

Abstract

Chapter 7: Terrorism: An Empirical Analysis

Walter Enders

The chapter surveys the empirical literature concerning the measurement of terrorism, effectiveness of counterterrorism policies, the economic consequences of terrorism, and the economic causes of terrorism. In Section 2, terrorist incidents are grouped according to incident type, victim, and location. It is shown that that terrorism began a steady decline in all regions (except for Eurasia) during the early to mid-1990s. However, the severity of the typical incident has been increasing over time. Also, several different data sets are compared in order to judge the reliability of alternative methods of obtaining and coding the data. Section 3 discusses a number of empirical studies that measure the effects of counterterrorism policies on the overall level of terrorism and on the various subcomponents of the overall series. In accord with the rational-actor model, an increase in the “relative price” of one type of terrorist activity induces a substitution out of that activity and into the now relatively less-expensive activity. Logistically similar activities display the greatest substitution possibilities. Moreover, periods of high-terrorism seem to be less persistent than periods with less terrorism. This is consistent with the notion that terrorists face a resource constraint. Section 4 pays special attention to the changes in terrorism due to the events of September 11, 2001 (9/11) and the resulting changes in counterterrorism policy. It is shown that the post-9/11 counterterrorism policies hampered al Qaida’s ability to direct logistically complex operations such as assassinations and hostage takings. The main influence of 9/11 has been on the composition, and not the overall level of terrorism. There has been a ratcheting-up of serious terrorist attacks against the US targets so that Americans are safer at home, but not abroad, following 9/11 and the enhanced homeland

security. Section 5 surveys a number of empirical papers that attempt to estimate the macroeconomic and microeconomic costs of terrorism. Papers surveyed in the first part of the section indicate that the overall macroeconomic costs of terrorism are low. However, it is argued that the methodological complexities of estimating the macroeconomic costs of terrorism on a cross-section of widely disparate nations are nearly insurmountable. The macroeconomic costs of terrorism are best measured on a country-by-country basis. The second part of the section summarizes empirical studies of the microeconomic costs of terrorism on tourism, net foreign direct investment, international trade flows, and financial markets in selected countries. Section 6 considers the economic determinants of terrorism. Particular attention is paid to the common presumption that terrorism is caused by a lack of economic opportunities. Conclusions and directions for future research are contained in Section 7.

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Chapter 7: Terrorism: An Empirical Analysis

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1. Introduction

The purpose of this chapter is to survey the empirical literature concerning the effectiveness of counterterrorism policies, the economic consequences of terrorism, and the economic causes of terrorism. A precondition for any successful empirical study is to have a clear and consistent definition of the variables used in the analysis. Toward this end, it is useful to consider what is generally meant by the term “terrorism.”

Terrorism is the premeditated use or threat of use of violence by individuals or subnational groups to obtain a political or social objective through the intimidation of a large audience beyond that of the immediate victims. For our purposes, there are two key ingredients in the definition. The first is that there needs to be a political or social motive for a crime to be defined as terrorism. Eric Harris and Dylan Klebold, the shooters in the Columbine HS rampage, were not terrorists because they had no political motive for their actions. The second is that the intent of the act must be to cause the intimidation of an audience beyond the immediate victims. Since terrorists undertake violent actions so as to pressure governments to grant political concessions, the motives of the individuals conducting the act are essential to the definition. John Wilkes Booth, the assassin of President Lincoln, was not a terrorist because he did not intend to intimidate a wide audience while Khalid Islambouli, the assassin of Anwar Sadat, was a terrorist because his actions were clearly geared to influence a worldwide audience. Terrorism is transnational when an incident in one country involves perpetrators, victims, institutions, governments, or citizens of another country.

Civil wars, insurgencies, and other forms of political violence may include terrorism as a tactic although this need not be the case. The usual distinction between warfare and terrorism is that attacks against armed forces and occupying armies are considered warfare while attacks against civilians are terrorism. There is a degree of ambiguity when peacekeepers and passive military targets are the intended victims of an attack. As such, there is not universal agreement about this important aspect of the definition. As discussed in Enders and Sandler (2006a), the US Department of Defense would include an attack against a roadside convoy in Iraq as a terrorist action. For our purposes, it is not especially important to focus on the most appropriate definition of terrorism. Instead, these ambiguities serve as a warning for empirical researchers using terrorism data. Regardless of the precise form of the definition actually used in a study, it is important to use a consistent definition across the entire span of the data. Pooling data from a source that uses a broad definition of terrorism with data from a source that uses a narrow definition is likely to result in biased results. Similarly, if a consistent definition is not used in a time-series study, the cyclical and trend components of the data are likely to be misidentified. For example, broadening the definition near the end of the sample period is likely to manifest itself in an apparent upward trend in terrorism.

Although the need for a consistent definition may seem obvious, coders of a particular data set may introduce a change in the definition in a number of subtle ways. For example, until 2003, the US Department of State (various issues) published a chronology of *significant* terrorist incidents in *Patterns of Global Terrorism* (PGT). However, the selection criteria were never clearly specified. What may be newsworthy or significant in one year may seem commonplace in another. For example, PGT reported no injuries on February 4, 1993 when a molotov cocktail was thrown at a tour bus located outside of a hotel near Cairo, Egypt. It is not clear whether such

an attack would appear in the chronology of a more recent issue. To be fair, any chronology of terrorism is necessarily faced with a host of coding problems. Such data sets rely on second-hand sources (i.e., newspaper and media accounts) so that incidents not deemed newsworthy are excluded from the counts. It is also the case that a number of terrorist actions, such as non-specific threats, are unknown to the media so that these actions are excluded from the data set as well. Moreover, coders must use their judgment since it is not always clear whether a crime is actually terrorism. For example, it may not be clear that a crime has a political motive because the perpetrator's identity is unknown.

The remainder of this chapter is organized as follows. Section 2 considers the statistical properties of a number of different measures of terrorism. When all terrorist incidents are grouped according to the incident type, victim, and location, it is possible to measure the changing nature of terrorism over time. Also, several different data sets are compared in order to judge the reliability of alternative methods of obtaining and coding the data. Section 3 discusses a number of empirical studies that measure the effects of counterterrorism policies on the overall level of terrorism and on the various subcomponents of the overall series. Section 4 pays special attention to the changes in terrorism due to the events of September 11, 2001 (9/11) and the resulting changes in counterterrorism policy. Section 5 discusses a number of empirical papers that attempt to estimate the macroeconomic and microeconomic costs of terrorism. The first part of the section shows that the methodological complexities of estimating the macroeconomic costs of terrorism on a cross-section of widely disparate nations are nearly insurmountable. The macroeconomic costs of terrorism are best measured on a country-by-country basis. The second part of the section summarizes empirical studies of the microeconomic costs of terrorism on tourism, net foreign direct investment, international trade flows, and financial markets in selected

countries. Section 6 considers the economic determinants of terrorism. Particular attention is paid to the common presumption that terrorism is caused by a lack of economic opportunities. Conclusions and directions for future research are contained in Section 7.

2. Statistical properties of the terrorist incident types

Unless otherwise stated, the data used in this article draws on *International Terrorism: Attributes of Terrorist Events* (ITERATE) developed by Mickolus et al. (2004). Note that domestic terrorist incidents are explicitly excluded from the data set. Also excluded are actions involving insurgencies, attacks on occupying armies, guerrilla attacks on military targets, and declared wars. However, ITERATE does classify attacks against civilians, military contractors, or the dependents of military personnel as terrorist acts when such attacks are intended to create an atmosphere of fear to foster political objectives. The ITERATE coders rely on newspapers and electronic media to record critical aspects of each incident's date such as the incident date, starting location, ending location, type of attack, the number of wounded, the number of deaths, the nationality of the terrorists (if known), and the number and nationalities of the victims. At the time of this writing, the data set contains 12803 incidents running from January 1, 1968 through December 31, 2004.

The classification of the incidents into twenty-five different types is reported in Table 1. Notice that there were 7176 total bombings (*Bombings*), (i.e., incident types 4-8 plus types 23-25), accounting for 56% of all recorded incidents). Kidnappings and hostage takings (incident types 1, 2, 9, and 10) account for almost 15% of the total.

[Table 1 Here]

Figure 1 shows the time series plots of the annual totals of selected incident series over the 1968 through 2004 period. Panel a shows the annual totals of all incident types (*All*) as well as the number of bombings. Since bombings are the largest component of the *All* series, it is not surprising that the two series track each other reasonably well. Although the incident totals have fallen since the 1980s, there is no clearly discernable downward trend in either series. Instead, it seems as if both series jumped in the early 1970s and fell sharply in the early 1990s. It is the case, however, that the proportion of bombings generally fell in the early 1970s through the late 1980s and then began to increase in 2001. For example, the proportion of bombings to all incidents was 67.8% from 1967-1977, 50.0% of all incidents from 1978-2000, and 55.6% of all incidents from 2001 to 2004.

Panel b of Figure 1 shows the number of incidents with at least one casualty (*Cas*) and the number of incidents with at least one death (*Death*). It is clear from examining Panel b that both series grew steadily throughout the 1970s, plunged in the early 1990s and jumped in 2003 and 2004. It is important to note that the typical incident has become more injurious over time. Beginning around 1995, the *Cas* and *Death* series virtually overlap suggesting that few incidents contain only wounded individuals. Moreover, the proportion of *Cas* incidents to *All* incidents, shown in Panel c, is far higher since the early 1990s than in previous periods. Panel d shows the time series of the number of incidents with a kidnapping or hostage taking; the series, labeled *Hostage*, is comprised by combining incident types 1 + 2 + 9 + 10. Although the series behaves quite erratically, there are no discernable changes in the overall level of the series. In contrast, *Armed Attacks* (types 7 + 8) does exhibit a number of structural breaks. After a gradual, but steady increase in the 1970s, the series reached a plateau lasting until the late 1980s. At that

point, *Armed Attacks* increased sharply and, in the early 1990s, fell back to its earlier levels. In spite of the attention paid to attacks against the United States and its citizens, the number of attacks with a US target (*UStgts*) fell in the early 1990s. However, in 1999, *UStgts* jumped from 51 to 157 and in 2003, the number jumped from 68 to 142.

[Figure 1 Here]

Table 2 shows the means and their standard errors for selected incident types, including suicide incidents, for several sample periods. As suggested by the discussion above, the subsample means of *All* for the 1980s and for the 2000-2004 period are significantly different from the overall sample mean of 345.73 incidents per year. It is interesting that the 2000-2004 subsample mean of the *Death* series is not significantly different from that of the overall period. However, the standard error of the mean for 2000-2004 ($SE(\bar{x}) = 18.19$) is far in excess of that for the overall period. This is due to the huge jump in *Death* incidents 2003 and 2004. Similar remarks can be made for the *Hostage*, *Bombings* and *UStgts* series in that the standard error of the mean is decidedly different from that of the overall period. Transnational suicide attacks (types 24 and 25) jumped to unprecedented levels, averaging 11 incidents per year, over the 2000-2004 period.

[Table 2 Here]

Figure 2 shows the regional breakdown of the *All* series using the identical regional breakdowns as in PGT. The regions are the Western Hemisphere, Africa (excluding North Africa), Asia (South and East Asia, Australia, and New Zealand), Eurasia (Central Asia, Russia, and the Ukraine), Europe (West and East Europe), and the Middle East (including North Africa). As such, most of the Islamic population falls into the Middle East, Eurasia, and Asia regions.

The interesting feature to note about the figure is that terrorism began a fairly steady decline in all regions (except for Eurasia) during the early to mid-1990s. However, the number of African incidents spiked in the years 1999 and 2000. Terrorism in Asia and the Middle East jumped markedly in 2002 and has remained high.

[Figure 2 here]

2a. Comparison of data sets

In addition to ITERATE, there are a number of other publicly available data sets recording terrorist incidents. The National Memorial Institute for the Prevention of Terrorism (MIPT) (2005) maintains an online data set that can be accessed without a fee. The data set begins in 1968 and is updated regularly. Like ITERATE, it is possible to obtain information about terrorist incidents by date, tactic, target, or the starting region. Beginning in 1998, the MIPT data set includes both domestic and transnational terrorist incidents. One drawback of the data set is that it is possible to obtain information about the individual incident types on a regional basis, but not on a country-by-country basis.

Another online data set is maintained by The International Policy Institute for Counterterrorism (IPIC) (2005). IPIC (2005) describes its 1427 terrorist incidents for 1986-2002 as “selected” transnational terrorist incidents. The IPIC website does not list its criteria for selecting which incidents to include and which to exclude. This is important because ITERATE and PGT record many times the number of incidents during the same period. For example, as compared to some of the ITERATE series shown in Figure 1, the IPIC (2005) data set lists only 22 incidents for 1988, 89 for 1989 and 26 for 1990 and 37 for 1991. Even though it excludes many incidents, the IPIC data set also has an over-reporting problem. Moreover, there seem to be a large number of incidents that might be crimes, rather than terrorism. Some Palestinian attacks

in Israel are considered transnational even though the act seems to be purely domestic. Consider an incident occurring on July 23, 1994. The description is “Two unknown Palestinians stabbed and seriously injured an American woman in the Arab quarter of the Old City of Jerusalem. The assailants escaped unharmed.” Moreover, no one ever took responsibility for the act, and the group conducting the act is “Unknown.” It is possible that this attack was a simple crime. In fact, IPIC data include a disproportionate number of incidents from the Middle East. This should not be too surprising since the data set is maintained by the Interdisciplinary Center Herzliya in Israel (<http://www.ict.org.il>).

As mentioned above, the US Department of State’s (various years) *Chronology of Significant Terrorist Incidents* appeared as an appendix in each issue of *Patterns of Global Terrorism*. The State Department discontinued publication of GPT after a controversy surrounding the possible omission of some incidents in order to make it appear that the so-called ‘War on Terror’ is being won. Some of the disagreement concerned the issue of whether attacks on US troops in Iraq should be included in the 2004 totals. This was on the heels of a political embarrassment in June 2003 when the number of incidents and fatalities had to be revised substantially upward in the face of acknowledged omissions from the original report. The incident count for 2004 is unavailable and it is unclear how subsequent reporting of terrorism will be conducted. Title 22 of the United States Code, Section 2656f, requires the Department of State to provide Congress with a complete annual report on terrorism.

Figure 3 shows a comparison of the yearly ITERATE, MIPT and PGT incident totals. For comparability, the ITERATE totals shown in the figure have been purged of threats and hoaxes. The reason is that beginning in 1996 ITERATE no longer used the Foreign Broadcast Information Service *Daily Reports*. Thus, the totals following this date may not be directly

comparable with those of earlier dates. Since most of the omitted incidents are likely to be threats and hoaxes, all threats and hoaxes are excluded from the ITERATE series shown in Figure 3.

[Figure 3 here]

The overall shapes of the three time series plots are somewhat similar. All rose from slightly over 100 annual incidents in 1968 and 1969 and reached their highest sustained levels in the 1980s. Beginning in 1991, all three series began to decline. Nevertheless there are enough differences among the series that the results of an empirical study might hinge on which of the three data sets is used. Notice that the values of PGT series generally exceed those of the other two series. This is especially true in the mid-1970s and in the 1980s. The gap remains quite sizable even if threats and hoaxes are added back to the ITERATE data. Also notice that the PGT data shows an increase in terrorism in the late 1970s while the MIPT data and ITERATE show declines. The PGT data indicates a sharp decline in terrorism following 9/11 while the ITERATE data shows a sizable jump. The simple correlation coefficient between ITERATE and MIPT series is 0.66, and between ITERATE and PGT is 0.65. The simple correlation coefficient between MIPT and PGT is 0.78.

Comparison by Type: It seems likely that major incidents get reported in any reasonable chronology. The main differences are likely to concern incident types such as bombings. Bombings usually account for approximately half of all incidents. However, it is unclear whether to record a letter-bombing campaign as a single incident or as the number of letter bombs actually received. Figure 4 records the annual incident totals of all bombings for ITERATE and for the MIPT data set through 1997. ITERATE reports far more incidents than the MIPT data set throughout the 1970s. The simple correlation coefficient between the two incident series is only

0.52.

