HOW DOES TERRORISM RISK VARY ACROSS SPACE AND TIME? AN ANALYSIS BASED ON THE ISRAELI EXPERIENCE

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We study the spatial and temporal determinants of terrorism risk in Israel, using a geocoded database of Israeli terrorist attacks from 1949 to 2004. In selecting targets, terrorists seem to respond rationally to costs and benefits: they are more likely to hit targets more accessible from their own homebases and international borders, closer to symbolic centers of government administration, and in more heavily Jewish areas. We also examine the waiting time between attacks experienced by localities. Long periods without an attack signal lower risk for most localities, but higher risk for important areas such as regional or national capitals.

Keywords: Terrorism risk; Spatial; Temporal; Israel;

JEL Codes: D74, N4

INTRODUCTION

Few countries have had as much experience combating terrorism as Israel. Even though it is unique in many ways, its experiences can serve as a guidepost for other countries beginning to face terrorist threats. For example, Bruce Hoffman, a RAND Corporation terrorism analyst, has argued that since terrorists are ‘more imitative than innovative,’ current experiences can teach us a great deal about the future. In particular, Hoffman has argued that understanding the threats Israel faces today can reveal a great deal about the brand of terrorism that the world will face in the future (Sela, 2003).

While the Israeli experience with terrorism is extensive, few if any researchers have conducted systematic, quantitative analyses of this history, in spite of its potential importance for the future of terrorism. Casual empiricism applied to the history of terrorism has provided a qualitative understanding of risk that serves as a useful foundation. It seems fairly certain, for example, that major cities are more at risk than minor cities, political and commercial centers more at risk than other locales. Lack of security or ease of access to terrorist groups can also play a role. However, these tentative conclusions raise questions

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that only quantitative analysis can answer: How robust are these effects, and which are the most important determinants of terrorism risk?

This paper focuses on two important questions concerning the determination of terrorism risk. (1) Do terrorists behave rationally when they decide which targets to attack most often? (2) What is the empirical pattern in terrorists’ decisions about when to attack? We investigate these questions using Israel as a source of data on terrorist behavior. To answer question (1), we explore how the spatial risk of terrorism varies with measures of target value and attack cost. To analyze question (2), we analyze the spacing, or the ‘waiting time’ between terrorist attacks on a given locality. The answers to these questions are useful for those who wish to forecast terrorism risk (e.g., insurers, risk planners), and for researchers who wish to validate models of terrorist behavior.

Four factors stand out as key determinants of spatial variation in risk: proximity of terrorist homebases and international borders, both of which likely improve access for terrorists and thus lower the cost of attack; the presence of a Jewish population and a center of government administration, both of which likely raise the expected benefit of attacks in the eyes of terrorist groups. Specifically, when distance to a terrorist homebase doubles, the frequency of attacks falls by around 30%. International border localities are more than twice as likely to be hit. Areas with a Jewish population are three times as likely to be hit as other areas, as is Jerusalem, and as are localities with a regional capital.

Our analysis of attack timing also leads to several important conclusions. First, in the wake of a terrorist attack, the risk of a subsequent attack climbs in the hours following it and peaks the following day. After that point, risk decays for 8 weeks. In fact, if a locality survives for 8 weeks without an attack, it returns to its low, pre-attack risk level. That is, localities that have experienced an attack within the past 8 weeks are at greater risk of an attack compared to other localities, but after 8 weeks, their risk is no longer elevated.

Interestingly, while this subsidence of risk occurs on average, patterns are very different for politically sensitive localities that are seats of government. For such localities, risk subsides within the first 8 weeks, but then begins a noticeable climb upward: apparently, terrorists are not content to leave such high-profile areas untouched, even though they may choose to do so for less attractive cities. These results imply that long periods without an attack signal higher risk for politically sensitive or symbolic areas, but lower risk for other areas. This suggests the importance of accounting for the symbolic importance of an area when predicting changes over time in risk.

Our analysis is related to a small but growing literature in economics and social science on the empirical determinants of terrorism. Much of the existing literature has focused on the way economic conditions, political arrangements, and security responses affect the risk of terrorism across countries. There is also an emerging literature studying patterns within countries, which provides more reliable empirical identification that is not subject to the problem of cross-country heterogeneity. Missing from the existing analysis is a study of how terrorism risk within a single country varies across space, and how the timing of attacks can also vary across localities. This paper begins to fill those two gaps.

1 Tavares (2004) conducts a cross-country analysis that concludes richer countries are more prone to terrorism than poorer ones, but that democracy often reduces the risk of terrorism. On the policy side, Barros (2003) has found that policy approaches, like economic growth or terrorism deterrence, have decidedly mixed effects on terrorist behavior and terrorism risk. Similarly, Li and Schaub (2004) find little evidence that countries with more foreign direct investment or global economic ties experience more terrorism.

