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THE RISK OF CATASTROPHIC TERRORISM: AN EXTREME VALUE APPROACH

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SUMMARY

This paper models the stochastic behavior of large-scale terrorism using extreme value methods. We utilize a unique dataset composed of roughly 26,000 observations. These data provide a rich description of domestic and international terrorism between 1968 and 2006. Currently, a credible worst-case scenario would involve losses of about 5000 to 10,000 lives. Also, the return time for events of such magnitude is shortening every year. Today, the primary threat is from conventional weapons, rather than from chemical, biological and/or radionuclear weapons. However, pronounced tails in the distribution of these incidents suggest that this threat cannot be dismissed.

Keywords: CBRN, extreme value theory, risk, terrorism.

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1. INTRODUCTION

One of the primary obstacles to the emergence of "complete" terrorism insurance markets has been the lack of accurate forecasts of the likelihood of large-scale terrorism (Kunreuther *et al.*, 2005). This became apparent post-September 11, as insurers reduced their exposure to these extreme risks. Unlike natural disasters, such as hurricanes and earthquakes, the terrorist threat is not well understood. In theory this ambiguity should be reflected in higher premiums rather than unwillingness by insurers to underwrite these risks (Kunreuther *et al.*, 1995). In practice the lack of precision in risk-forecasts in conjunction with government regulations constrain the provision of terrorism insurance.

Understanding the nature of low-intensity, high-impact, terrorist events, is therefore a crucial first step for developing efficient terrorism-risk insurance markets. Yet, the prevailing approach has paid almost no attention to the stochastic structure of these events. Emphasis has fallen instead on vulnerability-assessments (Kunreuther *et al.*, 2005).[1] Inevitably, this implies focusing on worst case scenarios leading to exorbitantly high premiums, which are only justifiable if the distribution of terrorism events is heavy-tailed. However, this remains an open question and is the subject of this paper.

By applying extreme value methods to a database on terrorist events, we estimate the asymptotic distribution of large-scale terrorism. Our data contain roughly 26,000 observations spanning a period from 1968 to 2006. The severity of terrorist attacks is gauged by the number of fatalities and/or casualties (i.e. the sum of fatalities and injuries)

[1] In this context, the secretary of Homeland Security recognized the need for risk analysis in place of vulnerability assessments: "…[R]esources are not unlimited. Therefore, as a nation, we must make tough choices about how to invest finite human and financial capital…To do this we will focus…on objective measures of risk," (remarks by Secretary Chertoff, Washington, D.C. July 13, 2005).

they cause rather than the loss to insurance underwriters. This was a constraint rather than a choice, given the lack of systematic data on the monetary costs of terrorism. Nevertheless, an analysis based on our proposed metrics, can provide an idea of the size of the risks insurance companies face.

Our research is related to a recent, highly publicized, study on complexity theory that gauges the threat from terrorism (Johnson *et al*., 2005). Using data from two recent conflicts, this study concludes that the underlying distribution of terrorist events follows a power law relationship, with a scaling parameter of 2.5. Our approach and theirs certainly share some common ground. The statistical theory that underlies the limiting behavior of extreme fluctuations is that common ground. In Johnson *et al*. (2005), the relevance of this theory is that it provides a justification for the emergence of a power law relationship. Here the connections to that theory are perhaps more transparent, but otherwise its role is the same. However, there are important differences that separate their work from ours. These are not limited to differences in methodology alone, but have to do with how we think about risk. Unlike many natural phenomena, which are characterized by *stable* (or slowly evolving) scale-invariant relationships, we view the risk of large-scale terrorism as an evolving threat. As such, the limiting-form of extreme fluctuations within our data is itself subject to fluctuation. It is in this respect that the two papers differ.

Man-made risks, such as terrorism, are inherently different from naturally occurring risks. The critical point of separation is the element of intent, present in acts of terrorism, but absent in natural disasters. Unlike Mother Nature, terrorists adapt. They do so by reorganizing and restructuring, by redefining parameters of attack, by adopting new tactics and by acquiring new weaponry. These innovations can be part of an ongoing effort to increase the potency of attacks, or they can be triggered by a change in counter-terrorist practices that disturb the status quo (Michel-Kerjan, 2003). At the same time an ever-changing geopolitical landscape seeds new political/terrorist movements with new ideologies and a higher propensity for violence. What all of this means is that the distribution of terrorism is unstable, more so than for any naturally occurring phenomenon.[2]

The critical issue is whether we can characterize this instability. Unfortunately, capabilities of terrorists as well as counter-terrorist agencies are typically unobservable except in the terrorism-data themselves. But *to the extent* that the probability law governing terrorist activities changes smoothly over time it may be feasible to forecast *current* and/or *near-term* risks on the basis of established patterns within existing data. Forty years ago an attack on the scale of 9/11 could not have been foreseen. Since then the distribution of extreme forms of terrorism has changed. Many of these changes took place smoothly over time thus establishing a pattern of non-stationarity well before the attack on the World Trade Center. So while 9/11 was an extraordinary event, by 2001 it was no longer as implausible as it was four decades earlier. At the same time, risk analysts cannot take a "black box" approach that focuses purely on patterns within data. It is important to identify factors that may affect the nature of terrorism, such as developing conflicts, or growing religious influence, and assess risk in conjunction with these changing trends.

Of course not all risks can be assessed on the basis of existing data: our best forecast of a nuclear weapons strike for instance is zero. Unfortunately, standard techniques, which

[2] While the distinction between disasters that are man-made and those that are natural is a necessary one, it is important not to lose sight of the fact that the distribution of natural events can also be non-stationary. Indeed much recent research in climatology has attempted to assess the strength of these trends either in support of, or as a rebuttal to, the global warming hypothesis. The critical difference is one of degree. The probability distributions underlying losses associated with natural disasters typically change far more slowly over time.

rely on empirical frequencies, are ill-equipped to predict probabilities of objects hitherto unseen. Despite the large number of recorded terrorist incidents, few have involved chemical, biological, or radionuclear (CBRn) weapons.[3] The largest open-source dataset on terrorism (maintained by Pinkerton Corporation's Global Intelligence Services) records only 41 incidents involving weapons of mass destruction (LaFree *et al.*, 2004). Even though we are able to dramatically improve upon these data (see below), it is precisely because of this limited experience with these forms of terrorism that forecasting our exposure to such risks is difficult.

As a consequence the insurance industry has shied away from providing CBRn coverage, except in rare circumstances when dictated by state or Federal mandates (President's Working Group, 2006). The result is an incongruous one, where the market for catastrophic terrorism has ignored precisely those threats that hold the greatest potential for catastrophe. Even with important Federal initiatives, such as the Terrorism Risk Insurance Act (TRIA), prospects for the development of a CBRn insurance market look bleak.

Nevertheless in this paper we make an attempt to better understand these risks. We do this by compiling original data on 450 CBRn incidents worldwide over the last half century. However, from the outset it should be understood that our analysis is at best crude. The uncertainty in our risk forecasts may be significant. Even so an analysis of existing data can provide insights into how these threats have evolved to date.

The remainder of our paper is organized as follows. Section two describes our data. Section three provides a discussion of extreme value theory. In section four, we estimate

[3] Because "CBRN" is a well known acronym in the literature, rather than dropping the "N" altogether, we have opted to use a lower case "n" to underscore the absence of nuclear terrorism.

the risk of large-scale attacks. Section five reevaluates this risk by region as well as by the type of terrorism—differentiating across tactics and weapons. In section six, we briefly discuss results from sensitivity analyses. Section seven concludes.

2. DATA

Economic methods have been applied to examine various facets of terrorism, including its implications for tourism (Enders and Sandler, 1991), its effects on capital flows (Enders and Sandler, 1996, Blomberg and Mody, 2005), and its consequences for growth (Abadie and Gardeazabal, 2003, Blomberg *et al*., 2004). With the exception of Abadie and Gardeazabal (2003), these studies have relied on the *International Terrorism: Attributes of Terrorist Events* (ITERATE) database, compiled by Mickolus *et al*., (2002). These data report roughly 12,000 *transnational* terrorist incidents, where an event is defined as "transnational" on the basis of criteria relating to the nationalities of the perpetrators, the location of the attack and the nature of the target (Mickolus *et al*., 2002).

By contrast, the *Terrorism Knowledge Base*, maintained by the National Memorial Institute for the Prevention of Terrorism (MIPT), is more comprehensive, in the sense that since 1998, both *transnational* (labeled "*international*" in MIPT) and *domestic* incidents are covered. MIPT data which begin in 1968 and continue to present day, define terrorism as politically motivated acts of violence, or the threat of violence, calculated to create an atmosphere of fear and alarm. While these data are in public domain, a complete or partial dataset is not released. Instead, each recorded incident is assigned a unique uniform resource locator (url). Since there are well over 25,500 recorded incidents, compiling a complete dataset can be time consuming.