[Figure 4 Here]

Domestic versus transnational incidents. Although transnational terrorist attacks usually receive more media attention than domestic incidents, there are far more domestic incidents than transnational incidents. Panel a of Figure 5 shows the annual total of domestic and transnational incidents in the MIPT data set. The proportion of transnational to all incidents (both domestic and transnational) was 12.7% in 1998, fell to 9.1% in 2000, and rose to 14.9% in 2004. It should be clear that the relationship between domestic and transnational terrorism is not 1:1. Studies that use transnational terrorism as a ‘proxy’ for all terrorism may be seriously flawed. The problem is exacerbated using subcomponents of the series. For example, most incidents within continental Europe have been transnational while Israel has many domestic incidents relative to transnational incidents.

It is interesting to compare the ‘selected’ incident totals from the 1998-2003 *Patterns of Global Terrorism*. I coded the type of each PGT-listed incident using the same classification system as ITERATE.¹ The time paths of the numbers of domestic and transnational incidents are shown in Panel b Figure 5. Notice that there was a strong bias toward transnational incidents although the totals for domestic terrorism grew relative to those of transnational terrorism. In part, this growth reflected changes in the US State Department’s preferences over the types of the various incidents. This shows the danger of using a data set containing “selected” incidents.

[FIGURE 5 Here]

¹ Ting Qin and Ashley Allen were especially helpful in preparing the data.

3. Counterterrorism policy: The substitution effect

Any counterterrorism policy that underestimates the wherewithal and resourcefulness of terrorists is doomed to fail. In order to predict new types of terrorist attack modes, the likelihood of an attack on a particular target or location, or the likely behavior of terrorists in response to a counterterrorism initiative, it is necessary to posit a theory of terrorist behavior. The rational-actor model leads to a number of straightforward predictions concerning the behavior of a terrorist network or cell. The hallmark of the rational-actor model is that terrorists use their scarce resources so as to maximize the expected value of their utility. This is not to say that the preferences of terrorists are, in any sense, laudable. Instead, the model posits that, for a given set of preferences, terrorists will make choices that are most likely to bring out their most preferred outcomes. In contrast, if terrorists are assumed to be completely irrational, there is no way of knowing how they will respond to future events. In contrast, the rational-actor model has a number of straightforward predictions that have proven to be consistent with the data.

Gary Becker (1971) developed the household production function (HPF) model to analyze decision making for a family group. Enders and Sandler (1993) formally extended the HPF model to study the behavior of rational terrorists. The basic premise of their model is that a terrorist group derives utility from a shared political goal. The shared goal could be the establishment of a religious state or the elimination of an unspecified grievance stemming from income inequality, racial or religious discrimination, ideological differences, or a lack of political or economic freedom. This shared goal can be obtained from the consumption of various basic commodities such as media attention, political turmoil, popular support for their cause, and the creation of an atmosphere of fear and intimidation. Each basic commodity can be produced using a number of alternative political and economic strategies. At one extreme, the group might

simply choose legal activities such as advertising its cause, marching on the capitol, or running its own candidates for office. Alternatively, acts of civil disobedience might be undertaken by blocking entry to university or government buildings or by sit-ins at racially segregated lunch counters. At the other extreme, the group might resort to direct armed conflict or guerilla attacks. The point is that the group must select among the various ways that can be used to produce the basic commodities. If the group chooses to use terrorist tactics, it can choose among attack modes such as skyjackings, kidnappings, or suicide bombings.

The terrorist group has access to a finite set of resources including financial assets, weapons and buildings, personnel, and entrepreneurial abilities. Given its resources a rational terrorist group selects the set of activities that maximizes the expectation of its attaining the shared goal. Since terrorists can "save" their resources for future attacks, rational terrorists will time their attacks to enhance their overall effectiveness. Of course, groups such as the PLO and the IRA have used combinations of various legal and illegal means in an attempt to bring about their shared political goal.

The choices made by the group will be influenced by the prices of the various terrorist and nonterrorist activities. The full price of any particular attack mode includes the value of the resources used to plan and execute the attack, and the cost of casualties to group members. Certain attack modes are more likely to expose the group's membership to capture than others. The price of a suicide bombing includes the direct costs of the bomb, the costs of grooming the perpetrator to ensure that the attack takes place, and the cost to protect the group's security for failed attacks. At the other end of the spectrum, threats and hoaxes typically require few inputs.

The key feature of any antiterrorism policy is that it can influence the prices, resource supplies and the payoffs faced by terrorists. Enhanced airport security increases the logistical

complexity of a skyjacking and raises its price. If, at the same time, governments do not increase security at ports-of-entry, attacks relying on contraband become relatively cheaper. Similarly, if immigration officials make it more difficult for terrorists to enter the United States, a terrorist group might attack US interests located abroad (for example, tourists and firms). Hence, a government policy that increases the price of one type of attack mode will induce a substitution away from that mode into other logistically similar incident types.

Enders and Sandler (1993, 2004) summarize the four key propositions of the model as:

Proposition 1: An increase in the relative price of one type of terrorist activity will cause the terrorist group to substitute out of the relatively expensive activity and into terrorist and nonterrorist activities that are now relatively less expensive.

Proposition 2: Terrorist attack modes that are logistically similar and yield similar basic commodities will display the greatest substitution possibilities. Since the effects of complementary events are mutually reinforcing, an increase (decrease) in the price of one activity will cause that activity and all complements to fall (rise) in number.

Proposition 3: An increase in the price of all terrorist activities or a decrease in the price of nonterrorist activities will decrease the overall level of terrorism.

Proposition 4: For normal goods, an increase (decrease) in the resource base will cause a terrorist group to increase (decrease) the level of nonterrorist activities.

3.1. Testing the HPF Model

Enders and Sandler (1993) test Propositions 1 and 2 by examining how a number of counterterror measures induced substitutions across the various terrorism attack modes. Although they consider a number of substitution possibilities, it seems most useful to examine their five-variable 'Model 2' that uses skyjackings (Skj), incidents involving a hostage

(*Hostage*), assassinations (*Assns*), threats and hoaxes (*Th*) and all other incident types (*OT*).² Since the data begins in the first quarter of 1968 (1968:1) and runs through 1988:4, it does not contain the period during which ITERATE stopped using information from *Daily Reports*. The policy interventions are dummy variables representing the installation of metal detectors in airports (*Metal*), two embassy fortifications (*Emb76* and *Emb85*) and the retaliatory raid on Libya (*Libya*). Specifically, in January 1973, metal detectors began to be installed in US airports and, shortly thereafter, in major international airports worldwide. *Emb76* refers to a more than doubling of US embassy security expenditures in 1976 and *Emb85* refers to another enhancement of embassy security in October 1985 resulting from Public Law 98-533. In April 1986, the US launched a retaliatory raid on Libya for its role in the terrorist bombing of the LaBelle Discotheque. Since the effects on the raid were temporary, *Libya* is a temporary dummy variable equal to one in 1986:2. Mathematical characterizations of the intervention variables are provided in Table 3.

Consider the standard vector autoregression (VAR) model augmented with dummy variables to capture the effects of the four interventions:

$$\begin{bmatrix} Sky_t \\ Hostage_t \\ Assns_t \\ Th_t \\ Ot_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & \dots & A_{15}(L) \\ A_{21}(L) & \dots & A_{25}(L) \\ \vdots & \ddots & \vdots \\ A_{51}(L) & \dots & A_{55}(L) \end{bmatrix} \begin{bmatrix} Sky_{t-1} \\ Hostage_{t-1} \\ Assns_{t-1} \\ Th_{t-1} \\ Ot_{t-1} \end{bmatrix} + \begin{bmatrix} c_{11} & \dots & c_{14} \\ c_{21} & \dots & c_{24} \\ \vdots & \ddots & \vdots \\ c_{51} & \dots & c_{54} \end{bmatrix} \begin{bmatrix} Metal \\ Emb76 \\ Emb85 \\ Libya \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix} \quad (1)$$

where the expressions $A_{ij}(L)$ are polynomials in the lag operator L such that $A_{ij}(L)Sky_{t-1} = a_{ij}(1)Sky_{t-1} + a_{ij}(2)Sky_{t-2} + a_{ij}(3)Sky_{t-3} + \dots$, the c_{ij} measure the influence of interventions contemporaneous effect of intervention j on incident type i ; and the ε_i are the errors from the

² To avoid overlap in the series, all hostage events not involving a skyjacking were added together to form *Hostage*. The *OT* consists primarily of bombings.

regression for incident type i .

The details of the estimation technique are described in Enders and Sandler (1993) and background on the VAR methodology is detailed in Enders (2004). For our purposes, it is sufficient to point out that ordinary least squares (OLS) provides efficient estimates of the coefficients $a_{ij}(k)$ and c_{ij} since all of the equations have the same set of regressors. It is important to note that a statistically significant value of c_{ij} means that intervention type j has a contemporaneous effect on incident type i . Also note that the presence of the various $A_{ij}(L)$ allow for a rich variety of interactions among the variables in that incident type j can have a lagged effect in incident type i . If, for example, any of the coefficients of $A_{12}(L)$ are statistically different from zero, then *Hostage* affects *Sky* with a lag. Finally, the contemporaneous interaction among incident types i and j are captured by the correlation coefficients between ε_i and ε_j .

[Table 3 here]

The actual quarterly totals of *Sky*, *Hostage*, *Assns* and *OT* are shown as the dashed lines in Figure 6. The solid lines are the estimated time paths of the one-step-ahead forecasts of the series using the various interventions. As a visual aid, the vertical lines represent the starting dates of the four interventions.

From Figure 6, you can see the abrupt changes in *Sky*, *Hostage*, and *OT* beginning in 1973:1. As recorded in Table 3, on impact, metal detectors decreased skyjackings by 14.1 incidents per quarter. However, as predicted by the HPF approach, an increase in the price of a skyjacking induces substitutions into similar incident types. We found that the impact effect of *Metal* was to significantly increase *Hostage* incidents by 11.6 incidents per quarter and assassinations by 6.58 incidents per quarter. The impact effects of *Metal* on *Th* and *OT* were not statistically significant. Hence, there is strong evidence that terrorists substituted from

skyjackings into logistically complex *Hostage* and *Assns* incidents.

[Figure 6 Here]

The first embassy fortification (*Emb76*) shows few important effects. Threats and hoaxes showed a significant jump but none of the other series showed any significant changes at the 5% level. Of course, it is possible for *Th* to increase without changes in the levels of the other series since threats and hoaxes require few resources. Another interesting substitution was that the second embassy fortification (*Emb85*) acted to decrease threats by about by -5.51 incidents per quarter but to increase *Hostage* by about 3.54 incidents per quarter.

There seems to be a slight increase in *OT* following the installation of metal detectors, but this increase is not statistically significant. The embassy fortifications seemed to have no significant effects on any of the series. Other than the installation of metal detectors, the only significant intervention was the Libyan bombing, which caused the number of other incidents (*OT*) to jump sharply and then fall back to its pre-intervention mean. Since bombings, threats, and hoaxes are usually logistically simple and utilize few resources relative to the other types of incidents it is fairly easy to ratchet-up the number of such incidents.

The interactions among the various incident types can be obtained from the impulse response functions. The upper right-hand portion of Table 3 shows the impulse responses using an eight quarter forecasting horizon. Notice that *Sky* explains 85.2% of its own forecast error variance; no other incident type explains more than 5.38% of the movements in *Sky*. This is consistent with the presumption that skyjackings are logistically complex incidents that are not easily substituted for by the other types of incidents. Nevertheless, *Sky* explains 13.9%, 13.1% and 34.4% of *Hostage*, *Assns*, and *Th*, respectively, Also note that *Hostage*, *Assns*, and *OT* explain 68.7%, 61.0% and 71.9% of their own forecast error variance, respectively. In contrast,

the low resource-intensive incident type, *Th*, is the only one that explains a small proportion (35.5%) of its own forecast error variance. The notion is that *Th* strongly responds to changes in the other incident types.

Enders and Sandler (1993) did not report the cross-equation correlations of the residuals from their seemingly unrelated regressions (SUR) estimation. Nevertheless, as reported in Table 3, it is interesting to note the correlations of the residuals from the *Th* equation with those of the *Sky* and *Assns* equations are 0.364 and 0.311, respectively. Since there are 80 residuals from each equation, the *prob*-values are both less than 0.01. Hence, it appears that *Th* is complementary with *Sky* and *Assns* in that the innovations in each are positively correlated. The cross-correlation coefficient between *Th* and *OT* is marginally significant at the 5% level. None of the others are statistically different from zero at the 5% level.

In a separate study, Enders and Sandler (2005b) indirectly tested Proposition 4 by comparing the durations of high versus low periods of terrorist activity. The basic notion is that in relatively tranquil times, terrorists can replenish and stockpile resources, recruit new members, raise funds and plan for future attacks. Terrorism can remain low until an event occurs that switches the system into the high-terrorism regime. Because each terrorist attack utilizes scarce resources, high-terrorism states are not likely to exhibit a high degree of persistence. On the other hand, periods with little terrorism can be highly persistent to shocks since few resources are expended when terrorism is low.

For the 1968:1-2000:4 period, the *Cas* series seems to be well-estimated by the linear process (with *t*-statistics in parentheses):

$$Cas_t = 5.91 + 0.261Cas_{t-1} + 0.310Cas_{t-2} + 0.209Cas_{t-3} + \varepsilon_t \quad (2)$$

(2.83) (2.98) (3.59) (2.40)

Enders and Sandler (2005b) report that this linear specification seems adequate in that it satisfies the standard diagnostic tests, the coefficients are significant at conventional levels, pretests for a unit-root indicate that the Cas series is stationary, and the Ljung-Box Q-statistics indicate that the residuals are serially uncorrelated. As an alternative, they estimated the Cas series as a 2-regime threshold autoregressive (TAR) process. Consider:

$$\begin{aligned}
 Cas_t = & [17.87 + 0.189Cas_{t-1} + 0.237Cas_{t-2}] I_t & (3) \\
 & (3.19) \quad (1.83) \quad (1.83) \\
 & + [3.92 + 0.423Cas_{t-1} + 0.398Cas_{t-3}] (1 - I_t) + \varepsilon_t; \\
 & (1.48) \quad (2.97) \quad (3.12)
 \end{aligned}$$

where $I_t = 0$ when $Cas_{t-2} < 25$ and $I_t = 1$ otherwise.

The TAR model allows for a low-terrorism regime and a high-terrorism regime. When terrorism is low (such that $Cas_{t-2} < 25$ incidents per quarter), $I_t = 0$ so that it is possible to write the equation for casualties as $Cas_t = 3.92 + 0.423Cas_{t-1} + 0.398Cas_{t-3}$. Instead, when terrorism is high (such that $Cas_{t-2} \geq 25$ incidents per quarter), $I_t = 1$ so that it is possible to write the equation for casualties as $Cas_t = 17.87 + 0.189Cas_{t-1} + 0.237Cas_{t-2}$.

The threshold model yields very different implications about the behavior of the Cas_t series than the linear model. Since the linear specification makes no distinction between high- and low-terrorism states, the degree of autoregressive decay is constant. Specifically, the degree of persistence is quite large as the largest characteristic root of the linear specification is 0.88. For the TAR specification, there is a different speed-of-adjustment in each of the two regimes. In the high-terrorism regime, the number of incidents gravitates toward the attractor 31.1 [=17.87 ÷ (1 - 0.189 - 0.237)]. As measured by the largest characteristic root, the speed of adjustment is 0.59: when terrorism is high, approximately 60% of each incident is expected to persist into the next period. In contrast, in the low-terrorism regime, the number of incidents gravitates toward

21.9 [=3.92 ÷ (1 - 0.423 - 0.398)]. The largest characteristic root is 0.88, indicating very persistent behavior following a shock. Thus, when the number of incidents is below the threshold value of 25, there is little tendency to return to a long-run mean value. As such, low-terrorism regimes are far more persistent than high-terrorism regimes. The explanation provided by Enders and Sandler (2005b) is that terrorists necessarily expend large quantities of their resources in the high-terrorism regime. As such, resources become scarce and terrorists need to wind-down their campaigns. In contrast, regimes in which the number of incidents is small can persist for long periods of time. They found similar patterns regarding the different rates of persistence in the *All*, *Death*, *Bomb*, *Assns*, and *Hostage* series. The only exception was for the *Th* series; for this series there is more persistence in the high-terrorism state than in the low terrorism state. Of course, this should not be too surprising since threats and hoaxes use relatively small quantities of resources. As such, the value of *Th* can remain high for long periods of time.