2 Berrebi and Klor (2004) show the potential importance of political cycles on terrorism level in Israel. Blomberg et al. (2004) have argued that, within rich, democratic countries, economic contractions are associated with upsurges in terrorist activity. Enders and Sandler (2005) note that sudden upsurges in terrorist activity tend to be more persistent when the overall level of terrorism is lower, but not very persistent otherwise.
A BRIEF HISTORY OF TERRORISM IN ISRAEL

Ever since the establishment of Israel on May 14, 1948, terrorism has been a regular feature of life in that nation. The starting point of global terrorism is often thought of as 1968. In the case of Israel, however, sectarian Arab–Jewish conflicts in Palestine degenerated into terror in the late 1920s (Crenshaw and Pimlott, 1997). This was accompanied by Jewish attacks on British soldiers in the region. The founding of the state of Israel in 1948 was followed by a war with neighboring Arab states, and the subsequent expulsion of many Palestinians. After the 1948–1949 war, Arab attacks against the Jewish population became attacks against Israeli targets and citizens. On the other hand, Jewish attacks became military and police retaliation by Israel against suspected Arab terrorists.

For the first few decades of its existence, Israel experienced only sporadic terror attacks. The first organized Palestinian terrorism campaign can be attributed to the Fatah movement, which emerged in 1956 and was solidified by Yasser Arafat around 1960. This later became the military wing of the Palestinian Liberation Organization (PLO). Other organizations imitated these tactics and expanded the scope of their targets to include Israeli interests outside Israel (e.g., hijacking of passenger jets, or assassination of Israeli athletes at the Munich Olympics).

While terrorist activity continued consistently, a new and more intense wave of it began in September 2000 with the onset of the second Palestinian Intifada. Currently, the main terrorist organizations perpetrating attacks against Israel are Hamas, the Palestinian Islamic Jihad (PIJ) and the Al Aqsa Martyrs Brigade, all of which engage in suicide attacks. Traditional (i.e., non-suicide) attacks are periodically perpetrated by older organizations such as the Popular Front for the Liberation of Palestine (PFLP), Popular Front for the Liberation of Palestine – General Command (PFLP-GC), and the Democratic Front for the Liberation of Palestine (DFLP), all of which were established following the 1967 war. The Hizballah is also worth mentioning in this context because it engages in terrorism directly from across the Lebanese border, and indirectly by sponsoring other local terrorist organizations.

CONCEPTUAL FRAMEWORK

A rational-choice framework provides predictions about how terrorists will behave and thus how terrorism risk ought to vary with incentives. To illustrate this point, we present a simplified version of the more detailed rational-choice terrorism equilibrium developed in Lakdawalla and Zanjani (2002, 2005). Suppose there is a single terrorist group with total resources $R$ that it can spend on terrorism. The group can attack any of $N$ potential targets. The group invests resources $r_i$ into attacking target $i$. If successful, it derives value $V_i$, which may vary across targets. Spending resources increases the probability of success, but success may be easier to achieve at one target than another. Define the probability of successfully attacking target $i$ as $\pi(r_i; b_i)$, where $\pi_b > 0$ and $\pi_{rb} > 0$. The parameter $b_i$ is ‘bang for the buck,’ or the marginal productivity of a given amount of investment at location $i$. For instance, if target $i$ is located very far away from the group’s homebase, a given amount of spending may purchase less success.

In this environment, the group maximizes its expected utility, according to:

$$\max_{\{r_i\}_{i=1}^N} \sum_{i=1}^N \pi(r_i; b_i) V_i$$

$$s.t. \sum_{i=1}^N r_i \leq R$$

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3 This refers to British mandate Palestine.
The group’s optimal behavior is characterized by the following first-order conditions:

$$\pi_r(r_i;b)V_i = \lambda, i = 1, \ldots, N$$

(2)

where $\lambda$ is the group’s marginal utility of financial resources. It is straightforward to show that, all else equal, the group will spend more resources on attacking higher value targets, and on targets where spending is more productive (i.e., that have higher values of $b$). Higher value (or productivity) targets pull resources away from lower value (or productivity) targets.

Empirically, we measure value $V_i$ along the following dimensions: presence of a Jewish population, presence of a regional or national capital, and the size of the local population. All these characteristics affect the symbolic and practical importance of terror and disruption in a particular area. We measure costs using distance to the terrorist group’s homebase, whether the locality has an international border, and distance to the nearest military checkpoint, all of which affect ease of access.

Our simple framework makes a useful distinction between preferences and productivity. Terrorists are more likely to hit more easily accessible targets, and more highly valued targets. We have not explicitly considered how terrorists may be deterred by self-protection investments made by targets. We have abstracted away from this issue in the theory, because we lack empirical data on such protective measures taken by targets. The theoretical framework for this type of interaction is built in Lakdawalla and Zanjani (2002, 2005). For the purposes of this paper, however, the absence of these data represents a limitation of the results.

Our list of empirical measures also makes clear an additional limitation: it can be difficult in practice to distinguish between preferences and productivity. For example, more densely populated areas may be more valued by terrorists, but population density may also affect ease of entry. Similar problems arise for the presence of a Jewish population, and of a capital. Nonetheless, the distinction between ‘supply-’ and ‘demand-side’ forces provides clarity for our thinking about the empirical results, even though the empirical results expose some subtlety that is not perfectly captured by a simple theoretical model.