We automated this process using data-mining software to extract relevant data by directing it to specific html tags identifying the start and end points for those data. The following example will make this concrete. Figure 1 shows the webpage corresponding to the 1995 sarin-attack in Tokyo. Several pieces of information are laid out according to a template. To retrieve data we direct the software to specific locations within each incident page. Locations are identified by their html tags. For instance the number of fatalities in the Tokyo attack was 12. This information is encoded into the incident webpage as follows: *Fatalities:* 12 *
*. Thus the starting point for data retrieval is "*Fatalities:*" and the end point is "*
*".

In this manner we compiled a dataset on all terrorist incidents recorded in the *Terrorism Knowledge Base* between January 1, 1968 and January 1, 2006. There were 25,594 incidents altogether, which resulted in 35,030 fatalities and 86,861 injuries. In addition to the number of fatalities and/or injuries in each attack, we collected data on the date of an attack, the tactics and weapons employed, as well as a dummy variable indicating whether the attack was a suicide mission.

The MIPT dataset reports only 67 incidents involving chemical or biological toxins and none involving radionuclear materials. To overcome the paucity of these data, we compiled our own data using primary-sources, internet postings, as well as existing literature on CBRn-terrorism.[4] The resulting dataset spans a period from 1950 to 2005 and

[4] Some of our data draw from a restricted database—the *WMD* database—compiled by the Center for Nonproliferation Studies. In addition we consult the open literature, as well as well as various primary source materials including newspaper articles and internet postings, see Mohtadi and Murshid (2006a) for details.

reports 450 incidents over that time.[5] We define a CBRn event as an attack that involves the direct use of chemical, biological and radionuclear materials, or an incident that implies a threat to their containment, by a group or an individual. Our data provide details on the type of agent employed and the number of deaths and/or injuries inflicted.

3. BASIC METHODOLOGY

Classical statistical methods are ill-suited for estimating extreme quantiles as small discrepancies in estimation over the main body of a distribution yield widely varying tail behavior. Extreme value theory (EVT) is unusual in that it develops methods for accurately estimating these tails.[6] The key insight explores the limiting behavior of the maxima, M_n, of a sequence $\{X_n\}$ of independent random variables with common distribution F. This is the *extremal types theorem* (Fisher and Tippett, 1928), which states that if an appropriately re-scaled and re-centered sequence, M_n^*, of maxima converges to a non-degenerate law, G, then G belongs to the family of generalized extreme value (GEV) distributions:

$$G(x) = exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}; 1+\xi\left(\frac{x-\mu}{\sigma}\right) \geq 0 .$$

Respectively μ and σ are location and scale parameters. The shape parameter ξ characterizes tail-thickness and accordingly divides the GEV-family into three subclasses: $\xi < 0$ corresponds to the Weibull family of distributions (bounded tails), $\xi = 0$ corresponds

[5] Excluded are all hoaxes, as well as accidental releases of CBRn material, including notable catastrophes such as the Chernobyl reactor meltdown, the explosion at a Union Carbide plant in Bhopal, and the release of weapons-grade anthrax from a bio-weapons plant in Sverdlovsk, Russia.
[6] For a lucid and eloquent introduction to the theory of extreme values see Coles (2001). Embrechts *et al*., (1997) is also essential for a more rigorous treatment of the subject.

to the Gumbel family (light tails)[7] and $\xi > 0$ corresponds to the Fréchet family of distributions (heavy tails).

A formal proof of the *extremal types* theorem is technical (Leadbetter *et al*., 1983). However, the result follows immediately once we recognize that the GEV distribution is the only distribution that is max-stable. Moreover G is the limit family for the sequence M_n^* under fairly mild regularity conditions and this continues to be the case under weaker assumptions than independence (Embrechts *et al*., 1997, Coles, 2001). Unfortunately, stationarity is a necessary assumption, but one which is often violated. In these contexts, pragmatism as opposed to rigor has dictated current practice, which is to introduce time dependence in the extreme value parameters, i.e. assume that $\mu = \mu(t, X)$, $\sigma = \sigma(t, X)$ and $\xi = \xi(t, X)$, where X is some other external variable. While this approach is somewhat arbitrary it has considerable intuitive appeal and is currently the conventional wisdom with regard to nonstationary extremes. This is the approach that we take here.

Applying extreme value theory typically involves "blocking" data into disjoint sub-periods and fitting a GEV distribution to the block maxima, M_n. In setting the block length, researchers face a tradeoff. "Blocking" too narrowly threatens the validity of limiting arguments leading to biases in estimation, while wider blocks generate fewer maxima, leading to greater variability in parameter estimates. Since we employ event-data, one option is to define block-lengths in terms of the number of incidents. For example, we could arrange our data into 100-event blocks and fit a GEV model to the resulting maxima.

[7] Clearly $G(x)$ is undefined when $\xi = 0$. Thus the subset of extreme value distributions for which $\xi = 0$ should be interpreted as the limit of $G(x)$ as $\xi \to 0$, which corresponds to the Gumbel family.

However, this approach leads to difficulties in interpretation, since the estimated probabilities are based on a period with no reference to a standard unit of time. To mitigate this problem, we transform our event-data into daily time series, where a given data point is the aggregate across all events on that day.[8] Below we report results based on the *semi-annual* maxima of these time series, although the sensitivity of our findings is checked against alternative blocking lengths (see section 6).

Once the data have been "blocked," estimation is done using maximum likelihood (ML). Although in general the asymptotic properties of ML-estimators do not carry over because the support of the GEV distribution is a function of parameter values. However, this issue can be tucked away behind an important result due to Smith (1989), who finds that all of the standard properties of ML-estimators carry over when $\xi > -0.5$. In practice, this will be the case in most situations. However, in some of our model specifications an estimate of $\xi = -0.5$ could not be ruled out at conventional levels of statistical significance. For this reason, we also apply Bayesian estimation (see section 6).

4. EXTREME VALUE MODELING OF TERRORISM

4.1. Extreme Value Modeling Of Terrorism

In Figures 2A and 2B respectively, we plot the largest number of fatalities and casualties (i.e. the sum of fatalities and injuries) from terrorist attacks on any given day over a six month period. These series, which are plotted on a logarithmic scale, cover a period from January 1968 to January 2006. As is evident, the extent of violence has grown over time:

[8] Another option would be to construct a sequence based on the maximum event over some given time. In earlier versions of this paper, we considered this approach. The results were essentially unaffected.

the largest number of single-day fatalities has grown at an average annual rate of 6.8 percent. When the metric is the total number of casualties, this trend is even more pronounced, showing an average annual increase of 7.8 percent.

Below our discussion reveals an involved pattern of non-stationarity, one which is not readily modeled by incorporating a simple trend in the "location" of the underlying probability distribution. Since the late 1960s, evolution in the nature of terrorism has been dramatic. In the past, the distribution of large terrorist attacks was concentrated and fatalities were low. Today, an act of terrorism can claim thousands of lives. Thus, the distribution of extreme terrorism differs not only in terms of its location, but also in its scale and shape.

In part, this evolution (both in general and its more extreme forms) can be understood as a consequence of political events such as the 1982 Lebanon war, the rise of Islamic fundamentalism and the end of the Cold War (Enders and Sandler, 2000). This escalation in violence has also mirrored advances in technology, which includes the adoption of new weaponry, as well as new tactics, such as suicide bombing. At the same time, the organization of modern terrorist groups has evolved from hierarchical structures to a system of horizontal networks of cells. Though this organizational structure is more robust to penetration, it lacks a well-defined chain of command; consequently the leadership has less control, increasing the influence of extremist elements within these groups. Perhaps though, the most important transformations have been in the ideologies and objectives of the organizations themselves (Gearson, 2002). What separates bin Laden's group from more traditional terrorists, is not better access to technologies, but its greater appetite for violence, which, though misconstrued, seeks its justification in theology. It is this base that provides al Qaeda and similarly motivated groups their added cogency.

Unfortunately, as our analysis is based on time-series variation in our data, we cannot explore all of these hypotheses. Even so, by better understanding patterns in the evolution of (extreme forms of) terrorism, we can start to think about when these changes occurred and what their proximate causes could have been. It is important though to recognize the limitations of this exercise. Our focus is on assessing worst-case plausible risks, not on measuring the causal effect of the determinants of terrorism. This necessitates that we separate the extreme variation in our data due to shifts in its distribution, from that due to the distribution itself. We recognize that these distributional dynamics are complex and difficult to characterize. A particularly important constraint is the precision with which we can estimate tail dynamics and to a lesser extent changes in scale.[9] Pre-transforming data can mitigate these concerns by lessening the variation in shape and scale parameters, thereby reducing, or even eliminating, the need to impose structure on these parameters. However, any such transformation is arbitrary and entails a loss of information with regard to the dynamic behavior in scale and shape.

Here we take a balanced approach, examining distributional dynamics using both log-transformations of the data and the original data themselves. As the nonstationarity in casualty data is greater, accurate risk forecasting is difficult without first taking log transformations. Thus, casualty-risks are assessed solely on the basis of transformed data.

