	(0.0493)	(0.0492)
Excluded Ethnic Groups	0.186*	0.188*	0.239**
	(0.0878)	(0.0878)	(0.0892)
Excluded Ethnic Groups Squared	0.0588	0.0586	0.0557
	(0.0365)	(0.0364)	(0.0364)
Infant Mortality Rate	−0.0254	−0.0239	−0.0276
	(0.0215)	(0.0214)	(0.0225)
Spatial Lag	1.673***	1.674***	1.626***
	(0.158)	(0.158)	(0.159)
Political Terror Scale	0.159***	0.159***	0.170***
	(0.0417)	(0.0420)	(0.0438)
Bureaucratic Capacity	−0.159	−0.172*	−0.197*
	(0.0871)	(0.0858)	(0.0891)
Bureau Capacity × Distance to Capital	0.00365	0.00407	0.0101
	(0.00779)	(0.00779)	(0.00814)
Military Capacity	−0.728***	−0.744***	−0.708***
	(0.107)	(0.105)	(0.108)
Milit. Capacity × Distance to Capital	−0.00701	−0.00727	−0.0107
	(0.00752)	(0.00751)	(0.00783)
Index of Democratization	−0.00627		
	(0.00547)		
FH Imputed Polity		−0.00818	
		(0.0195)	
Combined Polity Score			−0.00442
			(0.00844)
Constant	−6.054***	−6.097***	−6.249***
	(0.260)	(0.279)	(0.254)
ln(α)	2.634***	2.638***	2.627***
	(0.0453)	(0.0452)	(0.0465)
σ^2	1.253***	1.235***	1.217***
	(0.249)	(0.245)	(0.251)
Country			
Observations	837,621	837,626	807,580

Standard errors in parentheses. Precipitation, Land Area, and Lagged Transnational Attacks included in the estimation but omitted owing to space considerations.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 6. Multilevel Negative Binomial models

	Multilevel Negative Binomial	Multilevel Negative Binomia	Multilevel Negative Binomia
Civil Conflict in Cell	0.751***	0.717***	0.684**
	(0.207)	(0.207)	(0.217)
Distance to International Border	0.0476*	0.0473*	0.0530**
	(0.0190)	(0.0190)	(0.0189)
Civil Conflict × Border Distance	−0.0350	−0.0353	−0.0586
	(0.0404)	(0.0403)	(0.0420)
Distance to Capital	0.0268	0.0250	0.00712
	(0.0188)	(0.0188)	(0.0199)
Civil Conflict × Distance to Capital	0.0272	0.0301	0.0461
	(0.0241)	(0.0242)	(0.0263)
Urban	0.140***	0.138***	0.119***
	(0.0181)	(0.0180)	(0.0178)
Population	0.302***	0.300***	0.284***
	(0.0446)	(0.0446)	(0.0444)
Economic Activity (logged)	0.130	0.133	0.126
	(0.0908)	(0.0908)	(0.0922)
Excluded Ethnic Groups	0.231*	0.225	0.257*
	(0.116)	(0.116)	(0.119)
Excluded Ethnic Groups Squared	0.0464	0.0461	0.0484
	(0.0433)	(0.0435)	(0.0434)
Infant Mortality Rate	0.0264	0.0211	0.0233
	(0.0267)	(0.0266)	(0.0273)
Nighttime Lights	5.449***	5.452***	5.602***
	(0.457)	(0.457)	(0.466)
Spatial Lag	2.756***	2.789***	2.840***
	(0.292)	(0.293)	(0.305)
Political Terror Scale	0.255***	0.231***	0.232***
	(0.0640)	(0.0641)	(0.0661)
Bureaucratic Capacity	0.444**	0.460**	0.466**
	(0.146)	(0.145)	(0.152)
Bureaucratic Capacity × Distance to Border	0.0135	0.0134	0.0203
	(0.0108)	(0.0108)	(0.0113)
Military Capacity	−0.966***	−0.976***	−0.994***
	(0.150)	(0.148)	(0.152)
Military Capacity × Distance to Border	−0.0170	−0.0162	−0.0112
	(0.0102)	(0.0102)	(0.0107)
Index of Democratization	−0.00507		
	(0.00842)		
FH Imputed Polity		−0.0721*	
		(0.0301)	
Combined Polity Score			−0.0234
			(0.0130)
Constant	−6.970***	−6.517***	−6.843***
	(0.366)	(0.393)	(0.332)
$\ln(\alpha)$	2.652***	2.655***	2.687***
	(0.0697)	(0.0697)	(0.0712)
σ^2	1.251***	1.206***	1.160***
	(0.275)	(0.267)	(0.263)
Country			
Observations	589,477	589,477	570,158

