The Developmental Dynamics of Terrorist Organizations

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Abstract

We identify robust statistical patterns in the frequency and severity of violent attacks by terrorist organizations as they grow and age. Using group-level static and dynamic analyses of terrorist events worldwide from 1968–2008 and a simulation model of organizational dynamics, we show that the production of violent events tends to accelerate with increasing size and experience. This coupling of frequency, experience and size arises from a fundamental positive feedback loop in which attacks lead to growth which leads to increased production of new attacks. In contrast, event severity is independent of both size and experience. Thus larger, more experienced organizations are more deadly because they attack more frequently, not because their attacks are more deadly, and large events are equally likely to come from large and small organizations. These results hold across political ideologies and time, suggesting that the frequency and severity of terrorism may be constrained by fundamental processes.

Introduction

Much research on patterns in terrorism has been inspired by particular historic events and “waves” of specific forms of terrorist attacks [1,2]. Just as the rise in international skyjackings in the 1970s led to a resurgence of studies of terrorism, the 11 September 2001 attacks renewed interest in why groups resort to terrorism, the specific choice of attack targets, and the relative effectiveness of particular counterterrorism measures. As a result, many researchers have developed typologies of specific forms of terrorism and highlighted the distinctiveness of different terrorist groups. By contrast, in this manuscript we examine whether there are fundamental patterns in the frequency and severity (number of deaths) of deadly events carried out by terrorist organizations and what mechanisms might generate them.

Little research on terrorism has focused on directly modeling individual event frequency and severity, and the way these change over an organization’s lifetime. When deaths are considered, they are typically aggregated and used as a covariate to understand other aspects of terrorism, e.g., trends over time [3,4], the when, where, what, how and why of the resort to terrorism [5–7], differences between organizations [8], or the incident rates or outcomes of events [3,9]. Such efforts have used time series analysis [3,4,9], qualitative models or human expertise of specific scenarios, actors, targets or attacks [10] or quantitative models based on factor analysis [11,12], social networks [13,14] or formal adversarial interactions [6,15,16].

Our approach is different and complementary to these approaches, focusing on global trends and patterns in the frequency and severity of events [17–23], rather than on event particulars or motivations. By focusing our analysis at the global scale, the importance of individual decisions in specific contexts is in fact lessened, due to the central limit theorem and the rough independence of individual events; as a result, the importance of generic non-strategic processes is enhanced and these processes, if any, may be studied. Explanations of such patterns must thus focus on processes or constraints that are independent of variations in context or specific motivation and may include physical constraints, network effects and endogenous population dynamics, which are well suited to explain the behavior of strategically uncoordinated populations of actors [24]. This approach to investigating the fundamental laws of terrorism has much in common with that of statistical physics, in which the self-averaging properties of independent events allows for interesting population-level properties to emerge from microscopic system chaos. This statistical physics-style approach is increasingly being applied to study complex social systems [26–28], yielding a number of novel insights.

Here, we aim to shed new light on the fundamental processes governing the frequency and severity of terrorist events by studying their statistical relationships with the organizations that generate them. Our aim is to identify global patterns in these relationships and to explain their origin mechanistically. We employ a combination of disaggregated data analysis, studying a large database of terrorist events worldwide from 1968–2007, statistical modeling and inference, computational modeling and regression analysis to validate our mechanistic hypotheses. By shedding new light on these large-scale patterns and trends in terrorism, and on how such patterns emerge from local-level behaviors, this large-scale statistical or pattern-based approach can supplement formal models of strategic interactions, inform counter-terrorism policy and clarify our general ability to forecast or anticipate future terrorist events or trends.
Patterns in global conflict

A pattern-based approach to studying conflict owes much to the seminal work in the early 20th century of Lewis Fry Richardson—a physicist and meteorologist known for collecting data on conflicts ("deadly quarrels"), modeling arms races using differential equations, as well as early contributions to understanding the frequencies and severities of wars. Specifically, Richardson [29,30] identified the remarkable pattern that the frequency of wars decays like the inverse power of their severity. (Power-law distributions can indicate unusual underlying or endogenous processes, e.g., feedback loops, network effects, self-organization or optimization. From a purely statistical perspective, power-law distributions generate large events orders of magnitude more often than we would expect under a Normal assumption. Recently, power-law distributions have been identified in a wide range of social and biological systems [31]. See [32], [33] and [34] for reviews, or Appendix A of [35] for a gentle introduction.) This empirical pattern implies that there is no fundamental statistical difference between rare but catastrophic wars and more common but less severe wars—the likelihoods of both are described by a single mathematical function:

\[ \Pr(\text{event with severity } x) \propto x^{-\alpha}, \]

where \( x \) counts the number of fatalities (severity) and \( \alpha \) is the "scaling exponent," which controls how quickly the frequency decreases as severity increases. It also implies that the underlying social and political processes for both large and small wars may be fundamentally the same, i.e., large wars may simply be "scaled up" versions of small wars. In general, the identification of a power-law implies that studying the statistically more common events can shed light on certain aspects of extremely rare events. (Seismologists study large earthquakes in this way: the frequencies of both large and small quakes follow a power-law distribution, called the Gutenberg-Richter Law, and the physical processes that generate both small and large quakes are fundamentally the same).