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[9] The difficulty of characterizing the variation in the scale parameter arises, because it is important to ensure the positivity of $\sigma(t)$. Typically this would involve fitting a linear trend in the log-scale parameter $\sigma(t) = \exp(\beta_0 + \beta_1 t)$, which can lead to difficulties in estimation.

4.2. Analysis of extreme terrorism using untransformed data

Below we fit a number of extreme value probability models to our (untransformed) data. To reiterate, these are the semi-annual maxima of single-day fatalities between January 1968 and January 2006. We consider the full sample of these observations as well as two important sub-samples. The first excludes the influential September 11 observation.[10] The second excludes domestic terrorism and focuses solely on international incidents.

To provide a benchmark for comparison we begin by fitting a stationary extreme value distribution to our data (Table I, column 1). As is evident from the QQ plot (Figure 3) the stationary model does not provide a satisfactory fit. This is not surprising since the severity of terrorist attacks has increased over time. To account for this trend, we consider a number of specifications that model the variation in μ as smooth functions of time (Table I, columns 2-4). These non-stationary alternatives do better than the stationary model: the likelihood ratio statistic for comparing these alternatives varies between 13.6 [=2(-415.8-(422.61)] and 14.4 [=2(-415.4-(-422.61)], which easily rejects the null that the data are generated from a stationary process. Moreover, corresponding QQ plots provide closer approximations to linearity (Figure 3).

However, not all changes in the distribution can be modeled as smooth functions of time. When the distribution changes abruptly we can specify breaks in the time profile of location, scale and shape parameters. We allow for this possibility below but additionally

[10] Once we exclude September 11, the second bloodiest day in terms of terrorist related fatalities was on August 11, when there were 259 fatalities. The majority of these (252) correspond to an incident in Angola.

incorporate a linear trend in the location parameter.[11] All possible break points beginning in the early 1970s and continuing into the post-9/11 era are considered. Whenever we pool domestic and international incidents, we allow for a break in the location parameter to reflect changes in data reporting practices in 1998. We present our results selectively on the basis of their statistical significance, but also on account of the historical significance attached to specific years.

The first important break in the distribution is evident in the late 1970s. In Table I we model this break as taking place in the second half of 1979. The choice of 1979 seems relevant for two reasons. First, it coincides with a regime change in Iran, which marks the *beginning* of the spread of Iranian influence through out the Middle East. Second, 1979 was the year in which Al-Masjid al-Haram (the Grand Mosque at Mecca) was besieged by rebels. The attack on the Grand Mosque marked the start of a new era of terrorism in which, for the first time, the number of fatalities exceeded 100.[12] Since that attack, there have been 33, 100-plus-fatality incidents. Five of these took place in the 1980s, 11 in the 1990s and between 2000 and 2006 there have already been 17 such incidents.

The pattern is obvious. Explained as an increase in scale and weight in the right tail of the underlying distribution (Table I, columns 5-8), these changes although first evident in the late 1970s have clearly continued through to present day.[13] Consequently, the possibility now exists for very large events, in which several hundred, perhaps several

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[11] As noted earlier estimation of the shape parameter is often imprecise. Consequently it is unrealistic to impose too much structure on ξ. At the same time it is not always feasible to allow $\sigma(t)$ to vary smoothly over time (see note 9). Thus in our analysis we limit the variation in ξ and σ to one break-point.

[12] The Grand Mosque at Mecca was besieged on November 20, 1979. The incident is shrouded in secrecy and exact casualty figures are unavailable. Our data report 158 fatalities. This is almost surely an underestimate. Other figures have placed the total number of dead close to 400 with casualty figures approaching 1000.

[13] Evidence of an increase in weight in the tail is weaker once we exclude the influential September 11 observation. Nevertheless the scale-effect remains (Table I, column 7).

thousand, are killed. Yet, it would be naive to view large-scale terrorism as solely a Middle Eastern phenomenon. By the 1990s this violent strain of terrorism had spread to the African continent and in other parts of the world an emergent class of apocalyptic “new-age” terror groups such as, Aum Shinrikyo, were raising the ante by experimenting with new weapons (Hoffman, 1997, Enders and Sandler, 2000).

It is important to ask therefore, whether the 1990s was a pivot point for the distribution of (large-scale) global terrorism. We find *some* evidence to suggest that it was. In Table I this break in the distribution is introduced in the latter half of 1991, which corresponds to the formal end of Communism and a decline in associated terrorism (Enders and Sandler, 2000, Wilkinson, 2001). It also serves as the natural demarcation between traditional terrorism, advanced by nationalistic and left-leaning groups, and more radical forms of terrorism. Yet the statistical evidence points to only small discontinuities in the distribution of terrorism-related fatalities (Table I, columns 9-11). This result is not completely surprising; after all, the lull in violence following the end of the Cold War was short-lived. At the same time the escalation of radical extremism in the 1990s, though dramatic for certain regions, was not unprecedented from a global perspective. Thus, while we document an uptick in μ, its implication for overall risk exposures is *slight* (this is more clearly evident in Figure 4A, which is described in greater detail below).

By contrast, a more significant break is evident in 1998. This coincides with the change in data reporting practices that took place that year. Yet, this should not be viewed as simply an artifact of the data. Our recent experience with domestic terrorism bucks an established pattern of low-level violence. At the core lie a number of particularly violent civil conflicts, such as the "war" in Chechnya and the uprising in Algeria. Thus, it is noteworthy that a number of data points (post-1998) representing peaks in terrorist-related violence correspond to domestic incidents. Undoubtedly, an important component is also the Iraq insurgency. Evidence of this conflict appears as a rightward shift in the location of the distribution (Table I, columns 12-15) and a greater concentration of the probability mass in a higher range. Thus, perhaps paradoxically, an implication has been a reduction in scale, although much of this is simply a negative "correction" for the additional structure on the distribution implied by the September 11 attacks.

The above analysis reveals a rich dynamic in the distribution of the first-order statistic of fatalities, captured almost entirely through changes in scale and shape. While we find evidence of shifts in location, these are not large enough to account for trends depicted in Figure 2A. This is evident in Figure 4A which plots the predicted 95^{th}- and 99^{th}-quantile-values for each of our estimated models. In essence therefore, these are dynamic risk forecasts, which vary little when we impose structure on the location parameter alone. Unfortunately, precise modeling of changes in scale and shape is difficult. Hence, a faithful representation of distributional dynamics is uncertain.

Scale-stabilizing data transformations can provide a way around these difficulties; by compressing higher-level variation the need to characterize dynamic behavior in the tails of distributions is circumvented, since much of this variation can now be modeled as shifts in location. However, the possibility then exists for attributing a disproportionate share of the variation in our data to shifts in the location of the distribution rather than the distribution itself.

4.3. Analysis of extreme terrorism using log-transformed data

In this section we examine log transformations of both fatality *and* casualty data. Models that fit to these data prove better predictors of nonstationary trends apparent in Figure 2 (see the dynamic risk forecasts in Figure 4B). Evidently log transformations can eliminate an important source of bias from our parameter estimates. Of particular importance are biases in estimation of the parameter ξ. This is so for two reasons. First, small discrepancies in its value can translate into large variances in risk forecasts. Second the discontinuity in extreme value distributions at ξ=0 leads to difficulties in interpretation because this point lies in the interior of the set of our parameter estimates. However, the null ξ=0 is easily rejected in favor of two diametrically opposed alternatives, i.e. $\xi > 0$ (see our earlier results, Table I) and $\xi < 0$ (see our analysis of the logged data, Table II).

Clearly, since model fits based on logarithmic transformations compress variation in the upper tail, an analysis of these data will necessarily yield smaller estimates for ξ. However, in this instance the sign of ξ changes. As a consequence we must conclude that the support of the extreme value distribution is bounded in one case $(\xi < 0)$ and unbounded in the other $(\xi > 0)$. These contrasting conclusions should be understood in terms of the extent to which our models predict distributional dynamics—in this respect the models perform better when the data are transformed, consequently, the "support" for random variation within the distribution of extreme value laws is smaller. While it seems reasonable to suppose that the true model lies in between these extremes, a conclusion in which the support of extreme realizations in our terrorism data is bounded seems reasonable given that the vast majority of terrorist incidents involve the use of conventional weapons.

These differences notwithstanding, our analysis of log-transformed data convey many of the same messages as before. For instance, there is evidence of a break in the late 1970s, when the distribution of extreme fluctuations in casualty data developed fatter tails (Table II, column 8). The consequences of the fall of Communism are also evident, appearing as a negative "locational" shift in the distribution (Table II, column 4) as well as an increase in the probability mass toward the upper tail (Table II, columns 4, 9 and Figure 4B).

Much of the structure in the levels data therefore seems to be preserved in the logged series, although not necessarily in a "homomorphic" way. Importantly, however, there are notable differences as well, some of which are to be expected. Even so, the implication of these differences for forecasted risks can be significant, as is discussed below.