Standard errors in parentheses. Precipitation, Land Area, and Lagged Transnational Attacks included in the estimation but omitted owing to space considerations.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Robustness checks

For the models in the Supplementary Material, the results are largely the same as those from the Rare Events Logit and the Negative Binomial models. Rather than recapitulate the similarities, this discussion will focus on the differences owing to space constraints. To begin with the year fixed effects (Online Appendix Table A6), the results of the Rare Events Logit and the Negative Binomial models are replicated, with the exception of the interaction term for civil conflict and distance from borders. Excluded ethnic groups, the squared term for ethnic exclusion, and urban areas are not significant when cell fixed effects are included, while distance to capital and distance to international border are not significant when country fixed effects are included.

For the models that exclude attacks at precision code 6 (Online Appendix Tables A7–A10), the squared terms for excluded ethnic groups are not significant in the Rare Events Logit and Negative Binomial models except when nighttime emissions are included, and the interaction terms for civil conflict and border distance are not significant (Online Appendix Tables A7–A8). Further, economic activity is only significant in one specification with nighttime lights in Online Appendix Table A7. Distance to borders, distance to capital, their interaction terms with civil conflict, and squared excluded ethnic groups are not significant for the multilevel models, with the exception that conflict and distance to borders is significant in one specification (Online Appendix Table A9). The same holds for Online Appendix Table A10, with the exceptions that distance to capital is significant in two model specifications and excluded ethnic groups is not significant in one model specification. For attacks with more than six fatalities (Online Appendix Table A11), the only non-significant variables are the interaction term for distance to borders and civil conflict, distance to capital, and excluded ethnic groups (squared).

For the models with temporal splits (Online Appendix Tables A12–A15), the interaction terms for civil conflict, distance to capital, and distance to border are not significant with the exception of civil conflict and distance to capital between 1990 and 2000 (Online Appendix Table A14) and one of the model specifications in Online Appendix Table A12. Squared excluded ethnic groups also tends not to be significant, and the urban variable is not significant in two model specifications in Online Appendix Table A15. When internationalized civil conflicts are distinguished from domestic civil conflicts (Online Appendix Table A16), the interaction terms of distance to capital and border with internationalized civil conflict are not significant, while the relationship between domestic civil conflict and borders is also not significant. For the models that differentiate foreign and domestic perpetrators and foreign and domestic victims, the interaction term for civil conflict and border distance and the squared term for ethnic exclusion are not statistically significant (Online Appendix Tables A17–A20). This analysis indicates that the effect size for civil conflict is more than three times larger for attacks with local perpetrators than it is for attacks with foreign perpetrators. Additionally, the sign of the coefficient for infant mortality was negative for attacks with foreign perpetrators and local victims. This may suggest that while local perpetrators are more likely to attack areas with high levels of infant mortality, foreign perpetrators may find areas with lower levels of infant mortality more valuable or accessible as targets.

Finally, we estimated an Arellano–Bond Dynamic Panel model (Online Appendix Table A40). Civil conflict, economic activity, population, and lagged transnational attacks are positive and significant significant, while excluded ethnic groups is negative and significant. The urban and precipitation variables are not significant. In sum, the models in the Supplementary Material help to bolster the main results presented in Tables 1 and 2.