4. Terrorism since 9/11

The unprecedented attacks of 9/11 led to unprecedented counterterrorism measures. The US-led invasion of Afghanistan, the passage of the USA Patriot Act, and the formation of the Department of Homeland Security all affected the ability of terrorist groups to organize and function. For example, the USA Patriot Act created a counterterrorism fund, a Federal Bureau of Investigation (FBI) technical support center, a National Electronic Crime Task Force Initiative, and allowed the government greater latitude in intercepting and seizing communications including voice-mail messages. The act also encouraged collaboration among foreign and domestic law enforcement agencies and made money-laundering more difficult by mandating greater regulations of international money transfers. The creation of the Department of Homeland Security (DHS) merged the activities of 22 different agencies by bringing them

together in a single cabinet-level department. As a result of this “war on terrorism,” about two-thirds of al Qaida leaders have either been killed or captured. Gerges and Isham (2003) report that more than 3,400 al Qaida suspects have been arrested since 9/11 and the White House (2003) reports that more than \$200 million of the network’s assets have been frozen since 9/11. At the same time, the War in Iraq has seemingly energized those with grievances against the United States and its Australian and UK allies. After successful al Qaida acts caused the Philippines and Spain to pull their troops from Iraq, it is expected that terrorist groups will be more vigorous in recruiting those willing to engage in terrorist acts.

4.1 Effects on the attack modes

Enders and Sandler (2005a) used several alternative methods to determine how the overall level of terrorism and the various attacks modes utilized changed since 9/11. For each attack mode considered, they estimated an intervention model in the form:

$$y_t = a_0 + A(L)y_{t-1} + \alpha_1 D_p + \alpha_2 D_L + \varepsilon_t \quad (4)$$

where y_t is the series of interest, D_p and D_L are dummy variables representing September 11, 2001. In equation (4), D_p is a dummy variable such that $D_p = 1$ if $t = 2001:3$ and $D_p = 0$ otherwise. This type of *pulse* variable is appropriate if the 9/11 attacks induced a temporary change in the $\{y_t\}$ series. The magnitude of α_1 indicates the initial effect of 9/11 on y_t and the rate of decay is determined by the largest characteristic root of $A(L)$. To allow for the possibility that 9/11 had a permanent effect on the level of $\{y_t\}$, the second dummy variable in equation (4) is such that $D_L = 0$ for $t < 2001:3$ and $D_L = 1$ for $t \geq 2001:3$. The impact effect of the *level* dummy variable on $\{y_t\}$ is given by α_2 and the long-run effect of D_L on $\{y_t\}$ is given by $\alpha_2/(1 - \sum a_i)$. Without going into great detail concerning the estimation methodology, the key features of

the estimated equation were such that the *pulse* dummies were not statistically significant for any of the attack modes considered. Hence, there were no statistically significant short-run effects in the behavior of any of the incident series that resulted from 9/11. Moreover, the level shift dummy was significant only for the *Hostage* series. The short-run effect is such that *Hostage* incidents fall by 6.05 incidents in 2001:3 and the long-run effect is a decline of approximately 9 incidents per quarter. However, even this finding is problematic because a careful inspection of the *Hostage* series (see Figure 1) shows that the sharp drop in hostage incidents actually occurred in 1999.

Although there is little evidence of shifts in the levels of the various attack modes, Enders and Sandler (2005a) used statistical methods to examine how the composition of the *All* series changed over time. Specifically, they estimated an intervention model in the form of equation (4) for the ratio of each incident type to *All*. The pulse dummy variable was statistically significant for the proportion of *Death* to *All* (P_Death) and for the proportion of *Cas* to *All* (P_Cas). On impact, the proportion of incidents with deaths rose by 54 percentage points and the proportion of incidents with casualties rose by 48 percentage points. The level dummy variables, however, were not significant at conventional levels. Hence, the jumps in the P_Death and P_Cas were not permanent.

The *level* dummy variable was highly significant for the proportion of hostage incidents ($P_Hostage$) and the proportion of deadly incidents due to bombings (P_Death_B). The short-run effect reduced $P_Hostage$ from approximately 13% to 4% of all incidents. After 9/11, the proportion of hostage incidents was estimated to be near zero. They also found evidence of a significant 16 percentage point decline in the proportion of assassinations to *All* (P_Assns). In contrast, the P_Death_B series was estimated to rise by 20 percentage points.

The conclusion was that the post-9/11 counterterrorism policies hampered al Qaida's ability to direct logistically complex operations such as assassinations and hostage takings. However, the main influence of 9/11 has been on the composition, and not the level, of the *All* series. In particular, *P_Hostage* and *P_Assns* fell after 9/11 as terrorists substituted into deadly bombings. As a consequence, the proportion of deadly incidents due to bombings has increased as the proportion of hostage-taking and assassination attacks have decreased. The net result is that al Qaida has substituted away from logistically complex attacks (e.g., hostage taking and assassinations) to logistically simpler bombings.

One possible weakness of these results is that there might be multiple structural breaks. Enders and Sandler (2000) reported significant changes in terrorism associated with the increase in religious fundamentalism and with the demise of the Soviet Union. The omission of any structural breaks from the estimating equation will result in a misspecified regression equation that might cloud the effects of 9/11. One research strategy is to reestimate equation (4) by including dummy variables for all such breaks. However, Enders and Sandler (2005a) warn that this strategy can be problematic because there is a danger of *ex post* fitting if break points are selected as a result of an observed change in the variable of interest. In addition, the efficacy of the estimates cannot rely on the usual asymptotic properties of an autoregression because an increase in sample size does nothing to increase the number of points lying between two break points. As such, Enders and Sandler (2005a) go on to use a purely data-driven procedure to select the break dates. Bai and Perron (1998, 2003) developed a procedure that can estimate a model with an unknown number of structural breaks that occur at unspecified dates. The key feature of the Bai-Perron procedure is that the number of breaks and their timing are estimated along with the autoregressive coefficients. Bai and Perron (1998, 2003) also showed how to form

confidence intervals for the break dates. This is important because there is visual evidence (see Figure 1) that key changes in some of the incident series actually began prior to 9/11. As such, it is desirable to ascertain whether the changes are due to 9/11 or to forces already in progress. The form of the Bai-Perron specification that was considered is the so-called partial change model:

$$y_t = \alpha_j + \sum_{i=1}^p a_i y_{t-i} + \varepsilon_t \quad (5)$$

where $j = 1, \dots, m+1$, and m is the number of breaks. Equation (5) allows for m breaks that manifest themselves by shifts in the intercept of the autoregressive process. The notation is such that there are $m+1$ intercept terms denoted by α_j . The first break occurs at t_1 so that the duration of the first regime is from $t = 1$ until $t = t_1$, and the duration of the second regime is from $t_1 + 1$ to t_2 . Because the m^{th} break occurs at $t = t_m$, the last regime begins at $t_m + 1$ and lasts until the end of the data set. In applied work, it is necessary to specify the maximum number of breaks; our estimation allowed for a maximum of five breaks. The procedure also requires that the minimum regime size (i.e., the minimum number of observations between breaks) be specified. Because the data ran through the second quarter of 2003, a minimum break size of six was used in order to permit a break occurring as late as the first quarter of 2002. In principal, it would be possible to allow all coefficients (including the autoregressive coefficients) to change, but this would necessitate estimating a separate AR(p) model for each regime. Since the data include only a small number of post-9/11 observations, this procedure was not possible. Instead, what Bai and Perron (1998, 2003) call the “partial change” model was adopted so that only one new coefficient (i.e., the intercept) was estimated for each regime.

For five selected series, Table 4 reports the point estimate of each break date, the lower and upper bounds of a 95 percent confidence interval around the break dates (lower and upper, respectively), the sample mean in the first regime (initial mean), and the short-run (SR) and long-

run (LR) changes due to the break(s). The short-run effect of break j is measured by $\alpha_{j+1} - \alpha_j$ whereas the long-run effect is measured by $(\alpha_{j+1} - \alpha_j)/(1 - \sum a_i)$.

The results using the Bai-Perron procedure reinforce those found for the intervention model. For example, a single structural break, not at 9/11, was found for the *All* series. The most likely estimate of this break is 1994:3; a 95 percent confidence interval for the break date spans the period 1993:4 through 1996:4. The crucial point is that a 95 percent confidence interval for the break date does not include 9/11. Given that bombings constitute half of the *All* series, a similar structural break characterizes *Bombings* at 1994:1.

The *Hostage* series was found to have a single break after 2000:3 (i.e., the new regime begins in 2000:4). The short-run and long-run effects were estimated to be -6.69 and -9.94 incidents per quarter, respectively. Since the 95 percent confidence interval includes 2001:3, it can be claimed that the long-run decline in the mean number of *Hostage* incidents from 13.79 to about 3.85 ($13.79 - 9.94 = 3.85$) may be attributable to 9/11. There is no evidence of a break in the *Assns* series. Notice that none of the other series contained a break associated with 9/11. However, a careful examination of the table indicates the breaks seem to be associated with the rise of Islamic fundamentalism and the decline of the Cold War. The results for the various proportion series seemed to reinforce this pattern.

[Table 4 Here]

It is possible to update the study since the ITERATE data set is currently available through 2004:4. In the following analysis, the first two years of the data were eliminated in that there seemed to be relatively few incidents recorded in these early years (see Figure 1). When the Bai-Perron procedure is applied to the updated data, little of substance changed in the analysis.

Instead of using the Bai-Perron procedure, it is possible to cautiously ignore the cautions of Enders and Sandler (2005a) and estimate the multiple intervention model:

$$y_t = a_0 + \sum_{i=1}^p a_i y_{t-i} + \alpha_1 FUND + \alpha_2 POST + \alpha_3 D_P + \alpha_4 D_L + \varepsilon_t, \quad (6)$$

where p is the number of lags, y_t is the number of incidents of a particular type in period t , c is a constant, the a_i s and α_i s are undetermined coefficients, and ε_t is an error term. Equation (6) is a standard autoregressive model augmented by four dummy variables. Again, D_P and D_L are dummy (intervention) variables representing potential impacts of 9/11. Equation (6) also includes dummy intervention variables to control for the rise of religious fundamentalism ($FUND$) and the post-Cold War era ($POST$). As identified by Enders and Sandler (2000), $FUND$ is a dummy variable taking a value of 1 beginning in 1979:4, and $POST$ is a dummy variable taking a value of 1 beginning in 1992:1. For each series, the lag length is determined by estimating the model using $p = 8$. If the p^{th} lag was not significant at the 5% level, the value of p was reduced by one and the model was reestimated. The tests are performed without including time as a regressor, because there is no evidence of a deterministic trend in any of the incident series.

As shown in Table 5, the *pulse* dummy, but not the *level* dummy, is associated with a statistically significant reduction in the *All* series. The *Bombing*, *USgtts* and the *All* series purged of threats and hoaxes (All_{nt}) behave similarly. Notice that the *level* dummy variable is not statistically significant for any of the incident series. An examination of Panel *d* in Figure 1 reveals the reason why the *Hostage* series is no longer associated with a significant decline resulting from 9/11. It is clear that *Hostage* jumps to near-record levels in last quarter of the data set.

The proportion series, except for $P_Bombing$, also show no permanent effects resulting from 9/11 in that all of the coefficients for D_L are within 1.96 standard deviations from zero. In the $P_Bombing$ equation, the coefficient for D_L is 0.12; since the sum of the autoregressive coefficients is about 0.26, the long-run increase is estimated to be 16.2 percentage points [$0.12/(1 - 0.26) \cong 0.162$]. The point is that controlling for other structural breaks in the data, there seems to be few statistically significant changes in the terrorism attack modes that can be attributed to the time period beginning with 9/11.

[Table 5 Here]

4.3 Effects on the location of incidents

Enders and Sandler (2006b) used a similar methodology to test for changes in the location of terrorist incidents within the six regional classifications shown in Figure 2. The specific types of incidents considered were the quarterly values of *All*, *Cas*, *USgtts* and casualty incidents with a US target (*CasUS*). In order to estimate the effects of 9/11 on the four types of incidents, they estimated each of these series using the intervention specification given by equation (6). Since the series are counts and some of the series are thin, they also obtain the maximum likelihood estimates for thin series using a Poisson distribution. A normally distributed variable can be positive or negative and the likelihood function is symmetric about the mean. A benefit of using the Poisson distribution to model count data is that it rules out the possibility of negative realizations of y_t and always predicts a positive value for the conditional mean. Moreover, the Poisson distribution is better able to capture a series containing many zero or near-zero, realizations. Panel a of Figure 7 shows a Normal and a Poisson distribution having the same mean value of 3 and the same variance of 3. Although both seem somewhat similar,

approximately 16% of area under the Normal distribution is in the region below zero. This illustrates the main problem with using a normal approximation for a variable that actually has a Poisson distribution since inference (such as t -tests and F -tests) concerning the estimated coefficients will be imprecise. However, this problem disappears as the mean of the variable in question increases since the distributions become increasingly similar. For example, in Panel b of Figure 7, the mean of each distribution is 7. The variance of the Normal distribution function has been kept constant at 3. Notice that there is very little difference between the Poisson and the Normal distributions in the right-hand portion of the figure. However, in applied work, one advantage of the Normal distribution is that it is possible to separately estimate the mean and the variance. In the Poisson, the mean and the variance are necessarily equal.³

[Figure 7 here]

Let x_t be the set of regressors $FUND$, $POST$, D_P , and D_L . Conditional on the set of regressors x_t , the Poisson model assumes that y_t is distributed with a probability density function:

$$f(y_t|x_t) = e^{-\mu_t} \mu_t^{y_t} / (y_t!) \tag{7}$$

where the conditional mean, μ_t , is modeled as

$$\mu_t = \exp \left[c + \sum_{i=1}^p a_i \ln(y_{t-i} + bI_{t-i}) + \alpha_1 FUND + \alpha_2 POST + \alpha_3 D_P + \alpha_4 D_L \right], \tag{8}$$

and I_{t-i} is an indicator function that equals 0 if $y_{t-i} > 0$ and 1 if $y_{t-i} = 0$.

The presence of lagged values in the equation for the conditional mean captures any persistence in the series. Since the natural logarithm function is undefined at nonpositive values of y_{t-i} , a small increment, b , is added to any values of y_{t-i} that are equal to zero. The standard

³ The negative binomial distribution has some of the advantages of the Poisson distribution. However, there are also estimations problems using the negative binomial.

practice to select the most appropriate value of b is to perform a grid search over the interval $0.1 \leq b \leq 0.9$. Select the value of b that provides the best fit.

Notice that equations (6) and (8) are similar in that $FUND$, $POST$, D_P , and D_L can all affect the mean of y_t . Unlike equation (6), we permit the mean to be influenced by $\ln(y_{t-i})$ instead of the level of y_{t-i} . The rationale for this specification is to prevent the $\{y_t\}$ sequence from becoming explosive.

Table 6 reproduces some of the findings for several selected series. The increase in fundamentalism was associated with a significant increase in casualty incidents in Africa, the Middle East, and Asia. Although there are sections in Africa with large Muslim populations, it is expected that the largest effects were in the Middle East and Asia. The post-Cold War ushered in a significant decline in casualty incidents in the Western Hemisphere and a significant rise in Eurasia. There is evidence that $POST$ caused a decline in European casualty incidents; although the OLS estimate is insignificant at conventional levels, the Poisson estimate is negative and highly significant. For the Western Hemisphere, D_P is positive and highly significant so that it is possible to conclude that the Western Hemisphere experienced a temporary increase in casualty incidents during the post-9/11 period. The Middle East and Asia experienced a temporary drop in these events after 9/11. The OLS estimates show that no region displayed a permanent and significant change (at the 5% level) in casualty incidents following 9/11. The decline for Europe is only significant for the Poisson estimation. Enders and Sandler (2006b) also found that there is less evidence of a permanent 9/11-induced fall in casualty events compared with ALL events.