DATA DESCRIPTION

Geographic Information System Data

Underneath our data on the chronology of terrorist attacks lies a Geographic Information System (GIS) for Israel. The Israeli Central Bureau of Statistics (ICBS) divides up the country into 270 localities. For the most part, each locality is defined by the presence of a single major city that holds administrative sway over the space of the locality. In a few cases, however, a single locality can include several smaller villages, each of which has jurisdiction over part of the locality, but not all of it.

Each locality is constructed as a polygon on the map of Israel by the Israeli CBS. We assign each attack in our database to one of these localities, according to whether it fell within the polygon on the map. Finally, distance between localities is always defined as the shortest distance between the two polygons, and similarly distance between a locality and a point (e.g., the point of a terrorist attack or a military checkpoint) is the shortest distance between that point and the polygon.

The geographic data are summarized in Table I, which provides a general description of the types of localities in our geographic coding scheme. Out of the 270 localities, about 40% have experienced a terrorist attack. Localities that border the West Bank, the Gaza Strip, or international borders make up a little more than one-quarter of all localities. Quite a few are
exclusively non-Jewish. In our nomenclature, a locality is defined as having a regional capital if one or more of its cities or villages hosted an official bureau of the Israeli Ministry of Interior in 2004.4

**Terrorism Chronology Data**

Overlaid upon the geographic data is a chronology of terrorist attacks in Israel from January 1, 1949 to June 30, 2004.5 Some of our data are taken from the RAND Terrorism Incident Database. The rest was collected by Claude Berrebi, as described below.

The RAND Terrorism Incident Database has been collected for more than 30 years by RAND analysts with regional expertise and language skills. RAND analysts collect information about terrorist attacks from newspaper accounts. For the purposes of the database, ‘terrorism’ is violence that is designed to create fear, in order to coerce a society or political group into behaving in a way they would not have done otherwise. There is an implicit distinction between ‘criminal’ acts and terrorist acts; the latter are designed to make a political statement or induce an action by a state or political entity. For marginal cases that may or not be classified as ‘terrorism,’ a Vetting Committee composed of experts convenes to decide on inclusion or exclusion.

The RAND database has two important limitations that caused us to supplement it with our own data collection. First, the database begins in 1968, even though terrorism in Israel goes back at least 20 years earlier. Second, prior to 1998, it excluded domestic terrorist incidents. From 1968 to 1998, the database included only acts of international terrorism, in which a country is attacked by a foreign group. From 1999 onwards, the database includes both international and domestic terrorism incidents. Therefore, while the pre-1998 data would include an incident in which a Palestinian crosses the border into Israel and perpetrates an attack, attacks within the Occupied Territories against Israeli targets would not be included.

Given these limitations, we undertook our own collection of Israeli terrorism incidents. In accordance with RAND’s database definition of terrorism, we culled data on terrorists’ attacks, creating a database that contains daily information on each and every fatal terrorist attack against non-combatants that occurred on Israeli soil from January 1, 1949 until June 30, 2004. In addition to meeting the RAND definition of ‘terrorism,’ an attack must meet three key criteria to be included in our database:

(a) Fatal: Due to the constraints of the data collection procedure, we only include attacks where someone (other than a terrorist) died.

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4 An ‘official bureau’ includes the following: National Election Inspection Bureau, Regional Appeal Committee, Regional Licensing and Supervising Bureau, and Regional or Sub-Regional Population Administration Bureau.

5 The database does not include attacks by the Israeli government against Palestinian targets; unfortunately, these data were never collected as part of the RAND Terrorism Chronology or as part of the Claude Berrebi data. However, it is important to note that previous research has suggested that Israeli attacks on Palestinian targets do not causally influence Palestinian attacks on Israel (Goldstein et al., 2001; Jaeger and Paserman, 2005).
(b) Non-combatants: This term is interpreted to include, in addition to civilians, military personnel who at the time of the incident are unarmed and/or not on duty.

c) Israeli soil: This includes occupied territories when under Israeli control.

The main sources of the data are the Israeli Foreign Ministry, the National Insurance Institute, the Israeli Defense Forces and the archives of two newspapers (Ma’ariv and Ha’aretz). A comparison of our data to the original RAND database shows the two to be in wide and general agreement. Comparing the periods common to both databases, fewer than 10% of the (unique) observations fail to be present in both. This suggests substantial agreement between the definitions of terrorism employed by the two databases.

To the terrorism chronology, we added information about the homebases or safe havens of the perpetrating organization at the time of the attack. We constructed the database on terrorist homebases or safe havens from a variety of public-domain sources and experts that we deemed reliable. We considered a location to be a homebase or safe haven for a group at a specific time either because one of our sources named it as such, or because the location was found (after an attack) to have been used for bomb-making, training, and/or preparations, according to news outlets. To the best of our knowledge, this is the most accurate and comprehensive unclassified data set regarding fatal terrorist attacks against non-combatants on Israeli soil.