4.4. Risk Assessments

We use parameter values reported in Tables I and II as the basis for calculating risks. These forecasts reported in Tables IIIA and IIIB present some of the same information shown in Figure 4 (A and B). However instead of showing quantiles these tables report the risk associated with attacks of different magnitudes. Moreover whereas in Figure 4 (A and B) the 99th (95th) quantile corresponds to the one percent (five percent) *semi-annual* risk level, the probabilities reported in Table III (A and B) are rescaled to reflect annual risks.[14]

[14] This is done simply by taking the following transformation: $1-(1-p)^2$ where p is the probability of an event occurring in any given six month period.

Lower values of $\hat{\xi}$ mean that assessments of *current* risk based on log-transformed data (Table IIIB) are relatively low (Table IIIA). However stronger trend components in $\hat{\mu}$ also mean that estimated *future* risks can be relatively high. Clearly, there is a tradeoff between transforming data and attributing a larger fraction of the variation to trends versus absorbing some of this into a fatter tail. The truth probably lies somewhere in the middle. Our forecasts are therefore expressed as a range of values: the risk of a 1000-fatality day for instance lies between 0 and 0.24. Notwithstanding this lack of imprecision, the underlying message is clear: threats of this magnitude can represent a non-negligible risk.

For larger events the message is less clear. The current annual risk of 10,000 fatalities on a single-day for instance varies between 0 and 0.06. While in many specifications this risk is negligible (in particular when the basis for risk forecasts are the logged data), it is difficult to dismiss this threat in light of recent terrorist activity. It is important to remember that we have already witnessed a 3000-fatality event as well as an attempt, by terrorists, to simultaneously blow up ten airliners. Consequently, terrorism on such a catastrophic scale is not unimaginable.

Naturally, risks are higher when the metric is the number of casualties, rather than fatalities. For instance the probability of 1000-casualties on a single day is roughly between 0.4 and 0.7 (this range of forecasts excludes our stationary model). This figure is likely to rise to between 0.8 and 0.9 by 2015. These forecasts seem high, but in actual fact are consistent with the pattern of terrorism in recent years. Between 1988 and 2006, casualties from terrorist activities exceeded 1000 on eight separate occasions. Thus, a frequency estimate would place the probability of an event leading to 1000-plus casualties at roughly

0.5. This corresponds well with our estimates. The risk of larger events such as a 10,000-casualty day is also high, varying between 0 and 0.13. By 2015 this risk could rise to 0.2.

5. WHAT POSES THE GREATEST THREAT AND WHERE?

Thus far, we have provided assessments of terrorism-risk as they apply globally. However, risks are likely to vary across regions, just as they have varied over time. In this section we provide a breakdown of the current threat by region. In addition, we ask what tactics and/or weapons currently pose the greatest threat.

5.1. Where is the Threat Greatest?

For some regions the paucity of available data makes inference difficult. In North America for instance there are relatively few recorded incidents. Of these, the majority resulted in no loss of life. Consequently, there is not enough variation within these data from which to estimate probability models. Nevertheless, we can model risk exposures in five regions—Africa, Latin America and the Caribbean, the Middle East, South Asia and Western Europe.

Here we do not present our results in full. Table IVA reports only risk-assessments derived from best-fitting models. Our results suggest that risks of large-scale attacks are greatest in Africa followed by the Middle East and South Asia. This is not surprising since all three regions have experienced terror attacks with hundreds of fatalities.

The range of plausible risks is widest in Africa. The one-percent risk level lies in a range between 4000 and 10,000+ fatalities (Table IVA, columns 1 and 6). This degree of variability reflects Africa's volatile experience with terrorism, which escalated in the 1990s with the rise of Islamic movements in countries such as Algeria before declining in the last few years. In the Middle East, political events, such as the Iraq war, proved influential over risks associated with large-scale terrorism. Currently, the one-percent risk is in excess of 3,000 fatalities. In South Asia, data on terrorism are sketchy prior to the 1980s. Nonetheless, it is evident that a number of recent attacks have elevated risks; currently the one-percent threat level is roughly between 2,000 and 4,000 fatalities.

In contrast to these three regions, the risk of large-scale terrorism is low in Latin America and Western Europe. For the latter these risks have fallen over time, reflecting a decline in IRA- and Basque Separatist-terrorism. At the same time, the end of the Cold War implied a reduction in the number of left-leaning terrorist organizations as well as related forms of terrorism. Accordingly, current risk assessments of large-scale terrorism are very low. However these forecasts need to be interpreted with care. The current threat that Western Europe faces is probably not from domestic groups such as the IRA, but from global terror organizations such as al Qaeda. However, this threat has yet to surface as an established pattern within the data, consequently, our risk assessments are at best a lower-bound of actual threats.

Our analysis of regional breakdowns provides insights by highlighting differences in risk levels across regions. Yet, it is important to recognize that terrorism today is a global phenomenon. As such regional risks cannot be inferred from regional data alone. This is apparent from events in the United States. With one notable exception, pre-9/11 terrorism on US soil was limited in its scope. Therefore, an analysis of this history could not have predicted an event of the magnitude of 9/11.

5.2. What Poses the Greatest Threat?

In this section we consider five forms terrorism: assassinations, armed attacks, bombings, kidnappings, and suicide attacks. In addition we differentiate between conventional and CBRn terrorism.

Our analysis reveals that risks associated with kidnappings and assassinations are lowest (Table IVB). This is not surprising given the low-impact nature of these events. Similarly, low risks were generally associated with armed attacks. However, one recent observation—the attack on a school in Beslan, Russia—has proved influential in elevating these risk forecasts (Table IVB, columns 1 and 6). Not surprisingly the threat from bombings is much higher. At present 2000 to 3000 single-day fatalities is plausible. The risk is even higher when we focus solely on suicide attacks.

Importantly this analysis focuses solely on conventional forms of terrorism. Recently however there has been considerable speculation as to the possibility of a catastrophic CBRn event. However much of this is just that--merely speculation. The incorporation of CBRn weapons into the terrorist arsenal has been slow. As a result, we have had very limited experience with CBRn attacks. This makes risk assessments difficult. Moreover, the vast majority of CBRn incidents, even the most sophisticated, have involved limited loss of life. Hence, there is not enough variation in our fatalities data from which to arrive at sensible risk assessments. However, it is possible to arrive at tentative forecasts on the basis of casualty figures (i.e. the sum of injuries and fatalities).

In Table IVB, column 11, we report the risk of CBRn attacks of various magnitudes. Our estimates are based on data from 1977 to 2005. We omit data from previous years, since data for these years are sketchy. Based on our model estimates we consider the risk of 1000, 5000 and 10,000-casualties on a single day. To provide a benchmark for comparison, we contrast these estimates with the risk of a similar sized event using non-CBRn weapons (Table IVB, column 12).

In contrast to conventional forms of terrorism, there is considerable variation in the effectiveness of CBRn-attacks. This variability is captured in the form of a heavy right tail. This has an important implication. While conventional weapons pose a much greater threat for smaller (*casualty*) events, for larger events the situation is reversed. For instance, the probability of 1000 casualties arising from CBRn attacks on a single day is 0.28. This compares to a risk of 0.56 associated with conventional terrorism (Table IVB, columns 11 and 12). When the number of casualties rises to 10,000 the respective probabilities are 0.08 and 0.03. In the last column of Table IVB, we combine probability estimates of CBRn and non-CBRn events into one estimate of the *conditional* probability that an attack is due to CBRn weapons.[15] For low-level attacks causing 1000 casualties, this probability is 0.33. However, this figure *rises* to 0.52(0.73) when an attack causes 5000(10,000) or more single-day casualties. Thus, conditional on an attack the probability of it coming from CBRn sources is higher the larger the number of casualties.

The overall message from this analysis is mixed. Thus far, use of CBRn weapons has failed to cause loss of life on a large scale. In this respect, the threat from conventional weapons is more significant. Still, risks associated with CBRn weapons are much higher when we restrict our analysis to casualties. It is important though to keep in mind that these

[15] This is calculated simply as $P(y \mid x) = P(y,x)/P(x) = P(y)/\left[P(y)+P\left(y^C\right)\right]$, where y, y^C and x are respectively, CBRN, non-CBRN and all events of magnitude z or greater.

risk assessments are based on a limited sample of observations. Thus, there is considerable uncertainty as to what threat CBRn weapons actually pose.

6. SENSITIVITY ANALYSES

To check the robustness of our findings we conducted some sensitivity tests. We considered the implications of using alternative "blocking" lengths, as well as a Bayesian estimation framework as an alternative to maximum likelihood. Though space considerations prevent us from reporting these results, we summarize the main conclusions of this analysis here.[16]

In order to check the sensitivity of our findings to alternative choices of block lengths, we re-estimated our regressions using quarterly and annual maxima of our daily fatalities- and casualties-series. Not surprisingly, the choice of blocking length proved inconsequential for comparing the risk of smaller attacks. However, the use of a quarterly blocking-window usually implied higher estimated values of both scale and shape parameters. By contrast, the tail of the limit family was shorter and trend components stronger when using an annual window. These differences proved to be important only at very high ranges within the support of the distribution. But for attacks leading to 5000 or fewer deaths our forecasts were not sensitive to the choice of blocking length.