[Table 6 here]

Enders and Sandler (2006b) also classified incidents according to the income level of the nation in which the attack occurred. Specifically, they grouped the 31 countries with the highest

levels of per capita GNI according to the World Bank (2000) to the high income group (HIC) and all others to the low income group (LIC). These 31 HICs include most member states of the Organization of Economic Cooperation and Development (OECD) plus some other countries. As shown in the middle portion of Table 6, when countries were grouped in this way, FUND was associated with a large and statistically significant increase in transnational terrorism attacks in LICs of 24.38 incidents per quarter. Since the POST coefficient for the HICs was not significant, this grouping showed that the impact of fundamentalism was entirely based in the LICs. POST was associated with declines in terrorism in both income classes; the D_P dummy was negative and significant only for the LICs; and the D_L dummy was not significant for either group. The lower portion of Table 6 contains the empirical results for *Cas* incidents with a US target. The important feature to note is that the D_L dummy is positive and statistically significant for both income groups. As such 9/11 is associated with a ratcheting-up of serious terrorist attacks against the US. Americans are safer at home but not abroad following 9/11 and the enhanced homeland security.

5. Measuring the economic costs of terrorism

The direct costs of terrorism are probably the easiest to measure. According to the Bureau of Economic Analysis (2001), the direct costs of the 9/11 attacks on buildings and equipment were \$16.2 billion. In conjunction with the clean-up costs of \$10 billion and a \$2.5 billion loss in wages in salaries due to the two-day work stoppage, the sub-total for total direct costs stands at \$28.7 billion. Navarro and Spencer (2001) estimate the value of a human life to be \$6.67 million. Given that almost 3000 died in the 9/11 attack, the total direct economic cost of 9/11 rises by another \$20 billion. Yet, the US economy experienced a number of additional economic costs that are indirectly attributable to 9/11. The cost of pain and suffering and the value of lost output

as a result of injuries are very difficult to value. Much of the federal government's current budget deficit is due to additional military and security expenditures necessary to fight the "War on Terror." Likewise, business firms had added new security measures and incurred additional insurance costs to protect themselves from another catastrophic terrorist attack. In a sense, the fear of terrorism acts like a tax on the entire economy. Given the impossibility of calculating and summing the various direct and indirect costs of terrorism, researchers have used other means. An alternative way to measure the full cost of terrorism is to compare the overall economic performance of countries or regions with high levels of terrorism to countries with low levels of terrorism. Of course, the comparison can also be done in a regression framework where terrorism is one of the variables affecting growth. To the extent that it is possible to control for all factors contributing to economic growth, the difference in growth rates between the high- and the low-terrorism nations is the estimated cost of terrorism.

Blomberg, Hess, Orphanides (henceforth BHO) (2004) used a cross section of 177 countries from 1968 to 2000 to measure the influence of various terrorist variables on real per capita GDP growth. In order to isolate the effects of terrorism on growth, they used dummy variables to control for the fact that African nations and non-oil commodity exporters tend to have low growth rates. The other control variables included each nation's initial level of income, the ratio of investment to real GDP, and dummy variables indicating whether the nation experienced internal and/or external conflicts. BHO found that if a country experienced transnational terrorist incidents on its soil in *each* year of the sample period, its per capita income growth fell by 1.587 percentage points over the *entire* sample period. As, each year of terrorism led on average to a fall in growth of only 0.048% ($=1.587/33$) so that the overall impact of terrorism in any particular year is small.

BHO's initial terrorism measure (T_{it}) was such that $T_{it} = 1$ if country i experienced one or more transnational terrorist incidents in period t and $T_{it} = 0$ otherwise. Notice that this measure treats a country such as Israel (with many incidents in a year) in precisely the same way as a nation with only one isolated threat or hoax incident in a year. The point is that their specification does not allow the level or intensity of terrorism to affect growth. Moreover, the paper uses only *transnational* terrorism incidents even though some sample countries experienced a substantial amount of domestic terrorism. As shown in Figure 5, the number of domestic terrorism incidents greatly exceeds transnational incidents. As such, it is likely that the "internal conflict" dummy would capture some of the influence of domestic terrorism on growth. The overall effect is that the cost of terrorism is likely to be biased downward.

As a check for robustness, BHO grouped countries into panels and estimated models for nondemocratic countries, OECD countries, African countries, the Middle Eastern countries, and Asian countries. The findings were surprising in that the terrorism variable was not significant for any grouping except Africa. However, for the years covered in the sample, Africa had the lowest number of terrorist events per year (see Figure 2). Moreover, many African nations have experienced negative growth for reasons that have less to do with the presence of terrorism than with the presence of AIDS, open warfare, and economic mismanagement. It is also surprising that the full panel estimates (as compared to the cross-sectional estimates discussed above) indicated that terrorism in a single year reduced per capita GDP growth by *over a half a percent*. No reason was offered to explain why terrorism's average influence on growth for the entire sample is not reflected in *any* of the individual regions such as the Middle Eastern and Asian nations.

In another set of panel estimates, BHO (2004) used the per capita number of incidents

within a country, rather than the dummy variable T_{it} , to measure the level of terrorism. The per capita measure means that a single incident in a country with a small population is somehow worse than the same incident in a more populous country. The results using this alternative measure are such that terrorism significantly affects per capita GDP growth for the full sample, the nondemocratic panel, the OECD panel, and the African panel. The impact of terrorism *varies widely* between the full sample and the subgroups so that there is no consistently measured cost of terrorism. Nevertheless, the authors provide an interesting explanation of the mechanism by which terrorism affects growth. In a second set of panel estimates, BHO found that terrorism increased government spending and decreased private investment. As such, they argue that increased security expenditures undertaken by the government to fight terrorism act to ‘crowd out’ private investment. The reduced level of investment limits growth in that the nation’s capital stock is reduced.

Tavares (2004) also argues that the overall macroeconomic costs of terrorism are low. His estimating equation for a large, but unspecified, sample of countries over the 1987-2001 period is:

$$\Delta y_{it} = \beta_1 \Delta y_{it-1} + \beta_2 Y_{it} + \beta_3 \text{Terrorism}_{it} + \text{Control Variables} + \varepsilon_{it}, \quad (9)$$

where Δy_{it} is real per capita GDP growth of country i in period t , Y_{it} is i ’s level of real per capita GDP in t , and Terrorism_{it} is either the total number of attacks per capita or the total number of casualties per capita. The Control Variables included a natural disaster index and a currency crisis index.

Given that Tavares (2004) obtained his terrorism measure from the IPIC, the results of his study are somewhat problematic because this data set is highly selective. Moreover, unlike BHO, Tavares (2004) does not control for internal conflicts. Nevertheless, using instrumental

variables to correct for any simultaneity between terrorism and real per capita GDP growth, Tavares found that the terrorism variable had a negative impact on annual GDP growth of 0.038%. Note that the magnitude of this estimate is similar to that of BHO. Moreover, once additional determinants of growth (e.g., an education variable, trade openness, primary goods exports, and the inflation rate) were introduced into the estimating equation, the terrorism variable was not statistically significant and/or negative. It seems reasonable to believe that the first set of results is inappropriate since the additional variables are in standard growth analyses. The finding that growth cost of terrorism is essentially zero is hard to believe. Of course, one explanation is that panel data estimates ‘average out’ the costs of terrorism for widely diverse nations. Another possible explanation is that terrorism is correlated with the education variable, trade openness, primary goods exports, and/or inflation so that coefficient magnitudes and the usual t -tests are misleading.

Tavares (2004) also compared the costs of terrorism in democratic versus nondemocratic countries. The key portion of his regression equation dealing with political rights is:

$$\Delta y_{it} = 0.261\Delta y_{it-1} - 0.029T_{it} + 0.121(T_{it} \times R_{it}) + \text{other explanatory variables}, \quad (10)$$

where R_{it} is a measure of political rights in country i in year t . R_{it} ranges from 0 to 1 with a sample mean of 0.53.

In contrast to Tavares’ original specification given by (9), all of the coefficients in the equation with R_{it} are statistically significant. The positive coefficient on the interaction term $T_{it} \times R_{it}$, means that the effect of a typical terrorist attack decreases as the level of political freedom increases. The argument is that democracies are better able to withstand terrorist attacks than other types of governments with less flexible institutions. This is consistent with the view discussed in Enders and Sandler (2006a) that the cost of an attack in a democracy is lower than

in other governmental forms because they rely on markets to allocate resources. The point estimates indicate that the growth effect of a single terrorist incident in country i in year t is $(-0.029 + 0.121R_{it})$ percentage points. Thus, for a nation with few political rights (so that R_{it} is near zero), terrorism reduces annual growth by -0.029 percentage points. Since the model is dynamic, this growth effect has some persistence. Nevertheless, the results are a bit problematic because the point estimates of the coefficients imply that terrorism can enhance growth. For a country with the average level of political rights (i.e., $R_{it} = 0.53$), the influence of a terrorist attack on growth is $+0.03513$ percentage points. It would have been interesting if results using T_{it} , R_{it} and $T_{it} \times R_{it}$ as explanatory variables were reported. In this way, the independent influence of R_{it} on growth could have been ascertained. Also, since the independent influence of R_{it} is excluded from the regression, the coefficient of $T_{it} \times R_{it}$ is probably biased upward.

Gupta *et al.* (2004) specifically analyzes the channel between economic growth, conflict, and government deficits using a simultaneous equation approach. If we modify their notation slightly, the growth equation can be written as

$$\Delta y_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Edu_{it} + \beta_3 Def_{it} + \beta_4 Age_{it} + \beta_5 Conf_{it} + \beta_6 Inv_{it} + \varepsilon_{it} \quad (11)$$

where y_{it} is real per capita GDP growth of country i in period t , Y_{it} is i 's level of real per capita GDP in the initial year of the sample period, Edu_{it} is secondary school enrollment in the initial year of the sample period, Def_{it} is the share of defense spending in total government spending, Age_{it} is a measure of the age profile of the population, $Conf_{it}$ is a measure of internal conflict and terrorism, and Inv_{it} is total investment relative to GDP. Note that the time index references the four time periods 1980-1984, 1985-1989, 1990-1994, and 1995-1999 so that the estimates actually use 5-year averages of the variables.

The other two equations of the model specify the formulas for defense expenditures (Def_{it}) and tax revenues (Tax_{it}). Since they allow Def_{it} and tax revenues Tax_{it} to be functions of the conflict variable, there are actually two channels by which conflict can effect growth; conflict affects Δy_{it} directly and conflict affects Def_{it} which affects growth directly.

The equations are estimated using the generalized method of moments (GMM) in order to control for the possibility that $Conf_{it}$ is endogenous. In the base version of their model, Def_{it} has a negative and statistically negative effect on growth ($\beta_3 = -0.37$) and conflict significantly increases Def_{it} . However, their conflict measure is an aggregate that does not separate out the individual effects of terrorism on growth. As such, they simply report that terrorism significantly inhibits growth, but do not provide the actual cost estimates for any of the countries used in the study. Moreover, most macroeconomists would argue government deficits raise interest rates, reduce real investment and, thereby, reduce growth. Hence, it is not clear why Gupta *et al.* (2004) treat Inv_{it} as an independent variable.

In summary, there are few clear conclusions to be drawn from these studies. All of the papers use different control variables and measure terrorism differently from each other. In the world of econometric textbooks, omitted variables are not a problem if they are uncorrelated with the variable of interest. However, if the omitted variables are correlated with terrorism, the key results of the study will be biased. For example, if terrorism is more prevalent in liberal democracies (and democracy promotes growth), all cross-section and panel studies need to control for changing levels of democracy within countries. The same problem arises because the age profile and the level of education within a country can affect the growth rate and the terrorism. There seems to be little consensus on whether terrorism is measured as a (0, 1) dummy variable, by the number of incidents, the number of incidents on a per capita basis, or as part of

an overall conflict variable. It does seem to be that case that more severe incident types (e.g., incidents with deaths or casualties) have larger effects than other types of incidents.

5.1 Case studies

Eckstein and Tsiddon (2004) used a four-equation VAR model to investigate the effects of terrorism (T) on real per capita GDP (GDP), investment (I), exports (EXP), and nondurable consumption (NDC) in Israel. The authors used quarterly data over the 1980 – 2003 period.

Consider the following VAR:

$$\begin{bmatrix} GDP_t \\ I_t \\ EXP_t \\ NDC_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & \dots & A_{14}(L) \\ \vdots & \ddots & \vdots \\ A_{41}(L) & \dots & A_{44}(L) \end{bmatrix} \begin{bmatrix} GDP_{t-1} \\ I_{t-1} \\ EXP_{t-1} \\ NDC_{t-1} \end{bmatrix} + \begin{bmatrix} c_1 T_{t-1} \\ c_2 T_{t-1} \\ c_3 T_{t-1} \\ c_4 T_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} \quad (12)$$

where the expressions $A_{ij}(L)$ are polynomials in the lag operator L , the c_i measure the influence of lagged terrorism on variable i , and the ε_i are the regression errors. Other right-hand-side variables included the real interest rate and seasonal dummies.

The measure of terrorism is a weighted average of the number of Israeli fatalities, injuries, and noncasualty incidents due to both domestic and transnational attacks occurring in Israel. Experimentation with alternative lag lengths indicated that the initial impact of terrorism on economic activity was one quarter. Notice that the specification in (12) treats terrorism as a pre-determined variable that can affect the four endogenous macroeconomic variables simultaneously.

The largest influence of terrorism was found to be on exports and investment. Specifically, the impact of T_{t-1} on investment was three times larger than on nondurable consumption and two times larger than on GDP. This is consistent with the notion that in the face of a wave of terrorism, investors can readily transfer their funds to relatively safe localities.

Given the point estimates of the various c_i , it is possible to estimate the costs of terrorism to the Israeli economy. Forecasts were conducted assuming either no subsequent terrorism or terrorism at the levels prevailing over 2000:4 - 2003:4. Eckstein and Tsiddon's (2004) first counterfactual exercise assumed that all terrorism actually ended in 2003:4 (so that all values of $T_j = 0$ for $j > 2003:4$). In this scenario, the annual growth rate of *GDP* was estimated to be 2.5% through 2005:3. Instead, if terrorism held steady at the 2000:4 - 2003:4 period average, the growth rate of *GDP* would have been zero. Thus, a steady level of terrorism would have cost the Israeli economy all of its real output gains.

Abadie and Gardeazabal (2003) estimated the per capita GDP losses from terrorism in the Basque region of Spain. The Euskadi Ta Askatasuna (ETA) and other smaller separatist groups, had waged a 25-year campaign against the Spanish government in order to achieve regional autonomy. Abadie and Gardeazabal (2003) argued that terrorism increases uncertainty and the expected return to investment. As such, open economies that are dependent on international capital flows should experience large losses from terrorism. In order to demonstrate their point, the authors construct a simulated economy that acts like the Basque region in all respects except that it experiences no terrorism. Specifically, this counterfactual Basque region is formed as a weighted average of other regions in Spain. The weights are chosen to yield values of real per capita GDP, the investment share of GDP, population density, and human capital measures that are nearly identical to those of the Basque region *prior* to the onset of terrorism. As such, the simulated region acts as a 'control' that allows the authors to compare actual Basque growth to what would have been attained in the absence of terrorism. It is important to note that the Basque region and the counterfactual region displayed similar per capita GDP values prior to the start of the terrorism campaign. Nevertheless, the counterfactual region had an average level of real per

capita GDP exceeding that of the Basque region by about 10% over the 1976 – 1996 period. The gap widened to 12% during some high-terrorism periods and fell to about 8% during periods when terrorism was low. Abadie and Gardeazabal (2003) were also able to construct a portfolio of common stock consisting of companies with sizable business dealings in the Basque region. The value of this portfolio increased by 10.14% after a cease-fire was announced by ETA in late 1998. The same portfolio fell by 11.21% when the cease-fire collapsed 14 months later. A control portfolio, consisting of non-Basque stocks, experienced no noticeable movements corresponding to the cease-fire announcements.

5.2 Microeconomic Consequences of Terrorism

Regardless of the magnitude of the overall macroeconomic costs of terrorism, certain sectors of the economy feel the brunt of terrorism more than others. Since it can be problematic to combine data from very different industries, most of the studies measuring the economic costs of terrorism use time-series methods (as opposed to panel data) to analyze the microeconomic costs of terrorism.