Several limitations of our data are worth noting. As mentioned above, we only include attacks in which a bystander died. Therefore, non-fatal attacks designed primarily to cause economic damage are not included. Moreover, access to a locality might also be affected by the availability of decent roads, alternative means of transportation, existence of barriers, rivers, as well as the level of security spending by local authorities. These data elements are unavailable to us, but may well be useful additions worth future research effort.

Linking the Chronology to the GIS Data

Using the detailed descriptions of each of the terrorist events in our data we were able to associate a latitude-longitude coordinate to each and every attack. The position of the coordinate depended on the specific details we were able to retrieve for each attack. For example, in cases where we had a street or a road intersection name we located the coordinate (with accuracy of up to 1 sq km) with the use of maps and GIS tools. In events where only a city name was available, we assumed the attack was located at the center point of the mapping polygon containing the city. Coordinates were attached to military checkpoints and terrorist homebases in a similar way.

Data Summary

Table II summarizes the terrorism chronology data. Over the entire period of study, the average locality faced 3.37 attacks, but among the 40% of localities that were ever attacked, the average climbs to 8.13. The median number of attacks is significantly lower, because the distribution of attacks is skewed to the left. The average Israeli locality is about 21 km away from a terrorist homebase; those that have ever been attacked are about 18 km away.

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7 Conflicting cases consisted (with a few exceptions) of incidents not recorded in the RAND database.
8 The following sources were consulted: the website of Jane’s (www.janes.com), the website of The Institute for Counter-Terrorism (www.ict.org.il), The MIPT RAND Terrorism Chronology, the website of the Israeli Ministry of Foreign Affairs (www.mfa.gov.il), works by Edward Mickolus and collaborators (Mickolus, 1980, 1993; Mickolus and Flemming, 1988; Mickolus and Simmons, 1997, 2002), newspaper articles, and RAND terrorism experts. A full list of all 670 sources consulted in the construction of the homebase data is available from the authors upon request.
The table also calculates the number of attacks per year at risk, recognizing that some localities were actually founded during our period of study and thus not exposed to attacks over the entire period. Making this correction reveals that the average locality faced 0.08 attacks per year, but among those who were ever attacked, the rate climbs to 0.19 attacks per year, or about two attacks every 10 years. The numbers in this table suggest that the distribution of attacks is highly skewed: 60% of localities were never attacked; even among those that were attacked, half faced fewer than 0.08 attacks per year. The skewness of terrorism motivates our later analysis of how local characteristics influence the distribution of terrorism risk.

RESULTS

Spatial Variation

In this section, we analyze how terrorism risk varies across space. We investigate variation in the risk of ever being attacked, as well as variation in the long-run frequency of attacks.

Risk of being Attacked

We first study the characteristics that determine whether or not a locality is ever targeted by terrorists. To do so, we estimate a logistic probability model for whether locality \( i \) has ever been attacked, according to:

\[
Pr(Ever Attacked_i = 1) = \frac{\exp(x_i' \beta)}{1 + \exp(x_i' \beta)} \tag{3}
\]
where \( x_i \) is a vector containing: locality \( i \)’s population in 2004 (cross-sectional variation in this number was fairly consistent throughout the period of study);\(^{10}\) the area in square kilometers of locality \( i \); the distance from locality \( i \) to the closest terrorist homebase;\(^{11}\) whether or not locality \( i \) has an international border; whether it contains a regional capital; whether it has a Jewish population; and a dummy for Jerusalem. All geographic variables are measured in 2004. The population density of the area (population holding area fixed), the presence of Jews, and the presence of a regional or national capital reflect the value of the locality to a terrorist group. As we noted previously, however, it is certainly possible that any of these variables might also affect ease of access for terrorists and can thus combine supply-side phenomena as well. ‘Distance to homebase’ and the presence of an international border affect the cost of reaching a target; these we think of as pure supply-side factors.

The results of this procedure are displayed in Table III. Each column in the table corresponds to a different set of covariates in the model. For instance, the first column includes only population and land area, the second column adds whether or not the locality contains a regional capital, and so on. The table also displays two measures of the relationship between each covariate and the risk of attack. The first is the odds ratio, which represents the percentage change in the odds of an attack. For example, increasing the population by 1000 people increases the odds of a terrorist attack by 1%. To make things concrete, if an area with 100,000 people faces 10 to 1 odds against attack,\(^{12}\) this would imply that an area with 101,000 people faces odds of 9.9 to 1. The numbers in parentheses are the standard errors associated with these odds ratios. In addition, the terms in braces measure the absolute change in the probability of attack associated with each covariate.\(^{13}\) Continuing with the estimates for population, an additional thousand people increases the probability of having been attacked by 0.2 percentage points. If an area with 100,000 people faces a 10% probability of an attack, an area with 110,000 people faces a 12% probability.

Here, as elsewhere, proximity to terrorist homebases is an important marker for terrorism risk. A locality that is 1 km farther from a terrorist homebase faces 3% lower odds of having been attacked, and a 0.5 percentage point reduction in the probability of having been attacked. Border localities are 44 percentage points more likely to have been attacked than non-border localities. Finally, non-Jewish areas are about 23 percentage points less likely to have been attacked.