To check the sensitivity of our findings to the method of estimation, we re-estimated our probability models using a Bayesian approach. This offers some advantages over maximum likelihood. The introduction of prior information can supplement existing data and sharpen estimates. Even when it is not possible to elicit prior information, large-sample properties of Bayesian estimators are to be preferred, since they are independent of

[16] A more detailed presentation is provided in the working version of this paper, which is available on request.

parameter values (Coles and Twan, 1996). This is often not a concern. In the current context, log transformations of our data imparted shorter tails on the distribution of the transformed series. Thus, in some instances, an estimate of $\xi = -0.5$ could not be ruled out at conventional levels of statistical significance. Moreover, Bayesian methods also account for model uncertainty and variability of future observations (Coles and Twan, 1996).

Our analysis using Bayesian methods compared well with our risk assessments based on maximum likelihood estimation. In particular, the posterior means of our parameters were very close to those obtained using ML-estimation. This is reasonable given the variability of our priors. Moreover, the "support" of our posterior also compared favorably with our risk assessments, based on maximum likelihood. This again supports the conclusion that our findings are not particularly sensitive to the method of estimation.

7. CONCLUSIONS

In this paper, we analyzed the risks of catastrophic terrorism using a unique dataset gathered from the internet and various other primary sources. Our results suggest that currently, a credible worst-case scenario is one that involves the loss of between 5000 to 10,000 lives on a single day. However, this conclusion is sensitive to the form of terrorism. The threat of CBRn-terrorism for instance is very different from that posed by conventional attacks. Our analysis reveals that CBRn terrorism is more likely to cause injuries, as opposed to loss of life. Although by this metric, the risk can be significant.

In interpreting our results, it is important to recognize that risks are continually evolving: the distribution underlying catastrophic terrorism is unstable. Over the last forty years this instability has manifested itself in two ways. First, the right tail of the distribution has got heavier. This has been accompanied by an increase in positive skewness, i.e. a redistribution of the probability mass into a higher range of values. Second, the scale of the distribution has increased dramatically.

These developments are consistent with an overall pattern of change beginning in the late 1970s, with the emergence of radical terrorist organizations, and continuing through to present day. It seems that earlier models of terrorism, which focused on maximizing disruption, have given way to new forms of terrorism in which the metric for success is the number of fatalities. Yet, there should be no presumption that this new paradigm represents the future of terrorism. If, for instance, the social and political causes for the revival of Islamic fundamentalism were to erode, probability laws governing the distribution of terrorism today will be of little significance for understanding future risks. It is critical therefore, to identify potential determinants of the distribution of large-scale terrorist attacks. However this is not simply to establish links between future risks and specific future outcomes. At issue is also the accuracy of current forecasts. These are affected by our ability to disentangle that variation in our data, which is due to structural breaks in the distribution, from that, which is due to the distribution itself.

Since the risks associated with catastrophic terrorism are in continual flux, risk assessments must be part of an ongoing effort. In assessing these risks it is important that we take a pragmatic approach which weighs model forecasts against data from other sources relevant for the future of terrorism risk.

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REFERENCES

Abadie A, Gardeazabal J. 2003. The economic cost of conflict: a case study of the Basque country. *American Economic Review* 93: 113-132.

Blomberg B, Mody A. 2005. How severely does violence deter international investment? Claremont McKenna College, Working Paper No. 2005-01.

Blomberg B, Hess G, Orphanides A. 2004. The macroeconomic consequences of terrorism. *Journal of Monetary Economics* 51: 1007-1032.

Coles SG. 2001. *An Introduction to Statistical Modeling of Extreme Values*. Springer Verlag: London.

Coles SG, Tawn JA. 1996. A Bayesian analysis of extreme rainfall data. *Applied Statistics* 45: 463-78.

Embrechts P, Klüppelberg C, Mikosch T. 1997. *Modeling Extremal Events for Insurance and Finance*. Spring Verlag: Berlin.

Enders W, Sandler T. 1991. Causality between transnational terrorism and tourism: the case of Spain. *Terrorism* 14: 49-58.

Enders W, Sandler T. 1996. Terrorism and foreign direct investment in Spain and Greece. *Kyklos* 49: 331-52.

Enders W, Sandler T. 2000. Is transnational terrorism becoming more threatening? A time-series investigation. *Journal of Conflict Resolution* 44: 307-332.

Fisher AR, Tippett LHC. 1928. Limiting forms of the frequency distribution of the largest and smallest member of a sample. *Proc. Cambridge Phil. Soc.* 24: 180-190.

Gearson J. 2002. The nature of modern terrorism. *The Political Quarterly* 73: 7-24.

Hoffman B. 1997. The confluence of international and domestic trends in terrorism. *Terrorism and Political Violence* 9: 1-15.

Johnson N, Spagat M, Restrepo JA, Bohórquez J, Suárez N, Restrepo E, Zarama R. 2005.From old wars to new wars and global terrorism. Universidad Javeriana--Bogotá, Documentos de Economía 002339.

Kunreuther H, Meszaros J, Hogarth RM, Spranca M. 1995. Ambiguity and underwriter decision processes. *Journal of Economic Behavior and Organization* 26: 337-352.

Kunreuther H, Doherty N, Goldsmith E, Harrington S, Kleindorfer P, Michel-Kerjan E, Pauly M, Rosenthal I, Schmeidler P. *TRIA and Beyond: Terrorism Risk Financing in the US*. Wharton Risk Management and Decision Process Center, University of Pennsylvania, Report.

Lafree G, Dugan L, Franke D. 2004. Materials prepared for workshop on non-state actors, terrorism, and weapons of mass destruction. Center for International Development and Conflict Management Working Paper.

Leadbetter MR, Lindgren G, Rootzen H. *Extremes and Related Properties of Random Sequences and Processes*. Springer Verlag: London.

Michel-Kerjan E.2003. Large scale terrorism: risk sharing and public policy. *Revue d'Economic Politique* 113: 625-648.

Mickolus FE, Sandler T, Murdock JM, Flemming PA. 2002. *International Terrorism: Attributes of Terrorist Events*. Vinyard Software.

Mohtadi H, Murshid AP. 2006. A global chronology of incidents of chemical, biological, radioactive and nuclear attacks: 1950-2005. National Center of Food Protection Defense, Working Paper.

President's Working Group on Financial Markets (PWG). 2006. *Terrorism Risk Insurance*. US Department of Treasury, Report.

Smith R. 1989. A survey of non-regular problems. *Proceedings, 47th Meeting of the ISI*: 353-72.

Wilkinson P. 2001. *Terrorism versus Democracy: The Liberal State Response*. Frank Class: London.

Table I. Extreme Value Models Fitted to Fatalities Data

		Dependent Variable: fatalities														
		Smooth trends in the location parameter				Iranian revolution; attack on the Grand Mosque				End of the Cold War; milllennium			Post September 11; Iraq insurgency			
		Stationary model	Linear trend	Quadratic trend	Exp. trend	Break in scale	Break in shape	9/11 obs. excl.	intl.	Break in location	9/11 obs. excl.	intl.	Break in location	Break in scale	9/11 obs. excl.	intl.
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
location parameter (μ)	constant	25.23	16.83	17.11	16.75	6.98	12.95	6.59	11.72	12.62	12.78	13.90	12.55	12.67	12.84	11.68
		(4.53)	(4.03)	(4.25)	(4.02)	(3.66)	(4.47)	(3.44)	(3.01)	(3.01)	(3.08)	(2.99)	(3.12)	(3.08)	(3.20)	(2.61)
	t		3.11	1.98		9.93	3.50	7.81	3.39	2.52	2.51	2.92	2.83	2.79	2.88	2.77
			(1.29)	(5.20)		(2.89)	(1.73)	(2.78)	(0.85)	(1.20)	(1.19)	(1.53)	(0.93)	(0.90)	(0.99)	(0.69)
	t^2			0.46												
				(2.04)												
	exp(t)				0.78											
					(0.27)											
	1991-06 dummy									-4.37	-4.54	-3.49				
										(3.99)	(4.06)	(6.21)				
	1998-06 dummy		13.88	12.82	8.10	-60.42	-49.80	-52.35		-59.98	-59.80		13.79	-46.00	13.66	
			(3.33)	(5.64)	(4.40)	(14.45)	(3.95)	(6.14)		(5.76)	(5.56)		(2.75)	(4.43)	(2.95)	
	2002-06 dummy												29.61		29.27	15.05
													(4.57)		(5.07)	(2.29)
	1991-06 trend									26.20	26.57	6.48				
										(12.53)	(12.86)	(8.49)				
	1998-06 trend					250.46	247.36	241.81		222.22	221.81			234.26		
						(25.90)	(8.06)	(13.33)		(15.07)	(14.89)			(11.93)		
	2002-06 trend												237.58		238.54	
													(19.06)		(20.47)	
scale parameter (σ)	constant	31.59	26.14	26.04	25.93	11.95	23.44	11.84	13.85	18.76	19.76	20.04	20.24	20.85	20.12	17.71
		(5.69)	(5.45)	(5.51)	(5.53)	(3.69)	(5.35)	(3.92)	(3.68)	(3.93)	(4.33)	(3.71)	(4.49)	(4.60)	(4.35)	(3.61)
	1979-06 dummy					16.75		13.48	12.79							
						(5.88)		(6.56)	(5.65)							
	2002-06 dummy													-9.77		
														(5.92)		
shape parameter (ξ)	constant	0.99	1.21	1.22	1.21	0.75	0.01	1.16	0.59	1.23	1.31	1.06	1.36	1.42	1.28	1.23
		(0.19)	(0.24)	(0.25)	(0.26)	(0.16)	(0.22)	(0.22)	(0.31)	(0.21)	(0.24)	(0.18)	(0.23)	(0.23)	(0.24)	(0.20)
	1979-06 dummy						1.39		1.30							
							(0.37)		(0.62)							
negative likelihood		422.61	415.80	415.77	415.40	404.47	406.83	396.40	394.89	402.87	398.11	391.92	402.64	402.86	398.32	388.32