5.2.1 Tourism

One reason terrorists attack popular tourist areas is to gather media attention and cause revenue losses as tourists redirect their vacation plans to relative safe areas. Enders and Sandler (1991) applied a VAR methodology to Spain for the 1970-91 period, during which Euzkadi ta Askatasuna (ETA) and other groups had terrorist campaigns. During 1985-87, ETA *directed* its bombs and threats against the Spanish tourist trade and even sent letters of warning to travel agents in Europe. Using monthly data, it was shown that the causation was unidirectional: terrorism affected tourism but not the reverse. Each transnational terrorist incident was estimated to dissuade over 140,000 tourists after all monthly impacts were included. This can

translate into a sizable amount of lost revenue when multiplied by the average spending per tourist. Transnational terrorist attacks denote the appropriate terrorism measure, because much of the ETA terrorist campaign was transnational attacks to chase away foreign tourists and FDI. Although Spain also experienced some domestic terrorism, data for ITERATE was used since the domestic attacks were performed away from tourist areas.

Enders, Sandler, and Parise (1992) used a transfer function to investigate the impact of transnational terrorism on tourism in Austria, Spain, and Italy for 1974-88 – three countries with highly visible transnational terrorist attacks against foreign tourists during this period. *Transfer function* analysis is particularly suited to estimate the short- and long-run effects of a terrorist attack on a country's tourist industry. Consider the following transfer function model of the effect of terrorism on Italian tourism:

$$y_t = A(L)y_{t-1} + B(L)x_t + C(L)\varepsilon_t \quad (13)$$

where y_t is the logarithmic share of the Italy's tourism revenues in period t , x_t is the number of terrorist incidents in Italy in period t , L is the lag operator, and ε_t is the error term. This equation reflects that Italy's share of tourism revenues in any period is affected by its own past, $A(L)y_{t-1} + C(L)\varepsilon_t$, as well as the number of current and past values of terrorist events in Italy $B(L)x_t$. At first, the transfer function might look like the equation for y_t in a two-equation VAR. The essential difference is that the current value of x_t can appear in the transfer function because it is assumed to be independent of the current level of tourism. The coefficients of $A(L)$ and $C(L)$ capture any persistence in the level of tourism and the coefficients of $B(L)$ capture current and lagged effects of terrorism on tourism. All coefficients of $B(L)$ should be equal to zero if terrorism has no effect on tourism; certainly, the sum of the coefficients should be negative if terrorism reduces tourism.

Details concerning the estimation of a transfer function are contained in Enders (2004).

The important point is that transfer function analysis can be used to estimate the indirect effects of terrorism of the tourism series. Once $A(L)$, $B(L)$ and $C(L)$ have been estimated, it is possible to perform a counterfactual analysis of what each value of y_t would have been in the absence of terrorism (i.e., all values of $x_{t-i} = 0$). Consider the final estimated equation for Italy:⁴

$$y_t = \frac{-0.0022x_{t-1}}{1-0.876L+0.749L^2} + \frac{(1+0.293L^4)\varepsilon_t}{1-0.504-0.245L^2} \quad (14)$$

It is possible to use equation (14) to construct a counterfactual series for y_t by allowing the coefficient on x_{t-1} to be zero instead of the estimated value -0.0022 . The difference between this counterfactual value and the actual value of y_t is then due to the effect of terrorism. It was found that terrorism had a significant negative lagged influence on these tourism shares that varied by country: one quarter for Italy, three quarters for Greece, and seven quarters for Austria. Since it takes time for tourists to revise plans, the lags are understandable. Losses varied by country: Austria lost 3.37 billion special drawing rights (SDRs); Italy lost 861 billion SDRs; and Greece lost 472 million SDRs. The authors also showed that some of the lost revenues left a sample of European countries for safer venues in North America.

Drakos and Kutan (2003) applied the Enders-Sandler-Parise methodology to Greece, Israel, and Turkey for 1991-2000. These authors used monthly transnational terrorism data, drawn from ITERATE. In addition to the home-country impacts, Drakos and Kutan were interested in cross-country or “spillover” effect – both positive and negative – that may arise if, say, a transnational attack in Israel shifts would-be Israeli tourists to safer venues in Italy, Greece, or elsewhere. They estimated a transfer function for each country’s tourist shares, where, say, the share of tourism in Greece depends on: past tourist shares in Greece; current and

⁴ The estimated equation reported here is slightly different from the one actually reported in Enders, Sandler, and Parise (1992). Enders (2004) reports the details of the estimation process.

past terrorist attacks in Greece; current and past terrorist attacks in Israel; and current and past terrorist attacks in Turkey. There was also an equation for tourist shares of Italy, which was a relatively safe haven. Based on transnational terrorist attacks, these authors calculated that Greece lost 9% of its tourism market share; Turkey lost over 5% of its tourism market share; and Israel lost less than 1% of its tourism market. Close to 89% of lost tourism due to terrorism in Europe flowed to safer tourist venues in other countries. Drakos and Kutan also uncovered significant spillover effects – low-intensity terrorist attacks in Israel reduced Greek tourism revenues.

5.2.2 Net foreign direct investment (NFDI)

Just as tourists avoid areas likely to suffer from a terrorist attack, international investors are likely to avoid high-terrorism areas. Obviously, a terrorist attack can destroy infrastructure and cause business disruptions. Firms also seek to avoid the increased costs necessary to protect a facility from potential attacks. Such costs include those of directly securing facilities, maintaining security clearances for employees, and additional insurance charges. Recruiting costs may rise since personnel from the home office may not wish to work in a terrorist-prone region. Moreover, terrorism augments the general level of uncertainty, which redirects NFDI to safer environs. The point is that terrorism raises the costs of doing business in a country; as such foreign firms will seek safer locations for their facilities and domestic firms will seek to locate abroad.

Enders and Sandler (1996) provided estimates of the effects of terrorism on NFDI in two relatively small European countries – Greece and Spain. Large countries – e.g., France, Germany, and the United Kingdom – draw their foreign capital inflows from many sources and appeared to endure attacks without a measurable aggregate diversion of inflows. Large countries

are also better equipped to take defensive measures after an attack to restore confidence. Greece and Spain were selected as case studies insofar as both experienced numerous transnational terrorist attacks aimed at foreign commercial interests during the 1968-91 sample period.

It turned out that a transfer function specification was appropriate for Spain because terrorism did not respond NFDI. However, a VAR model was used for Greece because of a potential endogeneity problem. For Spain, there was a long delay of 11 quarters between the advent of a terrorist incident and the response in NFDI. The counterfactual analysis indicated that a typical transnational terrorist incident in Spain was estimated to reduce NFDI by \$23.8 million. On average, transnational terrorism reduced *annual* NFDI in Spain by 13.5%. For Greece, the story was similar, transnational terrorism curbed annual NFDI by 11.9%. These are sizable losses for two small economies that were heavily dependent on NFDI as a source of savings during the sample period.

5.2.3 Trade influence

In a recent contribution, Nitsch and Schumacher (2004) estimated the effects of transnational terrorism on bilateral trade flows using a standard trade-gravity model. In their model, trade flows between trading partners depended on terrorist attacks, the distance between the two countries, an income variable, an income per capita variable, and a host of dummy variables. They formally estimated the effects of terrorism within each country on all of the nation's trading partners. The data set consists of 217 countries and territories over the 1968-79 period. Their terrorism data were drawn from ITERATE and only included transnational attacks, even though domestic terrorism would have also affected trade flows. The authors found that the first transnational terrorist attack reduced bilateral trade by almost 10%, which is a very sizable influence that may be picking up the effect of domestic terrorism. Nitsch and Schumacher also

found that a doubling of the number of terrorist incidents reduced bilateral trade by 4%; hence, high-terrorism nations had a substantially reduced trade volume.

5.2.4 Financial markets

Chen and Siems (2004) applied an event-study methodology to investigate changes in average returns of stock exchange indices to 14 terrorist and military attacks that dated back to 1915. Their event study computed daily excess – negative or positive – following 14 occurrences, such as the Japanese attack of Pearl Harbor, the downing of Pan Am flight 107 and 9/11. Specifically, daily excess returns (AR_{jt}) for stock j on day t are computed as the difference between the stock's observed return on day t (R_{jt}) minus the average return that prevailed in the recent past (\bar{R}_j):

$$AR_{jt} = R_{jt} - \bar{R}_j \quad (15)$$

where the average return is calculated as:

$$\bar{R}_j = 0.05 \sum_{t=-30}^{-11} R_{jt} . \quad (16)$$

The date on which the event occurs is normalized to be day 0 so that the average return is a 20-day mean of recent returns. Of course, if the event had no effect on stock prices, the return on day 0 should just equal the average return so that AR_{jt} should not be statistically different from zero. These authors showed that the influence of terrorist events on major stock exchanges, if any, is very transitory, lasting just one to three days for most major incidents. The sole exception is 9/11 where DOW values took 40 days to return to normal. These authors also showed that this return period varied according to the stock exchange – exchanges in Norway, Jakarta, Kuala Lumpur, and Johannesburg took longer to rebound, while those in London, Helsinki, Tokyo, and elsewhere took less time to rebound. Most terrorist events had little or no

impact on major stock exchanges. The paper goes on to claim that US capital markets are more resilient than in the past and recover sooner from terrorist attacks than other global capital markets. Although their argument that a more stable US financial sector has promoted stability is plausible, there is another explanation for the reason why recent market recoveries occur more quickly than in the past. The early events include the torpedoing of the Lusitania, the German invasion of France, the Pearl Harbor attacks, and the North Korean attacks on South Korea. Unlike the downing of an Air India flight (June 1985), a Korean Air flight (Nov. 1987), and a Pan AM flight (Dec. 1988), the earlier incidents signaled major long-term conflicts.

Eldor and Melnick (2004) applied time-series methods to ascertain the influence of the Israeli terror campaign following September 27, 2000 on the Tel Aviv 100 Stock Index (TA 100) and on the exchange rate. Given the continual nature of these terrorist attacks, the time-series method is clearly appropriate. As a preliminary check for the presence of a unit-root, Eldor and Melnick (2004) conducted augmented Dickey-Fuller tests on the data and found that stock prices and the exchange rate are both nonstationary. As such, they estimated their equations using first-differences. Consider the specification:

$$\Delta x_t = \alpha + \beta f_t + \gamma_0 T_t + \gamma_1 T_{t-1} + \gamma_2 T_{t-2} + \varepsilon_t \quad (17)$$

where x_t is either the log of the TA 100 or the exchange rate, f_t is a measure of the market fundamentals, and T_t is a measure of the level of terrorism in Israel in period t .

If any of the coefficients for the terrorism variable are statistically significant, it can be concluded that terrorism has important informational content for x_t . If the sum of the coefficients $\gamma_0 + \gamma_1 + \gamma_2$ is not statistically different from zero, terrorism has only a transitory effect on x_t . Otherwise, the effect on terrorism on x_t is permanent. When x_t was the log of the TA 100, suicide attacks, attacks with deaths, and attacks with injuries all had permanent effects on the level of

stock prices. However, when T_t measured attacks on transport or the overall level of attacks, the effects were only transitory. Analogous to the other time-series studies, they performed a counterfactual exercise to determine losses to the value of the TA 100 index by using the *estimated* time-series equation for returns but substituting a zero value in for terrorist attacks. Their analysis estimated that the TA 100 was 30% lower on June 30, 2003, owing to the terrorist campaign. However, they found little influence of any form of terrorism on the exchange rate.

Instead of looking at the effects of terrorism on a broad index of stocks, Drakos (2004) examined the effects of the 9/11 attacks on airline stocks. Let R_{it} , R_{ft} and R_{mt} denote the period t rate of return on airline stock i , on a risk-free asset, and on the market portfolio, respectively. His estimating equation is:

$$(R_{it} - R_{ft}) = \beta_i(R_{mt} - R_{ft}) + \varepsilon_t. \quad (18)$$

The value of β_i shows how the excess return of stock i is correlated with the overall market rate of return over the risk free rate. If 9/11 had no effect on the systematic risk of the airline's stock, the pre-9/11 value of β_i should be equal to the post-9/11 value. Instead, if the average market participant perceived an increased risk of holding an airline's stock, β_i should rise to compensate asset holders for the increased risk. Similarly, if 9/11 had no effect on the stock's volatility, the pre-9/11 value of $Var(\varepsilon)$ should be equal to the post-9/11 value. Drakos (2004) found that eleven out of the thirteen stocks studies showed increased systematic risk in the post-9/11 period. Only KLM and Qantas (two non-US carriers) showed no increased systematic risk. Moreover, in nine of the cases the variance rose implying that risk of airline stocks increased.

6. Measuring the economic determinants of terrorism

In many instances, it is straightforward to point to the grievances of a particular group and designate those grievances as a cause of terrorism. The IRA was formed to achieve Irish independence, the Irgun was formed to achieve a homeland for the Jews, and the PLO was formed to fight against Israel and to achieve an independent Palestinian state. Yet, social scientists want to know why some groups choose to fight using terrorist tactics while others do not. After all, some terrorist groups (such as the Red Brigades and Aum Shinrikyo) failed to achieve their ultimate ends while other groups using legal tactics have been successful. The real issue is to find out the underlying reasons why one group will seek to alleviate a grievance using terrorism instead of a host of other tactics.

Hoffman (1998) argues that liberal democracies are more prone to terrorism than other forms of government. In liberal democracies terrorists have the same freedoms as nonterrorists in that they can freely associate with each other, are free to communicate with each other and spread dissent, and have the same ability to obtain funding and weapons as any other member of society. Moreover, political pressures arising from terrorist attacks may induce the government to concede to some of the terrorists' demands. As such, there is more incentive for a group to resort to terrorism in a liberal democracy. Even though a number of studies, including those by Li (2005) and Weinberg and Eubank (1998), seem to verify this result, the issue seems to be straightforward and the policy implications are few. A more interesting issue is whether poverty and poor economic conditions breed terrorism.

If the motives for terrorism, rather than some political tactic, are purely economic, one might be tempted to conclude that the alleviation of poverty might reduce terrorism. However, there is little statistical evidence that poverty 'causes' terrorism. In an informal study, Sageman

(2004) assembled biographical information on approximately 400 Salafi Mujahedin terrorists using publicly available information. The approximately seventy-five percent of the terrorists came from upper-class or middle class backgrounds and sixty-three percent attended college. Moreover, many had professional backgrounds and sixty-three percent were married. Since Sageman's (2004) sample of terrorists was not drawn scientifically, it is possible to argue that it is not representative of the large number of terrorists that were excluded from his data set. However, in a more formal study, Krueger and Maleckova (2003) find little relationship between the lack of market opportunities and terrorism. They begin by analyzing a public opinion poll conducted by the Palestinian Center for Policy Survey Research (PCPSR). From 19 December 2001 through 24 December 2001, the PCPSR surveyed 1,357 Palestinians aged 18 or older living in the West Bank and Gaza Strip. The results of the survey are quite striking in that at least 72% of every educational and occupational group supported (or strongly supported) armed attacks against Israeli targets. It is particularly interesting that the percentage supporting such attacks did not decrease with income or educational levels. In fact, support was especially strong among students and lowest among the unemployed. Corroborating evidence was provided by comparing the economic characteristics of 129 killed Hezbollah fighters with those from a similar population demographic in Lebanon. They found a 28% poverty rate for the militants compared with a 33% percent for the more general population. Moreover, the Hezbollah fighters were more likely to have attended secondary school.

Krueger and Maleckova (2003) used US State Department data to formally test for a relationship between terrorism and income. Let n_i denote the number of terrorist events perpetrated by individuals from each country i over the entire 1977-2002 period. In a very simple regression controlling only for population, they found a negative relationship between n_i and per

capita GDP. Hence, in accord with the conventional wisdom, there tends to be a negative correlation between income and terrorism. However, the poorest countries tend to be those with low levels of civil liberties. When they included a measure of civil liberties in the regression equation, the GDP variable becomes statistically insignificant. However, regardless of the form of the regression equation, the civil-liberties variable was always significant at better than the 0.02 level. The point they make is that it is the lack of political freedom, and not poverty, that spawns terrorism.