The last column of the table tests the importance of the 1995 peace agreement between Jordan and Israel. In the last column, we repeat the fully specified model, but using only attacks between 1995 and 2004. Observe that, during this later period, the only difference is the sharp decline in the importance of an international border as a determinant of risk. Since Israel’s longest border is with Jordan, this is consistent with the idea that Jordan became less tolerant of terrorist groups operating across its border with Israel. Or, alternatively, Jordanian-based groups may have had fewer grievances to take out against the nearest (border) Israeli localities.

**Attack Frequency**

We now study what determines the frequency of attacks faced by the different areas. Specifically, we correlate the number of attacks on a locality over the entire period of our data, with

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\(^{10}\) The ratio of population between any two localities remained fairly constant over this period of time. Moreover, most of the attacks in our sample happened during the last decade (after the Russian immigration of the 1990s), so that total population was reasonably constant over the period of interest.

\(^{11}\) Distance is computed as the shortest distance between two points and does not reflect potential geographical or physical barriers such as rivers or fences.

\(^{12}\) 10 to 1 odds against attack mean the area can expect an attack 1 out of every 11 times.

\(^{13}\) In particular, these are the mean marginal effects, computed across all observations.
several possible determinants of risk.\footnote{Only years at risk were considered. A locality is at risk for a terrorist attack from the date of its founding, or from the date of its first attack, whichever is earlier.} We estimate the number of attacks as a function of: population, area, the distance to the nearest terrorist home base, the presence of a Jewish population, and contiguity with an international border.\footnote{We also estimated the effect of distance to a military checkpoint, but found it to be a widely insignificant predictor of risk.}

Since the dependent variable in this analysis is an integer-valued count, ordinary least squares regression is inappropriate. Earlier research has shown that count data with a large number of zeros (158 of our 270 localities experience no attacks) is best modeled using negative binomial regression, which dominates Poisson regression in this case (Gurmu and Trivedi, 1996). The negative binomial model assumes that the dependent variable (number of attacks) is distributed Poisson with mean/variance parameter $\exp(x_i\beta + \nu_i)$, where $\nu_i$ is a random variable that is distributed $\Lambda(\alpha)$. Under these conditions, the number of attacks is distributed as a negative binomial with mean $\exp(x_i\beta)$, where the coefficients can be interpreted as semi-elasticities.

\begin{table}[h]
\centering
\caption{Determinants of the probability that a locality has ever been attacked}
\begin{tabular}{|l|c|c|c|c|c|}
\hline
 & 1 & 2 & 3 & 4 & 5 & 6 \\
\hline
Population (thousands) & 1.01 & 1.01 & 1.01 & 1.01 & 1.01 & 1.01 \\
 & (0.006) & (0.006) & (0.006) & (0.007) & (0.006) & (0.004) \\
 & [0.002] & [0.001] & [0.000] & [0.001] & [0.001] & [0.001] \\
Area (SqKm) & 1.01 & 1.01 & 1.01 & 1.01 & 1.01 & 1.01 \\
 & (0.004) & (0.004) & (0.004) & (0.004) & (0.003) & (0.001) \\
 & [0.002] & [0.002] & [0.002] & [0.002] & [0.001] & [0.000] \\
Regional Capital & 4.46 & 5.67 & 5.08 & 3.24 & 6.21 & \\
 & (3.02) & (3.99) & (3.55) & (2.26) & (3.52) \\
 & [0.270] & [0.310] & [0.280] & [0.180] & [0.290] \\
No Jews in locality & 0.2 & 0.14 & & & & \\
 & (0.089) & (0.107) & & & & \\
 & [0.230] & [0.180] & & & & \\
Distance to closest terrorist & 0.97 & 0.97 & 0.97 & 0.97 & 0.97 & \\
homebase (km) & (0.01) & (0.01) & (0.01) & (0.02) & (0.02) \\
 & [0.005] & [0.005] & [0.004] & [0.006] & [0.006] \\
International border & 17.7 & 23.1 & 5 & & & \\
locality & (28.24) & (35.50) & (3.80) & & & \\
 & [0.440] & [0.440] & [0.230] & & & \\
Pseudo R-squared & 0.27 & 0.28 & 0.30 & 0.32 & 0.36 & 0.31 \\
Observations & 270 & 270 & 270 & 270 & 270 & 247 \\
\hline
\end{tabular}
\end{table}

Note: The models in columns one through five include a variable for the number of years the locality was at risk. For the model in column 6, all localities were at risk for the same number of years. None of the localities established after 1995 was attacked. We thus had to drop all 23 of these observations from the post-1995 model. Table reports odds ratios. Standard errors for the odds ratios appear in parentheses, and mean marginal effects in braces. For dummy variables, mean marginal effects represent the effect of a discrete change in the covariate from zero to one. Significance of the odds ratio reflects whether it is different from unity.