Individual country cases

In the Supplementary Material to this article, we considered a set of individual cases to address the large number of zero counts of events in our sample. We created a series of country maps and single country statistical models for each of five countries: Peru, Argentina, Colombia, India, and Turkey. These cases are meant to illustrate the accuracy of the cross-national results in individual settings rather than test any additional hypotheses. We used several criteria to select cases to investigate. First, we limited our interest to countries that experienced civil violence at some time between 1968 and 2013, so that we could estimate a coefficient for civil conflict at the local level. Second, we considered countries which had a large number of grid cells and the ability to evaluate patterns of transnational terrorism statistically in single country models. In other words, we selected relatively high terrorism countries. See Online Appendix Table A29 for a summary applied to these five cases. These cases can be considered exploratory probes into the geographic dynamics of transnational terrorism in single countries. In the Supplementary Material, we briefly discuss each case in turn to show that regardless of the variation among these variables, similar geographic patterns of terrorism emerge. We also identify some disagreement between the cases and the cross-national models and suggest some possible explanations and areas for future research. Overall, however, the results largely support those in the cross-national analyses. These results are reported in Online Appendix Figures A2–A6 and Online Appendix Tables A30–A39.

Conclusion

From a global perspective, it is clear that not all locations are equally likely to host a transnational terrorist attack. In this paper, we posited five factors, including security, accessibility, symbolism, material harm, and exclusion, that help us to explain this variation in local experiences of transnational terrorism. We explicitly modeled local and country-level factors together. The results provided evidence for all of these factors. We introduced new, sub-nationally geo-coded data on transnational terrorism and demonstrated that local factors are strongly correlated with transnational terrorism, even when accounting for country-level variables. We derived eight hypotheses regarding local characteristics and experiences that ought to influence the likelihood of terrorism locally. Our analyses offer considerable evidence in support of these expectations. While transnational attacks often reach across borders, many of the factors that influence where the attacks occur are local.

The primary purpose of this study is to provide an exploratory examination of how sub-national factors are associated with transnational terrorism. In particular, we seek to establish the benefits of adopting the sub-national level of analysis, instead of only using the cross-national level of analysis that has until recently dominated the literature. We find that local experience with civil war battles, as well as population and proximity to urban areas, especially capital cities, each increase the likelihood of a transnational terror attack. Ethnic exclusion is also found to increase the likelihood of a terror attack. While prior research has established a relation between domestic terrorism and civil wars at the sub-national level (Findley and Young, 2012), our study is the first to show a relationship between sub-national transnational terror attacks and civil wars at the local level. We also identified relationships that help to shed light on the relationship between urban areas and terrorism. We employ variables, such as distance to international border and distance to capital, that can only be utilized at the sub-national level. Nevertheless, our exploratory analysis should thus be seen as a first step towards a more comprehensive analysis of a set of theoretical expectations based on specific research questions and theories.

We used matching techniques and an Arrellano-Bond dynamic panel model (Online Appendix Table A40) to begin to address endogeneity, which is a challenge with all observational data. Nevertheless, we recognize the need for more work in this area to examine the precise impact of these processes and to make sure the results hold across different contexts. The case illustrations, included in the Online Appendix, reduce some of the complexity by examining individual countries, and may be the basis for future work that could then apply more rigorous identification strategies in controlled settings.

There are a number of other analytical extensions that could be considered. Scholars could analyze more complex, potentially interactive relationships such as whether civil conflict occurs across the border in the neighboring state that could unpack future results. Our multilevel modeling was a first attempt at this, but future cross-border and cross-level tests are quite feasible. Furthermore, a future direction is to examine the sub-national variation of different modes of transnational terror attacks. For example, we have not unpacked any of the differences between, for instance, hijacking vs assassinations. Just like types of crime, we suggest that these different modes of attack might have different logics of target selection. Finally, future work could examine whether different types of terrorists, such as left-wing vs right-wing terror groups, differ or coincide in terms of which types of locations they targeted.