In a more recent paper, Blomberg, Hess, and Weerapana (BHW) (2004) estimate the relationship between economic conditions and the level of terrorism within a panel of 127 countries from 1968 to 1991. The intent is to measure the extent to which the business cycle helps to explain the level of terrorism within a country. Towards this end, BHW define a contraction as a period of negative per capita GDP growth and an expansion as a period of positive growth.⁵ The terrorism variable, drawn from ITERATE, is a (0, 1) measure of whether a nation was a target of a terrorist attack in year t . They show that there are some links between economic contractions and increased levels of terrorism in high-income and democratic countries. To explain, in any year t , there are four regimes depending on whether the economy was in a state of contraction or expansion and depending on whether the country experienced a terrorist attack. Let $P_{t-1} = 0$ if the country in question was in a state of peace in period $t-1$, otherwise $P_{t-1} = 1$ (*i.e.*, $P_{t-1} = 1$ if the country experienced at least one terrorists attack in $t-1$). Also let $C_{t-1} = 1$ if the country in question was in a contraction in period $t-1$, otherwise $C_{t-1} = 0$. As an example of the notations, for a country experiencing an expansion and no terrorism in year

⁵ Note that this is not the conventional way to define business cycle expansions and contractions. The typical definitions of recessions and expansions are measured relative to a long-term trend. Nations with sustained negative growth rates, such as many of the African nations, are generally not said to be experiencing a recession.

$t-1$, $C_{t-1} = 0$ and $P_{t-1} = 0$. Thus, the four distinct regimes can be described by $(C_{t-1} = 0, P_{t-1} = 0)$, $(C_{t-1} = 0, P_{t-1} = 1)$, $(C_{t-1} = 1, P_{t-1} = 0)$ and $(C_{t-1} = 1, P_{t-1} = 1)$.

The issue is how readily countries switch between the four regimes. In other words, does a country in a high-terrorism, low-growth state tend to remain in that state while a country in a high-terrorism, high-growth state tends to switch into a low-terrorism, high-growth state? Let $\text{PR}(P_t | P_{t-1} = C_{t-1} = 1)$ denote the probability that the country experiences no terrorism in t given that P_{t-1} and C_{t-1} both equal 1. Analogously, $\text{PR}(C_t | P_{t-1} = C_{t-1} = 1)$ probability that the country has a contraction in t given that P_{t-1} and C_{t-1} both equal 1. If you follow the notation, it should be clear that $\text{PR}(T_t | P_{t-1} = C_{t-1} = 1) = 1 - \text{PR}(P_t | P_{t-1} \text{ and } C_{t-1})$ is the probability that the country is in the high-terrorism state given P_{t-1} and C_{t-1} both equal 1.

The various transition probabilities can be estimated by maximum likelihood methods. Some of the key BHW findings are summarized in Table 7. The first two rows of the table show that for all countries transitions into the high-terrorism state from a state of peace are almost 0.20 regardless of whether or not the economy experiences a contraction. As such, there is an 80% chance that a country experiencing no terrorism in the current year experiences no terrorism in the subsequent year. The probability of switching into the high-terrorism state is slightly higher for the high-income countries than for the low-income countries. Moreover, since for the high-income nations $\text{PR}(T_t | P_{t-1} = C_{t-1} = 1) > \text{PR}(T_t | P_{t-1} = 1, C_{t-1} = 0)$, contractions are associated with terrorism for nations with already high income levels. The next two rows of the table show that the probability of remaining in a high-terrorism state is quite high regardless of whether or not the economy experiences a contraction. If the economy does not have a contraction, the probability is 65.4% and is 69.4% if there is a current contraction. Thus, both the terrorism state and the no-terrorism state are quite persistent. Also note that the probability of being in a high-

terrorism state is always greater for the high-income nations. As such, there tends to be more terrorism in high-income nations than low-income nations. Finally, for the high-income nations $PR(T_t|P_{t-1} = 1, C_{t-1} = 0) > PR(T_t|P_{t-1} = 0, C_{t-1} = 1)$ so that it again follows that contractions are associated with terrorism for nations with already high income levels.

[Table 7 here]

7. Conclusions and assessment

Assessing the state of the empirical literature on terrorism, it is clear that there is much to learn. In fact, the game-theoretic models of terrorism seem far more sophisticated than many of the empirical papers surveyed here. Part of the reason for the disparity is the nature of the available data measuring terrorism. Even though most definitions of terrorism involve the notion of a political crime committed against noncombatants, important differences in coverage, coding, and consistency appear in the available data sets. The ITERATE, PGT and MIPT data sets do seem to have similar long-run patterns. Chronologies of “selected” incidents, such as the IPIC data set, seem inappropriate for research purposes. Unfortunately, beginning with 2004, updates to the PGT data were suspended for political reasons. From an economic perspective, this makes little sense since the collection and widespread dissemination of information has public good aspects that typically involve some form of government subsidization. Although the MIPT data set is publicly available, it is difficult to use and does not contain country-specific breakdowns of terrorist incidents. The complete ITERATE data set is available for a fee large enough to dissuade some potential researchers from acquiring it. Although the number of domestic terrorist

incidents far exceeds that of transnational incidents, there is not a long time series of domestic terrorism data.

In spite of the data problems, the implications of the rational-actor model of terrorism have been the subject of a number of empirical tests. Specifically, an increase in the relative price of one type of terrorist activity does induce a substitution out of that activity and into the now relatively less-expensive activity. Logistically similar activities do seem to display the greatest substitution possibilities. Moreover, periods of high-terrorism seem to be less persistent than periods with less terrorism. This is consistent with the notion that terrorists face a resource constraint. Terrorism can remain in an elevated state only as long as they have sufficient resources to sustain the struggle. Once resources have been sufficiently depleted, the intensity of terrorism will fall as the group replenishes its resources, funds and personnel.

Since 9/11, the nature of terrorism has changed in ways that are quite different from those typically reported in the media. There has not been a dramatic increase in the number of transnational terrorist incidents since 9/11. Instead, the post-9/11 counterterrorism policies have hampered al Qaida's abilities to conduct resource-intensive and logistically sophisticated attacks. The proportion of bombings has increased at the expense of assassinations and hostage takings. Another change in the composition of the incident series is that there have also been increased efforts to attack US interests. However, Americans are safer at home, but not abroad, as a result of these terrorists' efforts and improved homeland security.

Far less is known about the macroeconomic costs of terrorism than the costs to specific countries and specific industries. The panel data estimates suggest that the costs of terrorism to overall economic growth are virtually zero. However, this is in direct contrast to the case studies of terrorism and the intuitive notion that the current macroeconomic climates in some countries

(such as the US, Iraq, Philippines, Afghanistan, Pakistan, Spain, and the UK) would be very different had 9/11 never occurred. The appeal of cross-sectional and panel data studies of the macroeconomic costs of terrorism is obvious. Such studies can pool the experiences of a large number of countries at once to gain enhanced degrees of freedom. The fact that many countries experience widely different levels of terrorism can help in the statistical identification of the consequences of terrorism. However, these gains seem to be offset by a number of difficult problems. It is likely that some countries are too diverse to pool into a single regression equation. It is difficult to obtain adequate controls for the vast differences in institutions and governments that exist across the array of nations. As discussed in Enders and Sandler (2006a), countries with market economies and democratic governments will respond to terrorism very differently than countries with nonmarket economies and/or nondemocratic governments. The price system and economic freedoms allow a country to reallocate resources in such a way as to absorb the shocks of terrorist attacks. Similarly, large and diverse economies are better able to absorb shocks than small economies with only a small number of viable sectors. As such, it is not surprising the panel data studies of the macroeconomic costs of terrorism are sensitive to the particular groupings used in the panel. Moreover, the microeconomic studies of terrorism indicate that it may take several periods for the effects of terrorism to manifest themselves. Such delay factors are difficult to analyze in a cross-sectional framework.

A problem endemic in all studies trying to measure the costs of terrorism is that it is not clear how to measure the level and intensity of terrorism. Some studies, such as Enders and Sandler (1996) and Nitsch and Schumacher (2004), use the number of incidents occurring in a region to measure the level of terrorism. Eckstein and Tsiddon (2004) use a weighted average of the number of fatalities, injuries, and noncasualty incidents occurring in Israel. BHO (2004)

alternatively used a (0, 1) dummy variable to indicate whether a country experienced an act of terrorism within a year and the per capita number of incidents within a country while Travares (2004) alternatively used the number of attacks per capita and the total number of casualties per capita.

Measuring the economic determinants of terrorism seems to be the most problematic endeavor surveyed in this paper. It is certainly true that many of the individuals engaging in terrorism are not among the most impoverished people, high-income countries experience more terrorism than low-income countries, and noneconomic factors (such as the US presence in Saudi Arabia) sometimes motivate terrorists. Yet, it is instructive to consider the large existing literature on the relationship between poverty and (nonpolitical) crime. The consensus opinion among social scientists is that poverty alone does not cause crime. However, there are subtle linkages between the two (such as glaring income disparities between two otherwise similar groups). The riots in France during the fall of 2005 provide strong evidence that terrorist acts can result from the lack of economic opportunities for some members of society.

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Table 1. Number of Incidents by Type (1968-2004): ITERATE Data

Incident Type Code	Incident Type	Number of Incidents
1	Kidnapping	1267
2	Barricade and hostage seizure	181
3	Occupation of facilities without hostage seizure	76
4	Letter or parcel bombing	452
5	Incendiary bombing, arson, Molotov cocktail	1018
6	Explosive bombing	4032
7	Armed attack involving missiles	48
8	Armed attack – other, including mortars and bazookas	1363
9	Aerial hijacking	363
10	Takeover of a non-aerial means of transportation	59
11	Assassination, murder	1101
12	Sabotage, not involving explosives or arson	32
13	Pollution, including chemical and biological agents	25
14	Nuclear-related weapons attack	1
15	Threat with no subsequent terrorist action	1127
16	Theft, break-in of facilities	111
17	Conspiracy to commit terrorist action	281
18	Hoax (for example, claiming a nonexistent bomb)	322
19	Other actions	402
20	Sniping at buildings, other facilities	130
21	Shoot-out with police	46
22	Arms smuggling	92
23	Car bombing	193
24	Suicide car bombing	40
25	Suicide bombing	30
	Unclassified	11
Cumulative Total:		12803

Table 2: Sample Means of Selected Incident Types (incidents per year)

		1968 – 2004	1968 – 1979	1980 – 1989	1990 – 1999	2000 – 2004
<i>All</i>	Mean (\bar{x})	345.73	364.80	464.60	334.10	171.00
	SE(\bar{x})	22.59	20.55	18.03	47.86	38.80
<i>Death</i>	Mean (\bar{x})	63.81	50.50	83.80	64.30	68.40
	SE(\bar{x})	4.63	5.91	5.28	8.14	18.19
<i>Bombings</i>	Mean (\bar{x})	193.95	236.60	242.40	168.60	94.20
	SE(\bar{x})	14.63	23.82	13.68	31.71	27.62
<i>Hostage</i>	Mean (\bar{x})	50.54	45.80	61.40	56.30	43.20
	SE(\bar{x})	3.53	3.67	5.00	6.49	14.05
<i>Armed Attacks</i>	Mean (\bar{x})	38.14	16.90	43.10	63.10	31.20
	SE(\bar{x})	4.72	2.61	4.18	12.51	6.49
<i>Suicide Attacks</i>	Mean (\bar{x})	1.89	0.00	1.10	0.40	11.00
	SE(\bar{x})	0.86	0.00	0.31	0.31	4.89
<i>Proportion</i>	Mean (\bar{x})	0.305	0.248	0.293	0.307	0.477
	SE(\bar{x})	0.016	0.013	0.005	0.015	0.010
<i>UStgts</i>	Mean (\bar{x})	115.89	152.00	134.20	92.00	68.40
	SE(\bar{x})	8.53	16.76	6.55	16.08	19.92

Mean (\bar{x}) denotes the sample (or subsample) mean of the series in question and SE(\bar{x}) denoted the standard error of the mean.

Table 3: Interactions Among the Five Incident Series and the Interventions

Correlation Matrix of the SUR Residuals						Variance Decompositions: 8-Quarter Horizon				
	<i>Sky</i>	<i>Hostage</i>	<i>Assns</i>	<i>Th</i>	<i>OT</i>	<i>Sky</i>	<i>Hostage</i>	<i>Assns</i>	<i>Th</i>	<i>OT</i>
<i>Sky</i>	1.000	0.103	-0.159	0.364	-0.129	85.2	4.90	5.38	2.54	2.00
<i>Hostage</i>		1.000	0.098	0.093	0.040	13.9	68.7	0.62	1.20	15.8
<i>Assns</i>			1.000	0.311	0.196	13.1	6.85	61.0	0.564	18.5
<i>Th</i>				1.000	0.211	34.4	7.97	11.4	35.7	10.5
<i>OT</i>					1.000	4.97	3.34	10.5	9.33	71.9
	<i>Short-Run Effects of the Interventions^a</i>					<i>Long-Run Effects of the Interventions</i>				
<i>Metal</i>	-14.1 ^{***}	11.6 ^{***}	6.58 ^{**}	1.75	11.3	-13.0 ^b	5.3 ^b	4.1 ^b	-9.5 ^b	17.8 ^b
<i>Emb76</i>	2.51 [*]	-1.41	3.56 [*]	8.67 ^{***}	-18.6 [*]	0.98 ^b	-0.20 ^b	8.2 ^b	11.8 ^b	-21.1 ^b
<i>Emb85</i>	0.100	3.54 ^{**}	-0.967	-5.31 ^{**}	-2.81	0.52 ^b	5.4 ^b	-1.7	4.1 ^b	-5.4
<i>Libya</i>	-4.83	-1.62	1.57	50.5 ^{***}	58.4 ^{**}	NA	NA	NA	NA	NA

Notes to Table:

^a ^{***}, ^{**}, and ^{*} denote significance at the 1%, 5% and 10% levels, respectively.

^b An intervention variable can significantly impact a series directly or have a significant indirect effect though the interaction of the variables in the VAR. At the 10% significance level, all of the long-run effects (except for *EMB85* on *Assns* and *OT*) are significant. By construction, *Libya* has only temporary effects.

Description of the Interventions

Metal: The United States began to install metal detectors in airports on 5 January, 1973. *Metal* = 0 for $t < 1973:1$ and = 1 otherwise.

Emb76: A doubling of spending to fortify and secure US embassies beginning in October 1976.

Emb76 = 0 for $t < 1976:4$ and = 1 otherwise.

Emb85: A significant increase in spending to secure US embassies was authorized in 1985:4.

Emb85 = 0 for $t < 1985:4$ and = 1 otherwise.

Libya In April, 1986, the US undertook a retaliatory raid against Libya for its involvement in the LaBelle Discothequet bombing. *Libya* = 1 in 1986:2 and = 0 otherwise.

Table 4: Estimates of Multiple Structural Breaks

Series	Break Date	Lower	Upper	Initial Mean	SR Effect	LR Effect
<i>All</i>	1994:3	1993:4	1996:4	106.62	-46.46	-62.63
<i>Hostage</i>	2000:3	2000:1	2002:3	13.79	-6.69	-9.94
<i>Bombings</i>	1994:1	1993:3	1996:1	61.50	-33.92	-40.43
<i>Bomb_Cas</i> ^a	1992:3	1989:4	1993:3	15.79	11.20	17.17
	1994:3	1994:1	1996:1		15.64	23.97
<i>Deaths</i>	1975:3	1973:2	1976:2	8.89	7.17	11.01
	1996:2	1994:2	1998:4		-5.81	-8.91

^a *Bomb_Cas* denotes bombings with at least one casualty.