Notes: Estimation was done in R using the ISMEV package. The ISMEV package is based on software written by Stewart Coles. Estimates are based on the maximum number of fatalities over a six month period. Standard errors are reported in parentheses. The last row reports the negative log likelihoods for each model. The time trend variables were scaled in order to facilitate estimation.

Table II. Extreme Value Models Fitted to Log Fatalities and Log Casualties Data

Dependent Variable:		log fatalities					log casualties				
		Stationary model	Trend in μ and σ	1979 break point	1991 break point	2002 break point	Stationary model	Trend in μ and σ	1979 break point	1991 break point	2002 break point
		1	2[a]	3	4	5	6	7[a]	8	9	10
location parameter (μ)	constant	3.26	2.15	2.40	2.03	2.12	4.49	3.09	3.18	3.21	3.08
		(0.17)	(0.30)	(0.40)	(0.32)	(0.32)	(0.17)	(0.26)	(0.26)	(0.26)	(0.29)
	t		0.62	0.51	0.95	0.66		0.87	0.79	0.79	0.86
			(0.18)	(0.22)	(0.25)	(0.19)		(0.17)	(0.17)	(0.16)	(0.18)
	1991-06 dummy				-0.93						
					(0.53)						
	1998-06 dummy		0.49	0.58	0.49	0.55		0.10	0.22	0.20	0.10
			(0.44)	(0.48)	(0.47)	(0.42)		(0.44)	(0.41)	(0.38)	(0.39)
scale parameter (σ)	constant	1.35	0.13	1.15	1.12	1.19	1.34	-0.06	0.98	0.98	1.07
		(0.12)	(0.17)	(0.12)	(0.11)	(0.12)	(0.11)	(0.19)	(0.09)	(0.08)	(0.10)
	t		-0.01					0.05			
			(0.09)					(0.12)			
	2002-06 dummy					-0.74					-0.55
						(0.15)					(0.16)
shape parameter (ξ)	constant	-0.22	-0.22	-0.52	-0.39	-0.27	-0.21	-0.23	-0.43	-0.31	-0.22
		(0.06)	(0.09)	(0.22)	(0.12)	(0.09)	(0.06)	(0.09)	(0.08)	(0.06)	(0.07)
	1979-06 dummy			0.29					0.31		
				(0.20)					(0.10)		
	1991-06 dummy				0.24					0.42	
					(0.18)					(0.23)	
Negative log likelihood		132.58	118.37	117.58	115.46	114.12	132.03	111.82	108.88	108.29	109.31

Notes: Estimation was done in R using the ISMEV package. The ISMEV package is based on software written by Stewart Coles. Estimates are based on the logarithm of the maximum number of fatalities and casualties over a six month period. Standard errors are reported in parentheses. The last row reports the negative log likelihoods for each model. The time trend variables were scaled in order to facilitate estimation.

[a] *To ensure that* $\sigma(t) > 0 \quad \forall t$*, we fit an extreme value model with a trend component in the log-scale parameter, i.e.* $\sigma(t) = \exp(\beta_0 + \beta_1 t)$.

Table IIIA. Predicted Probabilities for Attacks of Various Magnitudes: Based on Raw (Fatality) Data

		Risk Assessments based on log fatalities data														
		Stationary model and models with smooth trends				Iranian revolution; attack on the Grand Mosque				End of the Cold War; milllennium			Post September 11; Iraq insurgency			
Size of event		Stationary model	Linear trend	Quadratic trend	Exp. trend	Break in scale	Break in shape	Break in shape (exc 9/11)	Break in scale + shape (intl.)	Break in location	Break in location (exc 9/11)	Break in location (intl.)	Break in location	Break in scale	Break in location (exc 9/11)	Break in location (intl.)
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1,000 fatality event	current risk	0.06	0.08	0.08	0.08	0.03	0.12	0.08	0.19	0.07	0.09	0.05	0.10	0.07	0.08	0.06
	risk in 2015	0.06	0.08	0.08	0.08	0.04	0.14	0.10	0.19	0.09	0.11	0.05	0.12	0.08	0.10	0.06
5,000 fatality event	current risk	0.01	0.02	0.02	0.02	0.00	0.03	0.02	0.09	0.02	0.02	0.01	0.03	0.02	0.02	0.02
	risk in 2015	0.01	0.02	0.02	0.02	0.00	0.04	0.02	0.09	0.02	0.02	0.01	0.03	0.02	0.02	0.02
10,000 fatality event	current risk	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.06	0.01	0.01	0.01	0.02	0.01	0.01	0.01
	risk in 2015	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.06	0.01	0.01	0.01	0.02	0.01	0.01	0.01

Notes: Probability estimates are adjusted to an annual basis. The columns correspond exactly with Table I.

Table IIIB. Predicted Probabilities for Attacks of Various Magnitudes: Based on Log-Transformed Data

Risk Assessments Based on:		log fatalities data					log casualties data				
Size of event		Stationary model	Trend in location and scale	Break in 1979	Break in 1991	Break in 2002	Stationary model	Trend in location and scale	Break in 1979	Break in 1991	Break in 2002
		1	2	3	4	5	6	7	8	9	10
1,000 fatality event	current risk	0.03	0.16	0.17	0.24	0.00	0.19	0.68	0.62	0.65	0.38
	risk in 2015	0.03	0.28	0.27	0.45	0.00	0.19	0.87	0.83	0.84	0.86
5,000 fatality event	current risk	0.00	0.00	0.01	0.03	0.00	0.02	0.14	0.12	0.22	0.00
	risk in 2015	0.00	0.01	0.02	0.08	0.00	0.02	0.33	0.25	0.33	0.01
10,000 fatality event	current risk	0.00	0.00	0.00	0.01	0.00	0.00	0.04	0.05	0.13	0.00
	risk in 2015	0.00	0.00	0.00	0.03	0.00	0.00	0.14	0.10	0.20	0.00

Notes: Probability estimates are adjusted to an annual basis. The columns correspond exactly with Table II.

Table IVA. Predicted Probabilities for Attacks of Various Magnitudes: By Region

	Risk assessments based on fatalities data					Risk assessments based on log fatalities data				
Size of event	Africa	Latin America	Middle East	South Asia	Western Europe	Africa	Latin America	Middle East	South Asia	Western Europe
	1	2	3	4	5	6	7	8	9	10
1,000 fatality event	0.03	0.00	0.03	0.03	0.00	0.13	0.00	0.01	0.02	0.01
5,000 fatality event	0.01	0.00	0.01	0.01	0.00	0.03	0.00	0.00	0.00	0.00
10,000 fatality event	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00
1% probability event	4094	442	3189	3764	166	10,000+	269	946	1696	467

Notes: Probability estimates are adjusted to an annual basis. Columns 1-5 report risk assessments based on fatalities data, columns 6-10 report risk assessments based on log fatalities data.

Table IVB. Predicted Probabilities for Attacks of Various Magnitudes: By Type of Weapon and Tactic

	Risk assessments based on fatalities data					Risk assessments based on log fatalities data					Risk assessments based on log casualties data		
Size of event	Armed Attack	Assassi-nations	Bombing	Kidnapping	Suicide Attack	Armed Attack	Assassi-nations	Bombing	Kidnapping	Suicide Attack	CBRN	Non-CBRN	Cond. Prob.
fatalities / casualties	1	2	3	4	5	6	7	8	9	10	11	12	13
1,000	0.00	0.00	0.03	0.00	NA	0.00	0.00	0.07	0.00	0.22	0.28	0.56	0.33
5,000	0.00	0.00	0.01	0.00	NA	0.00	0.00	0.00	0.00	0.07	0.11	0.10	0.52
10,000	0.00	0.00	0.00	0.00	NA	0.00	0.00	0.00	0.00	0.05	0.08	0.03	0.73
1% probability event	576	94	2848	101	NA	628	101	2218	58	10,000+	10,000+	10,000+	10,000+

Notes: Probability estimates are adjusted to an annual basis. Columns 1-5 report risk assessments based on fatalities data, columns 6-10 report risk assessments based on log fatalities data and columns 11-12 are risk assessments based on log casualties data spanning a period from 1977 to 2005. The last column is simply a conditional probability estimate based on columns 11 and 12.