Moving forward, we expect that our approach could contribute to risk analysis and to predict out-of-sample locations that are particularly attractive to groups that utilize terrorism. Similar to efforts by police departments to map crime, this approach could be used by homeland security professionals to identify likely targets. With the expansion of ISIS beyond the Middle East, and the activity of numerous other transnational terrorist groups, the US and many other countries should be particularly interested in understanding transnational terrorism targeting. Given increasing concerns in academe about engaging policymakers, this approach provides clues about the location of transnational terrorism.

Acknowledgement

We thank Oliver Babcock, Michael Cheroff, John Clary, Alex Davis, Halley Ham, Ethan Hendrickson, Catie Sauer, Juliette Sieve, Sierra Smith and the Innovations for Peace and Development team for research support.

Authors' note

All replication materials will be made available upon publication of the manuscript. Replication materials available at www.michael-findley.com. Paper presented at the 2015 International Studies Association Annual Meeting, New Orleans, LA, 19–21 February.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Notes

1. We follow the convention of distinguishing *transnational* terrorist attacks from *domestic* attacks as discussed in Enders et al. (2011). We provide more detailed definitions below.
2. Numerous terms could be used to describe terrorist events at different levels. We use the terms "sub-national" and "local" interchangeably to refer to factors specific to geographic areas *within* countries. Examples include civil war zones within a country. We use "country" and "national" to refer to characteristics of countries themselves. Examples include the level of democracy. We employ the term "regional" or "transnational" to refer variably to country-level characteristics or to broader regional dynamics that span more than one country. Examples could include interstate rivalries. It is worth noting that most literature on "transnational" terrorism exclusively uses country-level variables in their analyses.
3. "Geocoding" refers to coding the latitude and longitude coordinates of attack locations.
4. Sandler (2014) offers a recent survey of some of the accomplishments of the analytical approach to understanding the causes and consequences of transnational terrorism.
5. Scholars quantifying the causes of *domestic* terrorism have also focused primarily on country-level determinants, although our focus in this paper is on transnational forms of terror.
6. Point locations have also been analyzed at the global level in order to uncover hot spots of militarized disputes (Braithwaite, 2006, 2010) and civil conflicts (Buhaug and Gates, 2002).
7. Enders and Sandler (1993) initiated research into substitution effects—the notion that certain targets will become more attractive to terrorist targeting when others are hardened or become more costly to targeting by the group.
8. For purposes of this paper, debating definitions would not advance the discussion productively. We follow Young and Findley (2011) who contend that the distinctions may not always matter for specific applications.
9. Libicki et al. (2007) argue that Al-Qaeda's transnational terror attacks were designed to coerce the US to accommodate the group's policy demands while also damaging the ability of the US to respond militarily.
10. Building on Enders and Sandler (1993), Nemeth et al. (2014) are mainly concerned with this dimension of attracting domestic attacks.
11. Building up the security of a target can lead terrorists to target less-secure assets. For example, research has found that increasing the security of public infrastructure has inadvertently shifted the focus of terrorist attacks towards private individuals, who are less easily secured from these attacks (Brandt and Sandler, 2010; Mathews and Lowenberg, 2012; Santifort et al., 2013). These findings suggest a negative relation between civil conflict and terrorism, if conflict attracts more security and military forces and so shifts terrorist activity away from the conflict. We posit that at this exploratory stage in the research, whether a positive or negative relationship exists between security and terror attacks is an empirical question.
12. Findley and Young (2012) theorize four factors (attrition, intimidation, outbidding, and spoiling) whereby civil conflict can accompany terrorism. We propose here that the degradation of security during civil conflict is a different mechanism by which civil conflict causes terrorism.
13. As we show in the Online Appendix, the correlation between urbanization and distance to international border is significant ($p < 0.001$) and negative (-0.515). In other words, higher levels of urbanization are associated with lower distances to international borders. However, this correlation leads to a conservative bias as these variables are competing for the same explanation.