\footnote{Significant at the 1\% level, \footnote{Significant at the 5\% level, \footnote{Significant at the 10\% level.}}
To implement this specification, we need to address the problem that localities are created at different times in the data and are thus at risk for different periods of time. A natural way to do this is to estimate the effects per year of being at risk. For example, the coefficient on population would measure the impact of population on attacks per year. One way to implement this is to interact all the covariates with $Y_i$, the number of years locality $i$ was at risk. The identifying assumption is that the effect of each covariate on attack risk is constant over time. Therefore, we model the number of attacks as a negative binomial with mean $\exp(Y_i x_i \beta)$.

The results of our analysis, displayed in Table IV, match the qualitative suggestions of casual empiricism. The table displays the results of negative binomial regression for several specifications. Coefficients are displayed, along with standard errors (in parentheses), and elasticities (in square brackets). Elasticities are calculated using the mean of the relevant covariate, along with the negative binomial coefficient, which represents the percentage change in the dependent variable associated with a unit change in the covariate. For binary variables, semi-elasticities are reported. These measure the percentage difference in attack frequency between localities with and without the binary characteristic.

Attacks are more frequent in larger and more populous cities, along with regional capitals, and less frequent in areas without Jewish populations. All these factors likely reflect

<table>
<thead>
<tr>
<th>Coefficients from negative binomial regressions of total attacks on a locality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>Population (millions)</td>
</tr>
<tr>
<td>(0.013)</td>
</tr>
<tr>
<td>[0.146]</td>
</tr>
<tr>
<td>Area (1000 SqKm)</td>
</tr>
<tr>
<td>(0.008)</td>
</tr>
<tr>
<td>[0.068]</td>
</tr>
<tr>
<td>Regional Capital</td>
</tr>
<tr>
<td>(0.006)</td>
</tr>
<tr>
<td>[0.879]</td>
</tr>
<tr>
<td>No Jews in locality</td>
</tr>
<tr>
<td>(0.011)</td>
</tr>
<tr>
<td>[–2.046]</td>
</tr>
<tr>
<td>Distance to closest terrorist homebase (km)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>International border locality</td>
</tr>
<tr>
<td>Jerusalem</td>
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<tr>
<td>Pseudo R-squared</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

Notes: All covariates are interacted with the number of years a locality is at risk. Each regression also includes a constant term and the locality’s number of years at risk. Robust standard errors appear in parentheses. Elasticities (evaluated at the means) appear in square brackets. For categorical variables, semi-elasticities appear: to construct these, we multiply the regression coefficients by mean years at risk for the relevant group of localities indicated by the categorical variable. For example, to construct the semi-elasticity for regional capitals, we multiply its coefficients by mean years at risk for regional capitals. $^a$significant at 1%; $^b$significant at 5%; $^c$significant at 10%
demand-side variation in the value placed on a particular locality. Attacks increase with an area’s accessibility to terrorist groups – those closer to terrorist homebases or to international borders get attacked more often. These findings largely accord with a rational-choice framework that stresses the costs and benefits of target selection.

Quantitatively, the biggest drivers of risk are: the presence of a Jewish population, the presence of an administrative center, proximity to a terrorist homebase, and proximity to an international border. Areas with some Jewish population experience nearly three times as many attacks as non-Jewish areas. Localities with regional capitals experience 52 to 95% more attacks per year. Jerusalem experiences more than twice as many attacks. Doubling a locality’s distance to a homebase lowers the number of attacks by 15 to 30%. Border localities experience more than twice as many attacks as those on the interior. These elasticities are much larger than the effects of population and land area. For example, doubling the locality’s population increases the number of attacks by around 6 to 10% (in the more fully specified models).

We have stressed causal interpretations of these relationships, particularly the way in which these covariates measure the costs and benefits of attacks. Selection-based interpretations are also plausible, particularly in the case of homebases. To be sure, homebase proximity causally lowers the cost of an attack. In addition, however, terrorists have incentives to site homebases nearer to higher value targets. This could also induce a correlation between attack frequency and homebase proximity. It is important to emphasize though that even this correlation is ultimately predicated on the fact that proximity lowers attack costs, and that this consideration affects terrorist behavior. Therefore, we may not be able to pin down the precise mechanism behind the correlation, but we can ascertain that travel costs matter and affect the decision-making of terrorist groups.

**Mapping Terrorism Risk**

A useful way of summarizing the econometric results is to create a map that displays gradients in terrorism risk. We have taken our predictions for risk (in terms of attack frequency) in different areas, and used them to construct a ‘risk map’ of Israel, depicting terrorist ‘hot spots’ and ‘cool spots’ across the country. We constructed the map by taking our estimated risk (from the most fully specified regression model) for each map ‘polygon’ and smoothing this risk across space, so that spatial risk varies continuously. The result is shown in Figure 1.