Table 5: Updating Enders and Sandler (2005a) Using an Intervention Model^a

Series	Lags	DW	Intercept	FUND	POST	Pulse	Level
<i>All</i>	5	2.00	49.92 (3.76)	16.08 (1.80)	-31.12 (-2.67)	-34.04 (-4.28)	-2.98 (-0.33)
<i>All_{nt}</i>	5	2.00	42.74 (3.53)	9.67 (1.30)	-23.45* (-2.40)	-29.34 (-3.84)	-0.49 (-0.06)
<i>Deaths</i>	2	2.05	4.80 (3.72)	1.89 (1.42)	-1.56 (-1.12)	-2.75 (-1.16)	3.98 (1.67)
<i>Cas</i>	2	2.13	8.09 (3.58)	2.14 (0.95)	-3.07 (-1.28)	-4.34 (-1.57)	3.19 (1.09)
<i>Bombing</i>	5	2.00	35.43 (4.04)	2.03 (0.32)	-20.93 (-3.12)	-18.67 (-3.50)	2.55 (0.46)
<i>UStgts</i>	1	2.04	33.45 (7.51)	0.04 (0.01)	-17.26 (-4.38)	-16.51 (-4.22)	4.82 (1.12)
<i>Arm</i>	7	1.99	1.67 (2.34)	2.38 (1.62)	0.20 (0.11)	-1.34 (-0.66)	-0.83 (-0.43)
<i>Hostage</i>	7	2.06	11.99 (5.38)	4.25 (2.98)	-0.98 (-0.71)	-4.71 (-1.25)	-4.87 (-1.50)
Proportion Series							
<i>P_Deaths</i>	8	2.15	0.07 (2.85)	0.00 (-0.27)	0.04 (2.27)	0.52 (10.96)	0.08 (1.87)
<i>P_Cas</i>	4	1.88	0.13 (3.51)	0.00 (-0.25)	0.05 (2.00)	0.44 (12.00)	0.06 (1.40)
<i>P_Bombing</i>	1	2.03	0.50 (8.55)	-0.09 (-4.11)	-0.07 (-2.69)	-0.05 (-1.30)	0.12 (2.75)
<i>P_UStgts</i>	2	2.04	0.13 (2.77)	-0.03 (-0.93)	0.02 (0.51)	-0.04 (-1.20)	0.02 (0.39)
<i>P_Arm</i>	1	2.07	0.04 (5.46)	0.04 (3.85)	0.07 (3.45)	-0.08 (-4.15)	0.00 (0.19)
<i>P_Hostage</i>	4	1.97	0.07 (2.97)	0.00 (0.34)	0.07 (3.20)	0.13* (2.78)	-0.05 (-1.24)

Notes to Table:^a *t*-statistics are in parentheses.

Table 6: Analysis of Selected Incident Types by Location and Income Group^a

Region	Model	Lags	c	FUND	POST	Pulse	Level	LR	F	Q(4)
Cas Incidents: Analysis by Location										
West. Hem.	OLS	2	2.50 (4.55)	0.63 (0.75)	-2.25 (-2.74)	3.64 (8.77)	-0.52 (-1.06)	-1.14	0.00	0.85
Europe	OLS	3	2.70 (3.53)	0.26 (0.25)	-1.66 (-1.39)	0.22 (0.42)	-0.53 (-0.70)	-1.80	0.78	0.98
	Poisson	1	1.32 (13.62)	0.17 (2.32)	-0.42 (-4.65)	1.18 (1.55)	-0.64 (-2.20)		0.06	
Eurasia	Poisson	1	-3.35 (-3.28)	1.29 (1.15)	2.50 (4.54)	-33.03 (0.00)	-0.91 (-1.71)		0.23	
Africa	OLS	2	0.92 (3.18)	0.99 (2.17)	1.10 (1.29)	-1.13 (-1.59)	-1.97 (-1.83)	-3.08	0.00	0.58
Mid. East	OLS	1	2.07 (3.66)	1.88 (2.38)	-1.03 (-1.02)	-6.64 (-3.17)	3.75 (1.69)	7.28	0.00	0.21
Asia	OLS	1	1.16 (3.71)	1.53 (2.73)	0.12 (0.19)	-3.37 (-3.03)	2.01 (1.57)	2.77	0.00	0.31
All Incidents: Analysis by Income Group										
LICs	OLS	1	34.54 (6.24)	24.38 (3.84)	-16.90 (-2.77)	-27.79 (-3.89)	-11.92 (-1.41)	-13.89	0.00	0.59
HICs	OLS	2	22.13 (4.91)	2.87 (0.77)	-16.99 (-2.71)	-1.99 (-0.76)	-1.16 (-0.26)	-2.27	0.54	0.97
Casualty Incidents with a US Target: Analysis by Income Group										
LICs	OLS	2	2.75 (4.79)	0.96 (1.60)	-1.31 (-1.90)	-6.62 (-4.03)	3.56 (2.09)	5.11	0.00	0.82
LICs	Poisson	1	1.24 (14.60)	0.28 (2.85)	-0.35 (-3.22)	-33.52 (0.00)	0.75 (4.99)		0.00	
HICs	Poisson	1	0.75 (7.26)	-0.10 (-0.67)	-1.20 (-4.58)	1.23 (2.29)	1.09 (3.11)		0.00	

Notes to Table:^a *t*-statistics are in parentheses.

Table 7: The Transition Probabilities into the High-terrorism state

	All	Low Income	High Income
$PR(T_t P_{t-1} = C_{t-1} = 1)$	0.197	0.171	0.252
$PR(T_t P_{t-1} = 1, C_{t-1} = 0)$	0.196	0.177	0.211
$PR(T_t P_{t-1} = 0, C_{t-1} = 1)$	0.694	0.577	0.782
$PR(T_t P_{t-1} = C_{t-1} = 0)$	0.654	0.515	0.718

Figure 1: Terrorist Incidents by Type

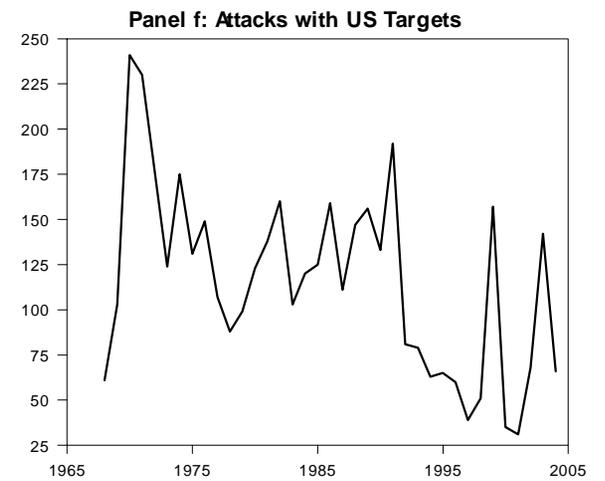
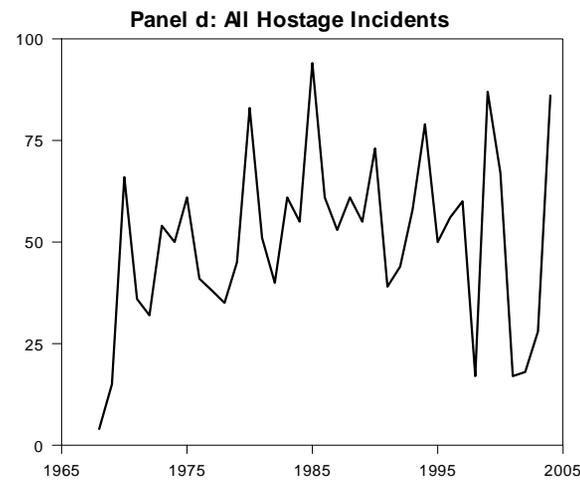
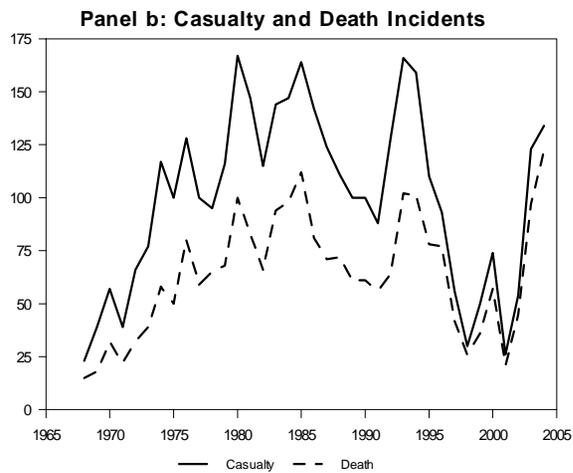
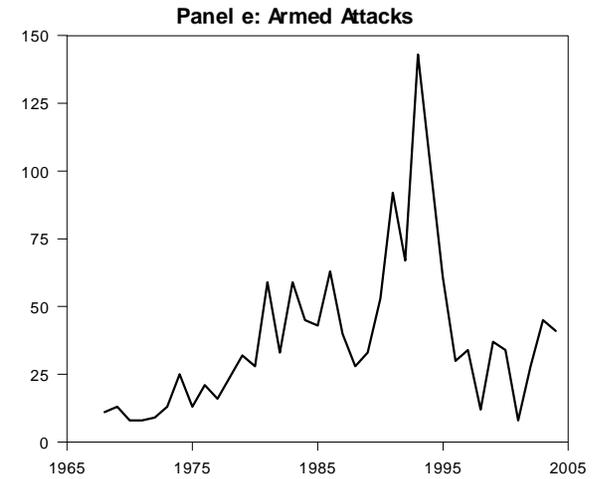
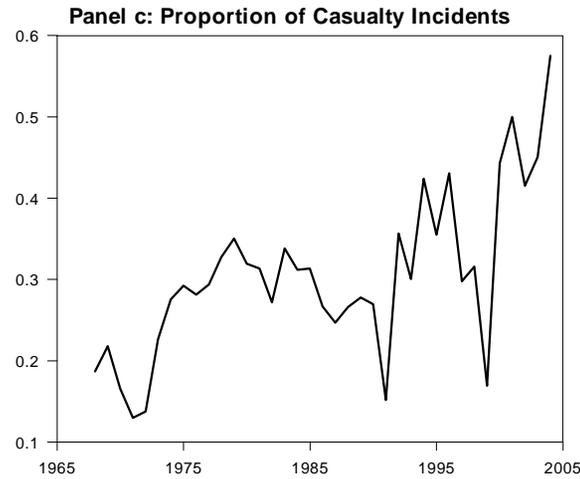
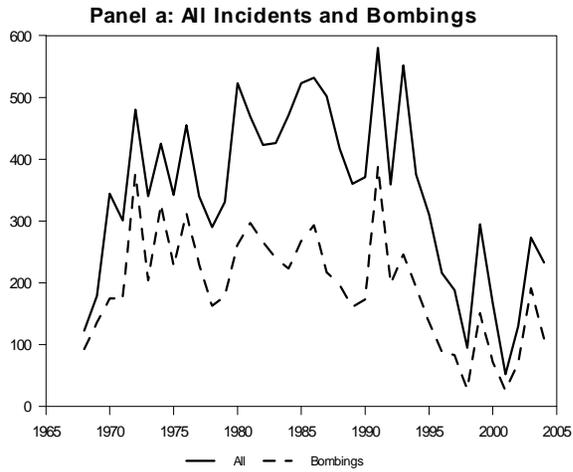


Figure 2: Regional Distribution of Incidents

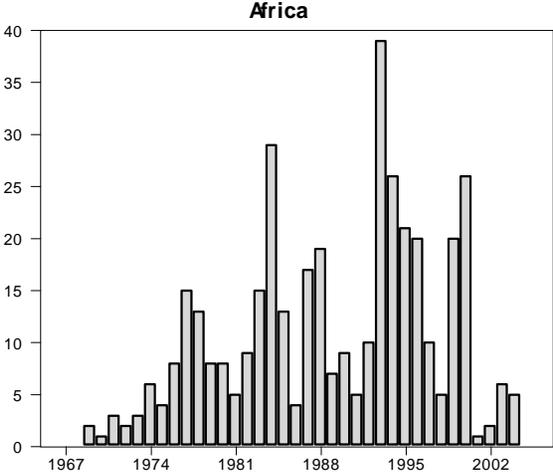
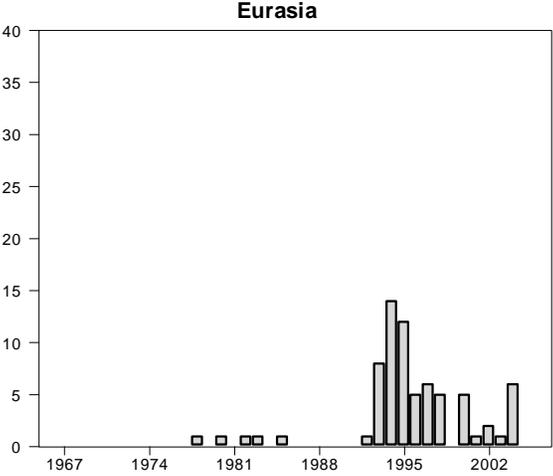
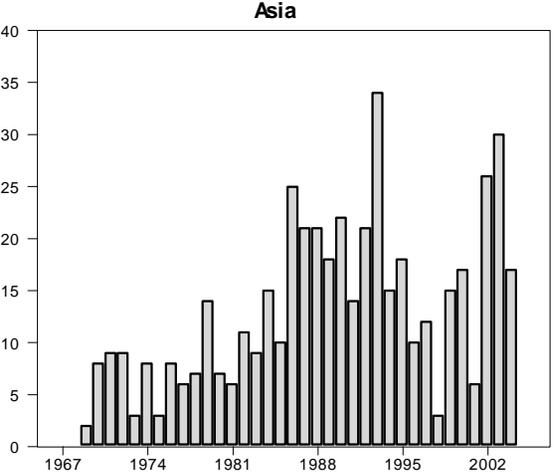
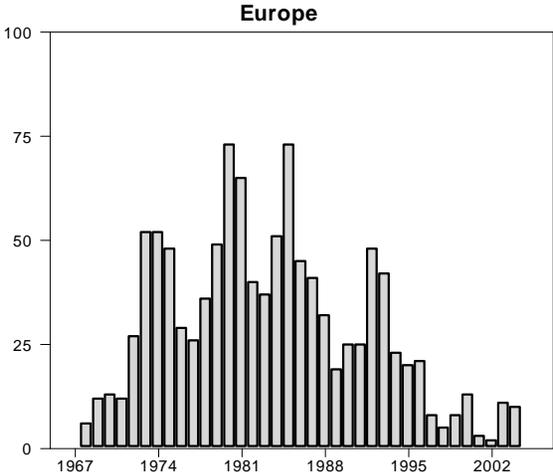
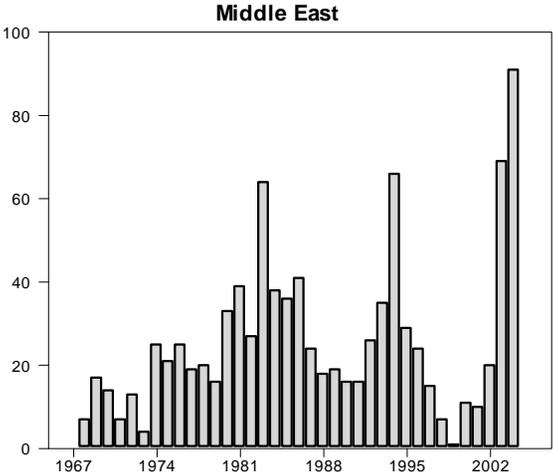
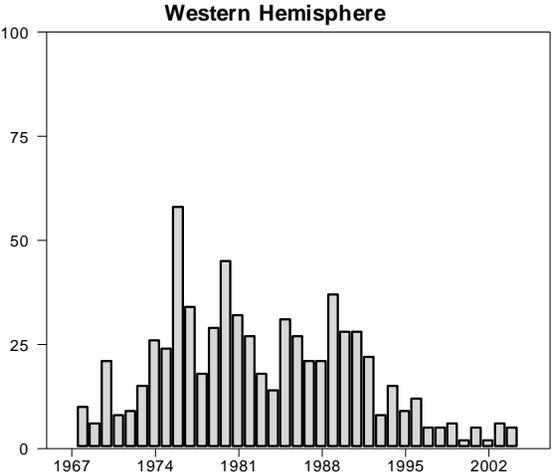