Figure 1. An Example of an Incident Record from the Terrorism Knowledge Base

MIPT TERRORISM KNOWLEDGE BASE

A Comprehensive Databa[se]
Global Terrorist Incidents and Organizat[ions]

HOME | ABOUT TKB | ANALYTICAL TOOLS | METHODOLOGIES | DOWNLOADS | LINKS | FAQ | FEEDBACK

AUM SHINRIKYO / ALEPH

quick facts >>

Date Formed:
1984
Strength:
Greater than 2,000 members
Classification:
Religious
Last Attack:
Mar. 20, 1995
Financial Sources:
Admission fees, seminar fees, selling of publications. Multiple enterprises and businesses.

key leaders >>

Asahara, Shoko

Hayashi, Ikuo

Lida, Eriko

Murai, Hideo

Ouchi, Toshiyaso

images >>

One of Aum Shinrikyo's biolabs

Victims of the Sarin Gas Attack

US State Dept. FTO >>

Designated:
1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005

Watched:
No

gov designations >>

US Terrorist Exclusion List Designee: No
UK Proscribed Group: No
Australia Specified Group: No
Canada Specified Group:

incident profile

AUM SHINRIKYO / ALEPH ATTACKED TRANSPORTATION TARGET (MAR. 20, 1995, JAPAN)

Incident Date: Mar. 20, 1995

Group(s): Aum Shinrikyo / Aleph

City: Tokyo

Country/Area: Japan

Region: East & Central Asia

Target: Transportation

Tactic: Armed Attack

Suicide: No

Weapon: Chemical Agent

Fatalities: 12

Injuries: 5000

US Attack: No

US Fatalities: 0

US Injuries: 0

Attack Claimed: No

Coordinated: No

Description: JAPAN. The Tokyo subway system was the target of an attack with nerve gas. The deadly gas, Sarin, was released from packages brought on to five different railway carriages. Twelve people were killed and over 5000 injured including several foreigners. Fifteen subway stations were affected by the gas. A Japanese extreme Buddhist sect called Aum Shinri Kyo (Sublime/Supreme Truth), is suspected of releasing the gas. On 7 June 1995, the leader of Aum Shinri Kyo, Shoko Asahara, was indicted for the murder of the people who died in the subway gas attack. Six followers were also indicted on murder charges and nine others on lesser charges. Asahara's trial started in late October 1995.

Information Source: Chronology Data 1968-1997

Publication Date: 04/03/2001

Incident-data Provider: RAND Corporation

search

incidents

Aum Shinril attacked Tr target (Mar Japan)

Figure 2A. Maximum Number of Single-Day Fatalities Resulting From Terrorist Attacks

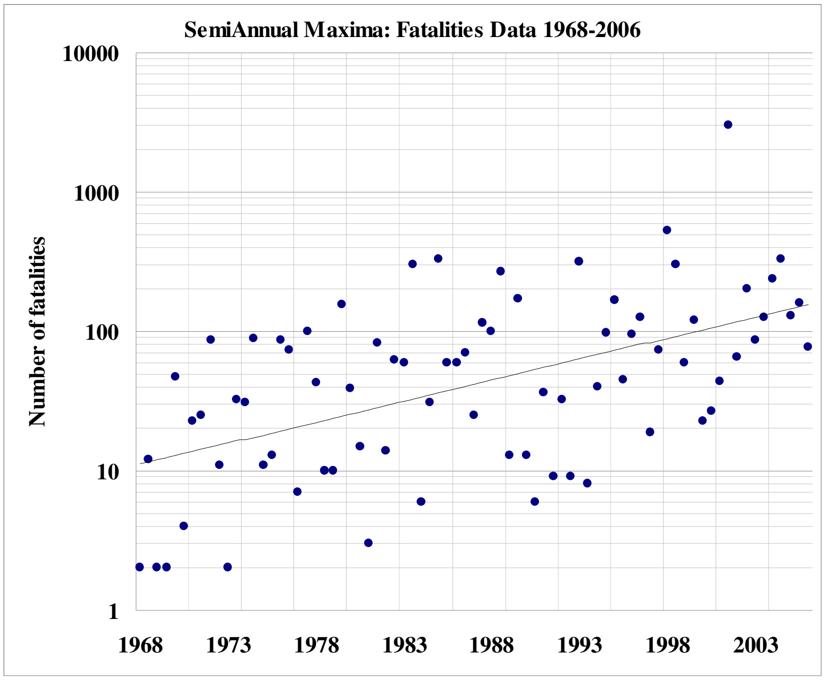


Figure 2B. Maximum Number of Single-Day Casualties Resulting From Terrorist Attacks