14. Urban areas are frequently the main targets of terror attacks, both in the developed world (Savitch and Ardashev, 2001) and the developing world (Beall, 2006).
15. Hoffman (2006) argues that left-wing terrorism targets sites of symbolic significance (see pp. 231–232). We extend this argument to include transnational terrorism.
16. Capitals often contain objects and buildings of cultural significance. While sub-national data on objects and buildings of cultural significance would be preferable, distance to capital is used as a proxy and represents the best data available.
17. Basuchoudhary and Shughart (2010) found that ethnic tensions increase transnational terrorism, while Choi and Piazza (2016) show that ethnic exclusion promotes domestic terrorism.
18. All geo-coded data through 2013 will be available with replication materials.
19. In fewer than 1% of cases, outside sources were used to gain information on the location of the terror attack. The documentation for these sources is included in the data.
20. The fact that country boundaries change over time, such as with the creation of South Sudan out of Sudan in 2011, can raise challenges for the geocoding of terror attacks over time. When available, we use the historical coordinates for attacks that occurred at the country level in countries that no longer exist, such as East Germany. The availability of data on historical sub-national administrative boundaries is more difficult to obtain. Nevertheless, we stress that the majority of our attacks are geo-coded at a high level of precision (82.1% are geo-coded at precision codes 1 and 2) and thus are not affected by the quality of administrative coordinate data at sub-national and national levels over time. Only 7.9% are coded at precision levels 3–5, levels which ostensibly may be affected by changes in sub-national administrative units over time.
21. We exclude terror attacks with precision code 6 (national-level attacks) as these attacks are mapped at the country centroid, and give the impression that the center of a country is experiencing a large number of attacks. We include these attacks in the analyses except for a series of models in the Online Appendix in which the precision code 6 level attacks are excluded.
22. Please see the Online Appendix Tables A1 and 2 for summary statistics and correlations between the covariates.
23. Mickolus et al. (2015) state that "Domestic attacks engaged in during the conduct of a civil war are not included" in the dataset. This exclusion criteria create the possibility that terror attacks may be under-counted during civil war. Yet this possible under-counting makes finding a relationship between civil war and terrorism more unlikely, and so our estimate is more conservative. To help address concerns about potential bias owing to undercounting we follow the suggestion of Weidmann (2016) and run the models on high-profile attacks with more than six fatalities as a robustness check. The results of this analysis is presented in the Online Appendix Table A11 and are overall consistent with our main findings
24. The difference between the Negative Binomial and the Zero-inflated negative binomial is the treatment of the zero counts. In the negative binomial, all zero counts are treated identically. The zero-inflated regression is used to model excess zeros that may be generated by a separate process from attacks. For this paper, the purpose of these zero-inflated models is to reflect that local areas may experience two distinct sources of zero counts. First, the inflation stage of the model identifies the effect of key parameters upon the likelihood that a location never experiences terrorist attacks—i.e., is always a zero. In contrast, the count stage of the model identifies the effect of parameters on the counts of terrorism at locations that do experience some level of terrorism. We estimate zero-inflated models in Online Appendix Tables A3 and A4 as a robustness check.
25. All marginal effects presented here are based upon the full model without nighttime lights presented in the leftmost column of Table 1.
26. Separately identifying covariates for the inflation and count stages of the zero-inflated model is a potentially interesting direction for future research. Theoretically, variables in the zero stage but not the count stage should only contribute to whether there is any terrorism, whereas variables in the count stage but not the zero stage should contribute to the number of attacks, given that there are one or more attacks. In this exploratory project and in keeping with standard practice in the

literature, we have opted to have the data speak for themselves on this account and included the same covariates in both stages of the model. In this context it is difficult to have a strong theoretical reason for putting variables in one stage vs another. It is the case that each of the variables could theoretically influence both the presence of any attacks and the number of attacks given that more than 0 occur. Thus, while it may be a misspecification to include a full set of covariates in both stages of the model, the results of this analysis give us insight into the relative importance upon the zero and count stage of the model. We explore the distinction between the inflation and count stage further through a stepwise process of backward elimination in which we eliminate the covariate with the highest p-value over 0.15 iteratively. The results from this variable selection process are presented in Online Appendix Table A4.

27. This result is consistent with previous findings that regime type may explain domestic terrorism, but it is less suited for explaining transnational terrorism (Chenoweth, 2013).

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