The figure reveals the risk centers identified by the regression analysis, and the gradual variation of risk across space. Areas close to home bases – such as Rafah, Jenin, Nablus, Ramallah and Hebron – face higher terrorism risk, which dissipates as distance to the homebase grows, all else being equal. Other sources of risk on the map are highly concentrated Jewish populations, and regional capital status; these elevate risk for Tel-Aviv, Rishon

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16 In principle, the authorities could exploit such a systematic basing strategy, and use it to discover terrorist groups. In practice, however, terrorists often situate their homebases in densely populated areas, where detection and removal is much more difficult even if the authorities are aware of a general location.

17 A well-suited method for data that varies gradually, like risk, is the spline. The spline method fits a minimum-curvature surface through the econometrically estimated risk points. More specifically, it fits a mathematical minimum curvature, two-dimensional, thin-plate Spline to a specified number of mapping points, while still passing through all estimated points.

One limitation of this approach was our inability to break down Palestinian areas into polygons that were as small as their Israeli counterparts. Owing to a lack of detailed demographic data, the Palestinian mapping polygons (the map contains four) frequently contained several major urban areas each. Therefore, taking our estimates at face value produced an unsatisfactory figure, with a hot spot in the center of each (large) Palestinian polygon, and continuously diminishing risk away from the center, even though the center of the polygon may not contain any inhabitants while the peripheries may contain a major settlement. As an alternative, for each Palestinian polygon, we imputed a risk level for each major urban area within it, under the assumption that risk was equally divided across urban areas within the same polygon. The map is based on these imputed values for the Palestinian cities.
FIGURE 1  Terrorism risk map of Israel.
Le-Zion, Hadera, Petah tikva, Afula, Ashkelon, Beer-Sheva and their surroundings. Border areas are also prone to attacks as reflected by the darker shades near the Northern Egyptian border, the Syrian border, the Jordanian border near the dead-sea as well as border cities like Qiryat-Shemona. Finally, Jerusalem represents the single riskiest location, and it seems to radiate elevated risk in its immediate vicinity. Risk drops to a minimum in the fairly unpopulated center of the Galil region (an area where non-Jewish presence is strong), and at the center of the Negev desert. Low risk areas are relatively unpopulated or have a small Jewish presence, are far from terrorist homebases, and are away from major administrative centers or capitals.

A different summary of risk is provided in Figure 2, a linearized representation of risk in Israel. This figure ranks risk in all areas of Israel and color-codes the results. The ‘thermometer’ moves from lighter areas of low-risk to darker areas of high risk. Jerusalem is the highest
risk area, in black, while the sparsely populated Negev desert is the lowest risk, in white. All the other areas fall between, as discussed above. This figure summarizes the interactions of several key variables: population, the concentration of Jews, distance to terrorist homebases, and the political symbolism or prominence of an area.

**Spacing of Terrorist Incidents**

In the long-run, the overall frequency of attacks is the key statistic of interest, but in the short-run, we would also like to investigate whether and how attacks are likely to be irregularly spaced. As a result, we investigated the distribution of waiting times between attacks. The first key finding is that, given a terrorist attack, the risk of the next attack climbs in the hours following the first attack and peaks the next day.\(^\text{18}\) This is somewhat surprising, since it is likely that a locality stiffens its protection against terrorism in the immediate aftermath of an attack.

However, it may equally be true that a terrorist group seeks to make a pronounced statement about the vulnerability of an area or that a group’s agents continue to operate in the vicinity. If an area survives for one full day without experiencing a second attack, the probability of a terrorist incident falls quite rapidly after that. About 8 weeks after the first attack, the probability reaches a plateau, where it remains for the foreseeable future. In sum, an area that has been hit within the last 8 weeks is at elevated risk for another attack, but otherwise similar areas that have been peaceful for longer than 8 weeks all have about the same risk. Interestingly, this implies that there is little difference in risk between an area hit 20 weeks ago and one hit 100 weeks ago, but both of these are very different from an area hit just 2 weeks ago. An important exception to these findings occurs in politically sensitive areas, where long periods of quiet actually signal elevated risk, not lower risk.

To arrive at these conclusions, we conducted an analysis of waiting times between terrorist attacks, using the statistical methods of duration analysis. In particular, we estimated the hazard of an attack occurring at time \(t\), given that the last attack occurred at time 0. This is equivalent to calculating the probability that there will be a waiting period of length \(t\) between attacks.

The familiar statistical approach to this problem is to compute a Kaplan–Meier hazard estimate, defined as follows. Consider a group of \(N\) localities that have experienced attacks at a particular time. Now suppose that \(x(1)\) of these localities experience an attack 1 day later, \(x(2)\) experience an attack 2 days later, and more generally, \(x(t)\) experience an attack \(t\) days later. The hazard of an attack at time 1 is given by \(x(1)/N\), the hazard at time 2 by \(x(2)/(N-x(1))\), the hazard at time 3 by \(x(3)/(N-x(1)-x(2))\), and so on.

This statistical construct is of considerable practical importance. The hazard rate is the proportion of localities experiencing attacks at time \(t\), among the localities that are still at risk at time \(t\). Conceptually, it reflects the probability that the waiting time between any two adjacent attacks will be \(t\) periods. Knowledge of the hazard function can help policymakers and insurers assess the timing and risk of a subsequent attack in the wake of an initial one.