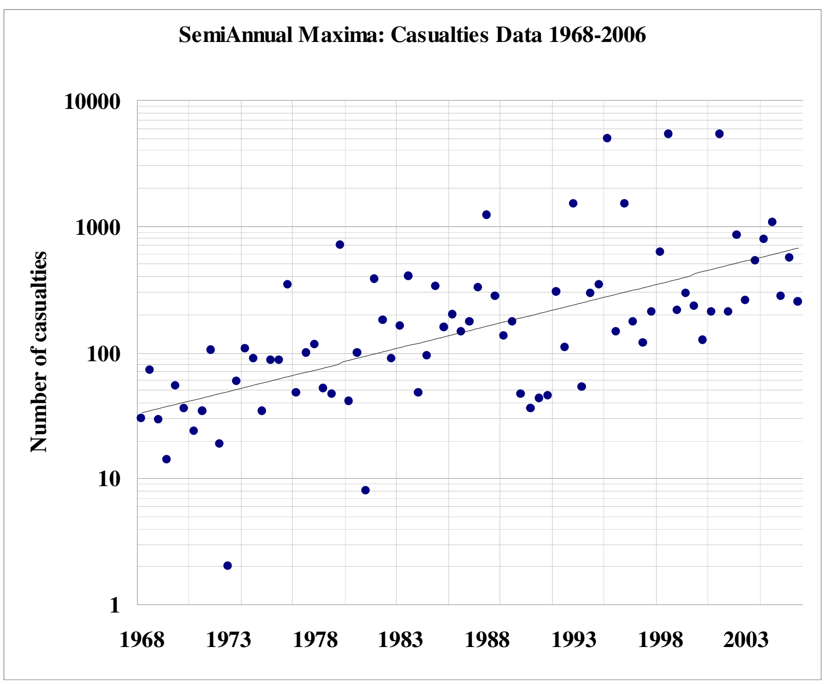
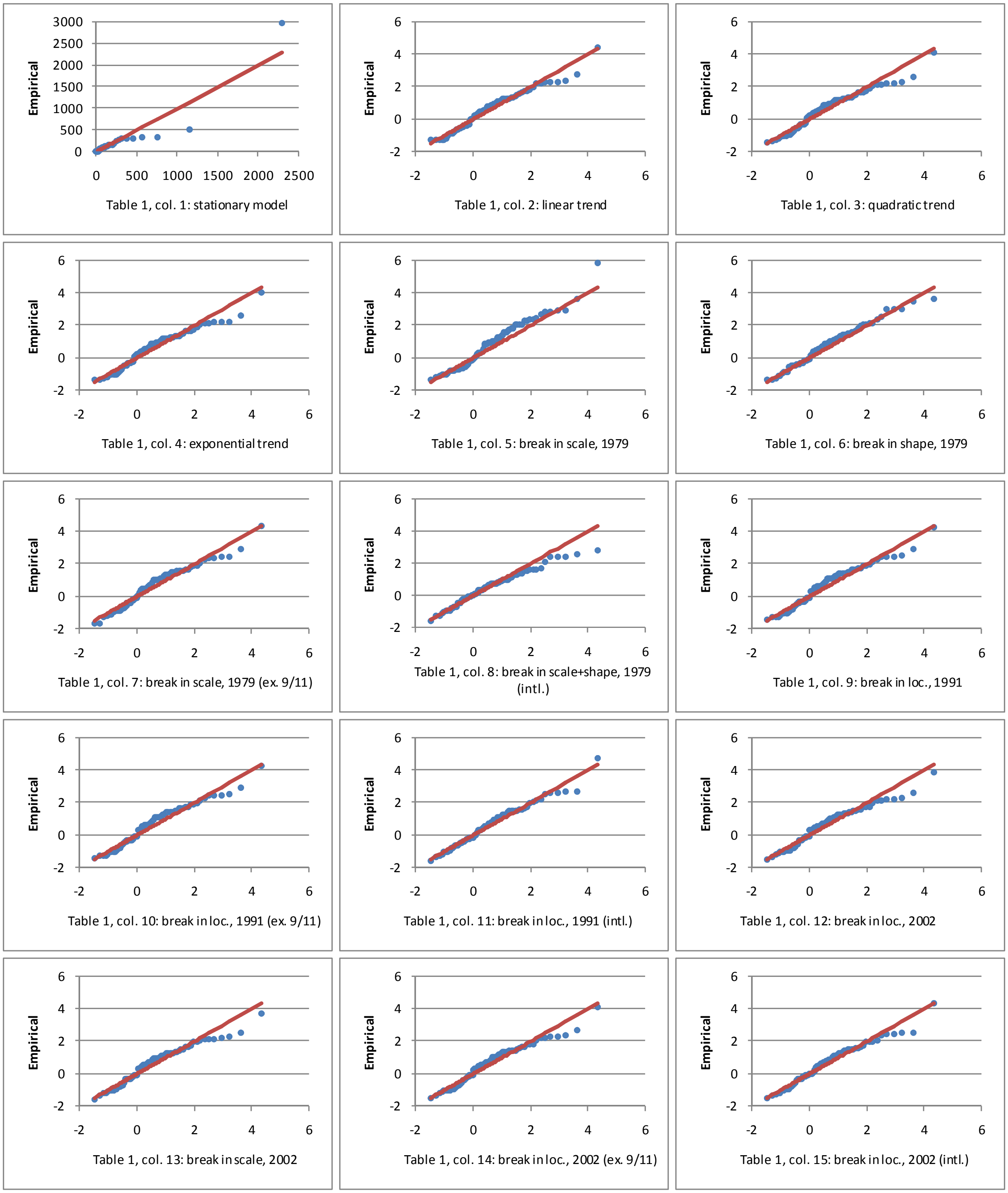
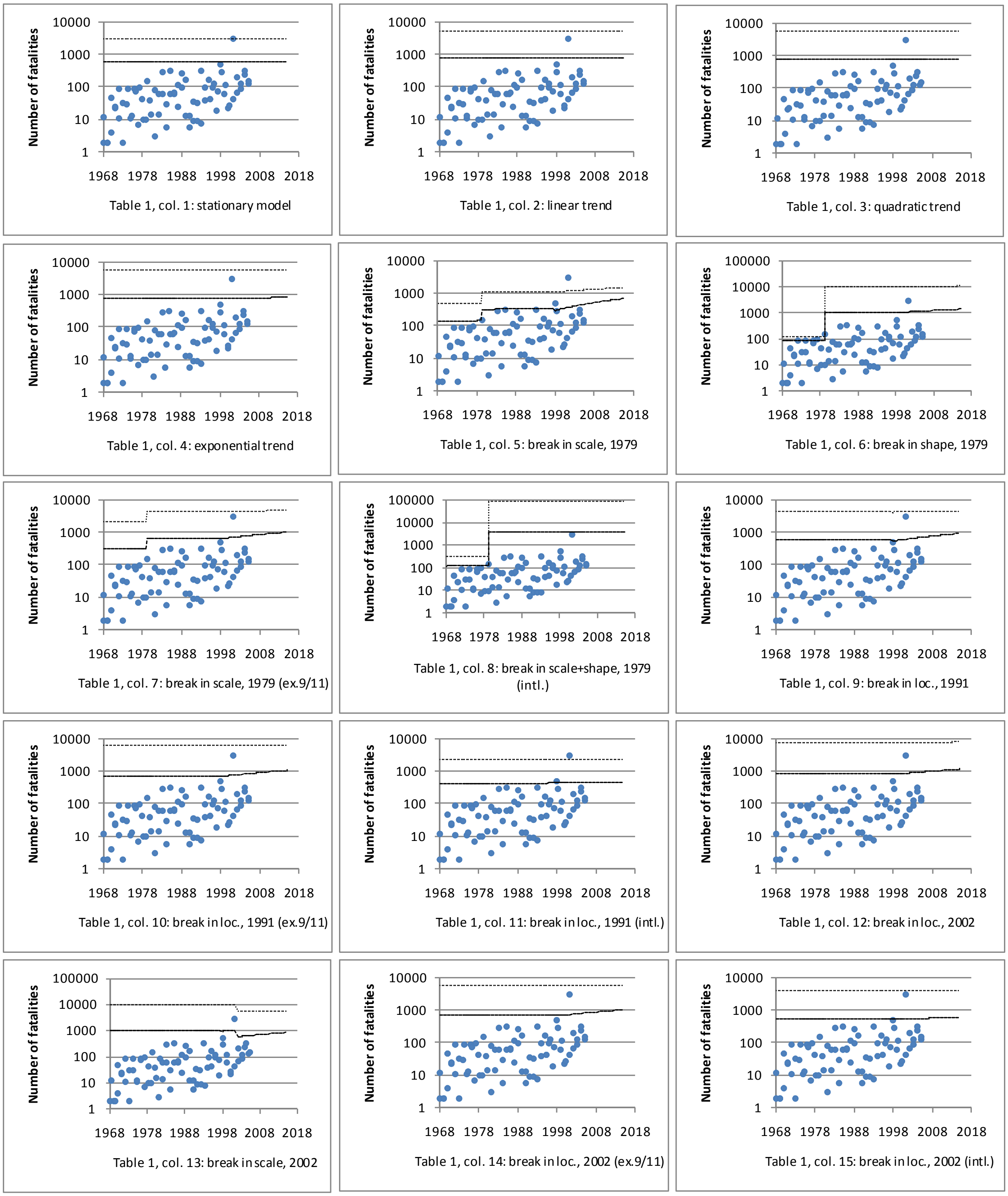


Figure 3. Diagnostic QQ Plots for Models Reported in Table I



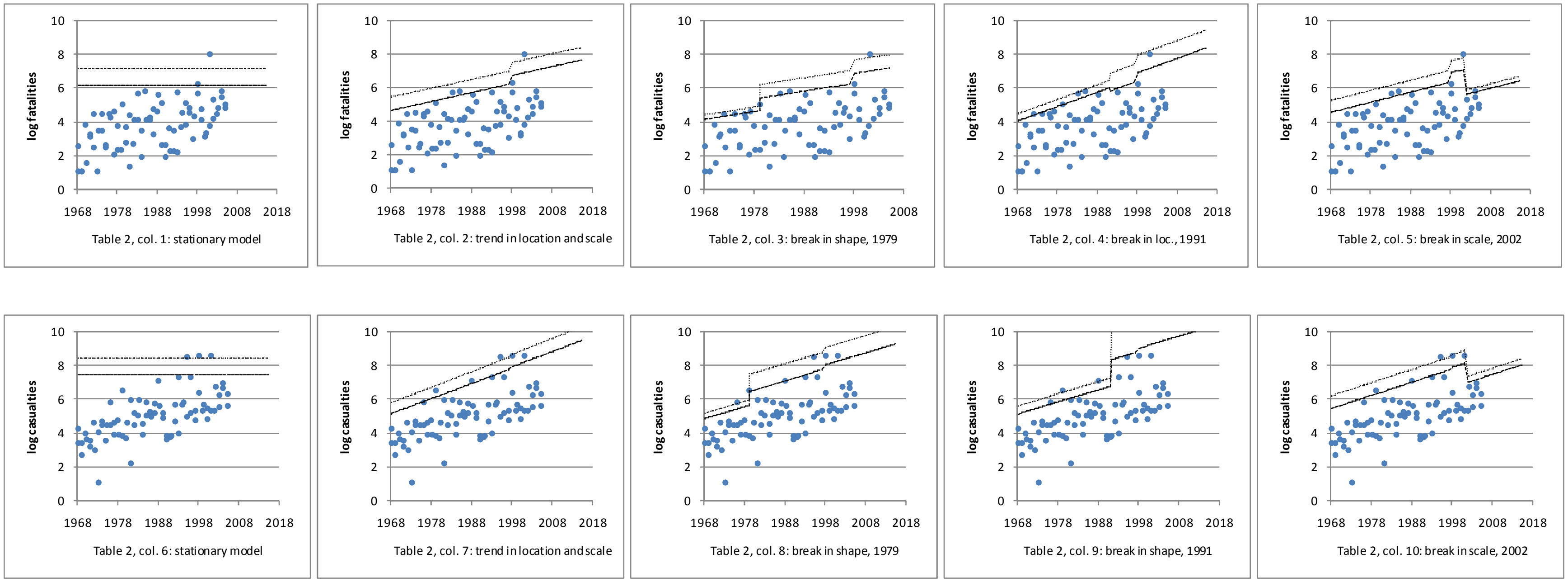
Notes: QQ-plots correspond to each of the models reported in Table 1.

Figure 4A. Predicted 95th and 99th Percentile Values for Estimated Models in Table I



Notes: Plots are the 95th and 99th percentile predicted values based on models reported in Table 1.

Figure 4B. Predicted 95th and 99th Percentile Values for Estimated Models Table 2



Notes: Plots are the 95th and 99th percentile predicted values based on models reported in Table 2.