Figure 3: Comparison of ITERATE, MIPT, and PGT Incident Counts

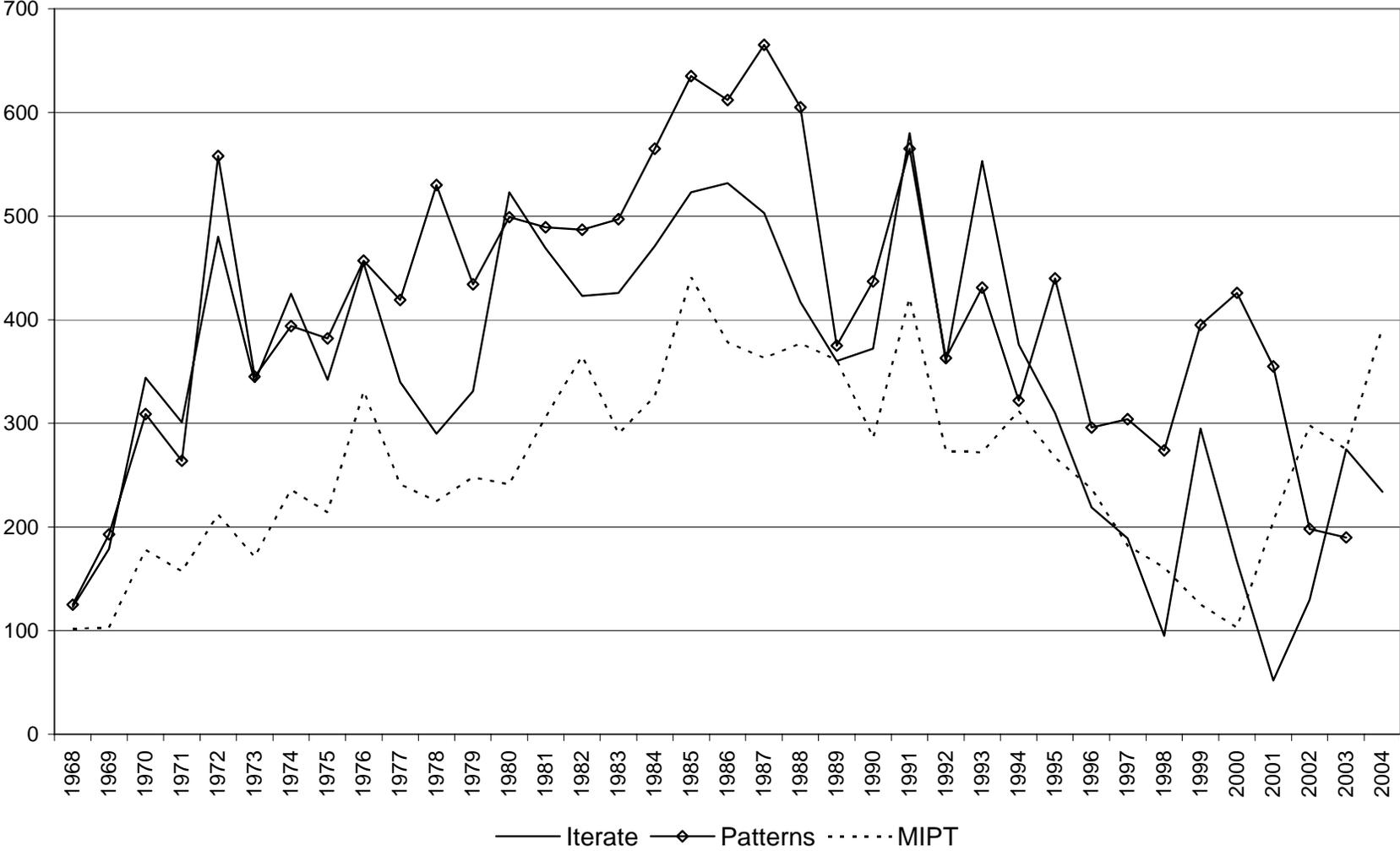


Figure 4: Comparison of ITERATE and MIPT Bombing Totals

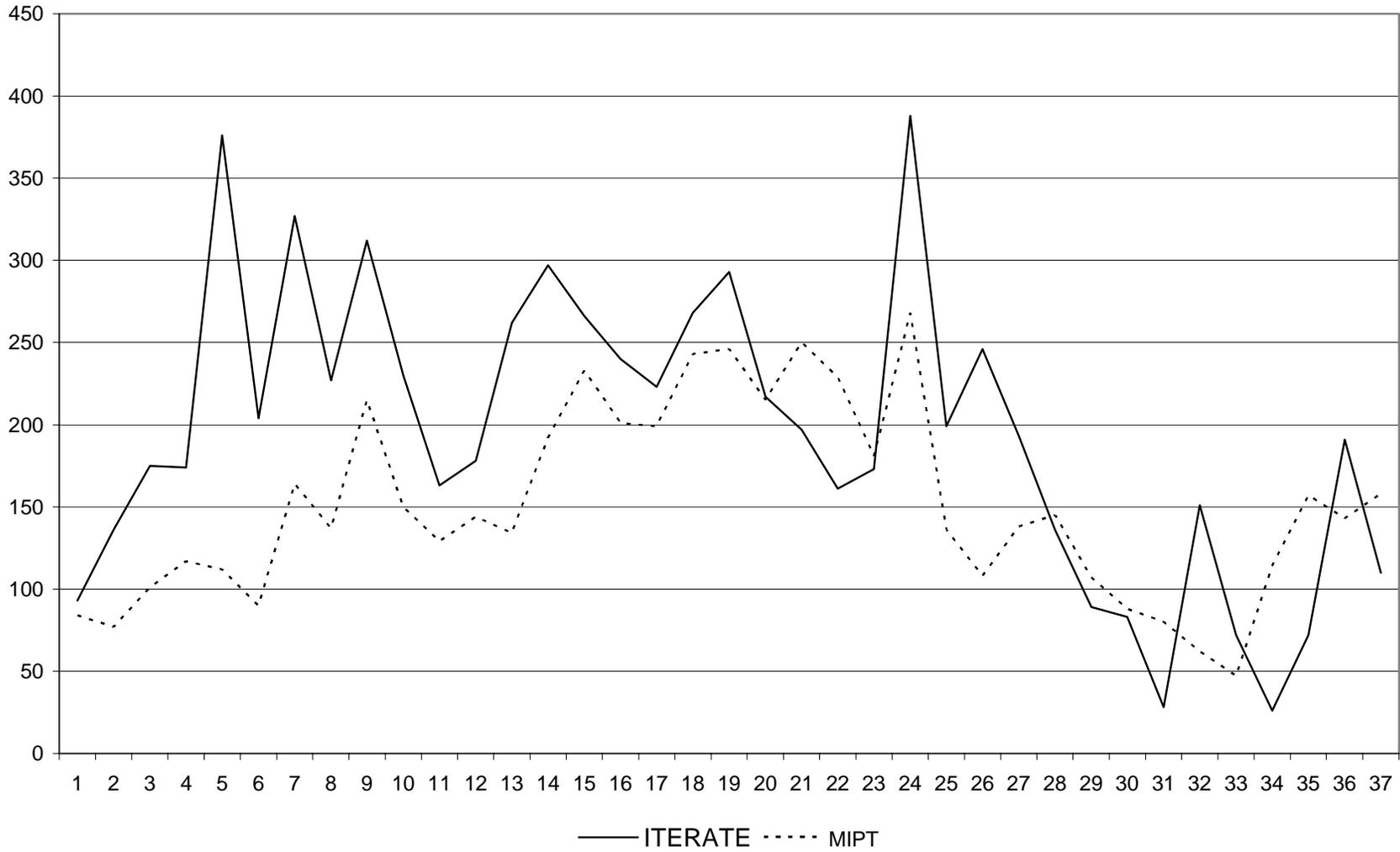
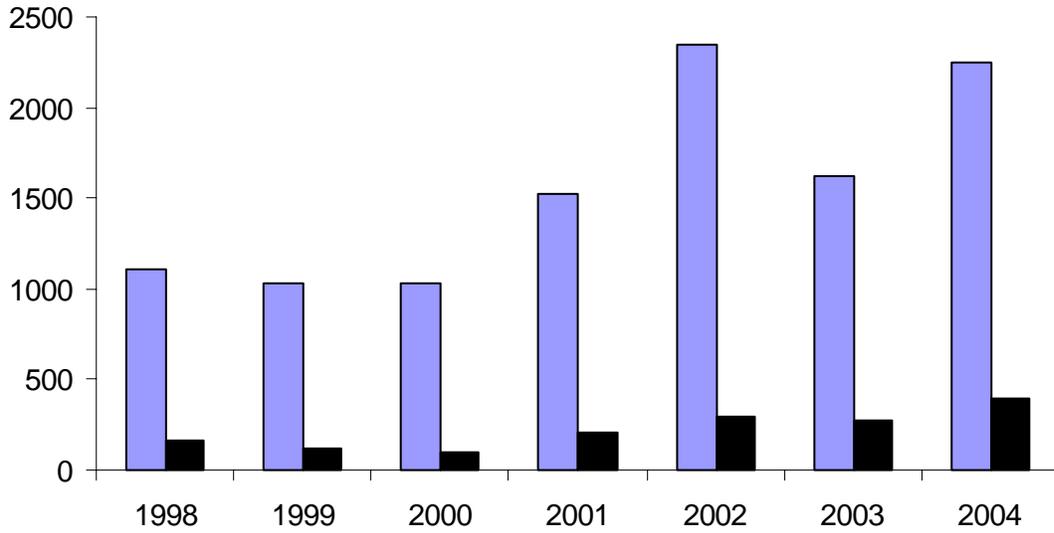


Figure 5: Domestic and Transnational Incidents
Panel a: MIPT Data Set



Panel b: Patterns of Global Terrorism

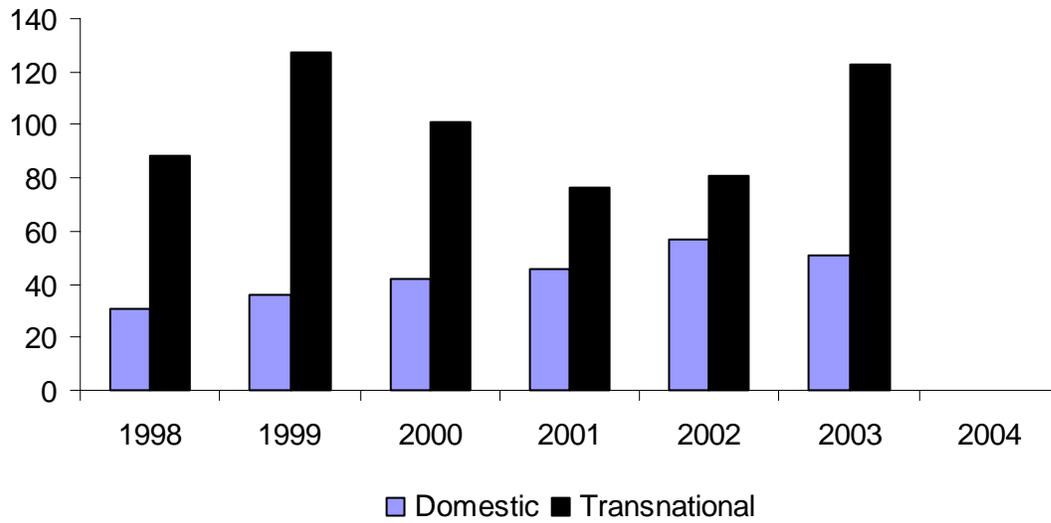


Figure 6: Substitutions Between Attack Modes

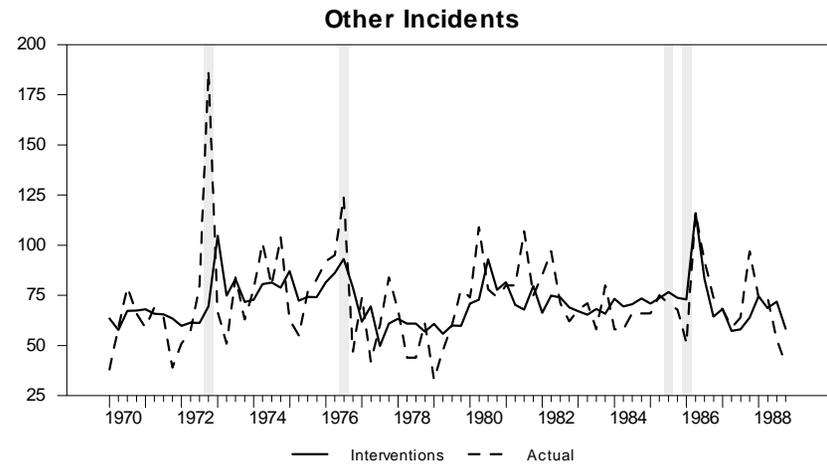
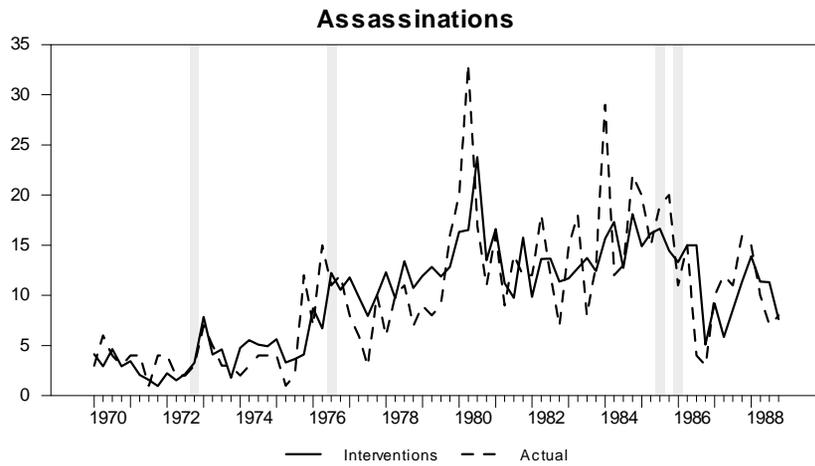
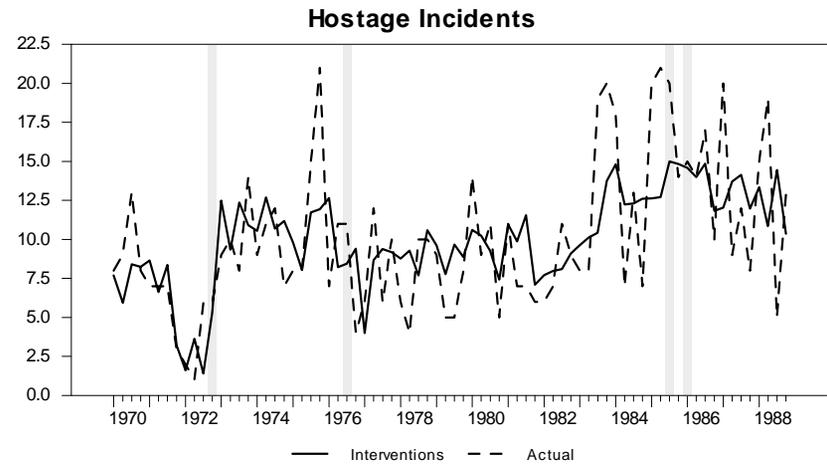
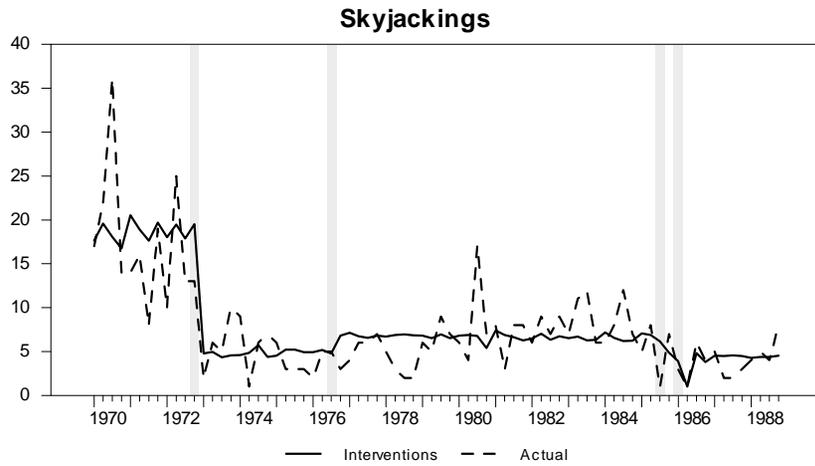


Figure 7: Comparison of the Normal and Poisson distributions