The estimated hazard function is shown in Figure 3, which plots the estimated hazard function for 52 weeks (after which point it is relatively flat). The probability of a subsequent attack peaks the day after the first attack occurs, at about 16 per 1000: groups tend to follow up attacks quickly, but not immediately.\(^\text{19}\) It then decays fairly continuously. An

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\(^{18}\) The shortest time we allow between attacks is one-third of a day. Therefore, an attack the next day should not be construed as immediate.

\(^{19}\) See Note 18.
interesting feature of our results is that the probability of a subsequent attack levels off after approximately 8 weeks. That is, once 8 attack-free weeks are completed, the locality returns to *and stays at a low level of terrorism risk, between 4 to 5 chances in 1000. Put differently, an area is most vulnerable during its first 8 weeks after an attack, but returns to a normal state thereafter. Moreover, an area that has experienced an attack within the past 8 weeks is more at risk for an attack than other areas that have made it through longer periods without an attack. However, the risks are essentially equal for all localities that have survived for 8 weeks without an attack, regardless of exactly how long it has been since the last incident.

The above patterns obtain for the average locality, but striking differences emerge when we confine our attention to politically sensitive localities. While risk subsides in the average locality, it rebounds in politically sensitive areas. Figure 4 breaks down our sample into localities with regional capitals, and localities without them. The presence of a regional capital is taken here as a measure of the political importance of an area, in the eyes of terrorists and society. While localities without capitals display the familiar pattern of risk that bottoms out after 8 weeks and does not rise again, those with a capital experience an upward trend in risk, after it bottoms out. This point is made even more forcefully when we compare Jerusalem to other localities: Jerusalem can be taken as the most politically or symbolically important target. Figure 5 compares hazard rates for Jerusalem with those for all other localities. Note the way that risk declines for Jerusalem, just as it does for all other localities, but then the consistent and sharp increase in risk that takes place thereafter. This suggests that terrorists are loathe to accept extended periods of ‘quiet’ in sensitive areas, even though they might do so for other areas. This has important implications for symbolic areas that have escaped attack for a significant length of time: such areas may face gradually heightened risk the longer they survive without an attack. Moreover, from the point of view of predicting risk, it suggests that long periods of quiet can signal low risk in most areas, but high risk in politically sensitive areas.
FIGURE 4  Waiting time between attacks, by political importance of locality.
FIGURE 5  Waiting times between attacks for Jerusalem and all other localities.
CONCLUSIONS

The analysis of Israeli data presented in this paper suggested several markers of terrorism risk. The importance of a city or locality is a motivation for attack: The risk of attack rises with population, status as a regional capital or seat of government, or the presence of a targeted ethnic group. This is likely to be a ‘demand-side’ driver of risk, since it is presumably much easier for terrorist groups to infiltrate and operate in heavily Arab areas and harder for them to operate in capital cities. These cost considerations, however, appear to be trumped by variation in the demand-side valuation of such areas.

Ease of access also matters: the proximity of a terrorist homebase or an international border both substantially increase the frequency of attacks. We have offered a causal interpretation of this result: proximity lowers the cost of an attack and is thus a ‘supply-side’ driver of risk. However, we have also discussed how the incentives of terrorists might give rise to a selection-based effect: if proximity lowers costs, terrorists have incentives to site their bases near high-value targets. Both effects, however, depend on the importance of travel costs in terrorism; therefore, our estimates imply that these costs are present and affect terrorist behavior.

Local characteristics play an important role in influencing the distribution of long-run attack risk. However, the recent history of terrorist attacks in an area has considerable influence on the timing of attacks, which clearly do not occur at fixed, regular intervals. Attacks may be clumped together, or spread far apart. Using Israeli data, we estimated how the time between attacks on a locality is distributed. Specifically, we found that, in the wake of a terrorist attack, the risk of a subsequent attack peaks the following day, and bottoms out after approximately 8 weeks. A locality that has experienced an attack within the last 8 weeks faces an abnormally high risk of attack, but terrorism risk subsides to its average levels after this period has been completed. An exception to this rule occurs for politically sensitive areas – those containing regional capitals, or the highly symbolic city of Jerusalem. In these cities, risk falls initially, but does not ‘bottom out.’ Instead, risk begins to climb after 2 quiet months. This suggests that long periods of quiet actually indicate elevated risk for sensitive areas, but lower risk for other areas. It is important to consider the interaction between a strategically valuable target and the risk-profile of terrorism over time.

This paper points to the need to collect accurate and comprehensive information about the location of terrorist safe havens, not just for military purposes, but for the risk-assessment tasks of insurers and policymakers. It also points towards the importance of collecting information about the timing and location of terrorist attacks, in the interest of quantifying the risk of a subsequent attack. The RAND Terrorism database, and its extensions can serve as a useful foundation for this data collection system. Finally, and perhaps most importantly, it points to the need for a theory of terrorist behavior that can be taken with available data and used to further our understanding of terrorism risk.

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