Recently, Clauset et al. [20,31] showed that this same pattern—a power-law, “Richardson’s Law” also holds for the frequency of severe terrorist attacks (reported fatalities) worldwide, while [23] suggest a similar pattern for events within insurgencies. The power-law pattern in terrorism is highly robust: it persists over the past 40 years despite large structural and political changes in the international system and is independent of the type of weapon used (explosives, firearms, arson, knives, etc.), the emergence and increasing popularity of suicide attacks, the demise of many individual terrorist organizations, and the economic development of the target country.

Thus, fundamental regularities in terrorism can and do emerge at the global level despite the highly contingent and context-specific nature of the individual attacks, conflicts and decisions. Insights into how these patterns’ arise will likely shed new light on the underlying social or political processes that drive and constrain global trends and on effective policies for responding to or managing those processes.

Methods

We consider the frequency and severity of attacks over the lifetime of individual terrorist organizations, and the question of whether organizations exhibit common statistical patterns in these behaviors. We argue that organization size (number of personnel) plays a fundamental role in limiting the overall frequency, but not the severity, of violent events by a group. The key idea is that organization size and its overall production rate of events are linked. If events lead to growth in any way, then this link implies a positive feedback loop in which each attack increases the production rate of future attacks. Thus, a terrorist organization can be viewed as a kind of factory whose principal product is political violence, and whose proceeds are reinvested in increased production capacity.

To test these "developmental dynamics" hypotheses, we present novel statistical analyses of the behavior of nearly 400 terrorist organizations worldwide over the period 1968–2008. We find strong evidence for precisely this kind of generic acceleration in event production. This supports the notion that an organization's available labor, i.e., the size of its militant wing, is a fundamental constraint on the overall frequency of its attacks. We further show that the rate at which an organization cycles through the positive feedback loop can depend on covariates like its political ideology, with religiously-motivated organizations accelerating (growing) the fastest. In contrast, we find no evidence that event severity depends on organizational size or experience. Instead, the distribution of attack severities follows a rough form of Richardson's Law independent of size, experience or political motivation.

These results imply that very large events are equally likely to be generated by small groups as by large groups, and that larger organizations are indeed more deadly [8], not because their individual attacks are systematically more spectacular but because they typically carry out many more attacks. That is, the size of the beast directly determines the overall level of terror activity (frequency) but not the quality (severity) of those actions.

Recently, Johnson et al. [25] used a similar approach to analyze the timing of events in the Iraq and Afghanistan conflicts, which was in turn based on an earlier version of this manuscript [22]. Although similar statistical patterns to the ones we describe here were observed in those conflicts, a different explanation was offered for their origin. We will revisit this comparison and comment on the problems our statistical results pose for the explanation offered by [25].

Impact of Size on Frequency

H1 Labor-constraints: the overall production rate of violent events by an organization depends on its size, and thus the time between consecutive attacks \( \Delta t \) is roughly inversely proportional to the size \( s \) of the organization. Mathematically, \( \propto 1/\Delta t \).

In other words, the production of terrorist events cannot be automated. If this were possible, organizations could produce arbitrary numbers of events without needing to grow in size, much like a fully automated factory requires essentially no human personnel to function. (In this light, cyber terrorism is an interesting case: it remains unclear to what degree the planning and execution of cyber terrorist attacks can be done automatically, by computers. Our current belief is that cyber terrorism is also not mass producable and thus some labor constraint will persist, although it may be substantially lessened relative to physical terrorism). Instead, we argue that each terrorist event requires significant human involvement, e.g., to conceive, plan and execute it. This requirement for human effort implies that for the production rate of an organization to decrease, it must add additional members to produce them. And, the resultant increased rate occurs not because more hands make any individual event proceed more quickly, but because multiple events may be carried out in parallel. That is, the overall production rate of the organization is like the production rate of an entire factory; as the factory (organization)
adds internal independent production lines (terrorist cells), the effective time between new events falls even though each production line operates at a constant rate.

It is important to recognize that H1 does not imply that the only way to increase the group-level production rate of attacks is through organizational growth. Indeed, many aspects of event production surely do benefit from technology or efficiency improvements [36–39]. Instead, H1 implies that such factors can only moderate, not eliminate, the fundamental constraint that size places on production. To the extent that these factors decrease the time between an organization’s events, the literature on learning suggests that the overall impact will be modest [39]. In contrast, increases in labor, which allow many terrorist cells to operate in parallel, can lead to much larger improvements.

Finally, we note that this constraint should be strongest for small organizations, who likely have the worst access to efficiency-improving resources like specialized personnel, training facilities or factories and who may reap the largest benefit, e.g., media visibility, from striving to maximize their event production. Because most organizations begin small and grow over time, this should be most evidence early in the lifetime of an organization. (A spatial corollary of H1 is that if an “organization” is defined as those militants within some geographic locale, e.g., a province or district, then the frequency of events within that locale will be roughly inversely proportional to the number of militants there. That is, the \( s \propto 1/\Delta t \) relationship should hold when both \( s \) and \( \Delta t \) are defined by a geographic boundary. Organizational “growth” can then be understood as either immigration or recruitment of new militants).

**Events, Recruitment and Growth**

What role do attacks play in changing organizational size? If an event gains the organization wider visibility among potential members or sympathizers, the organization may grow in size as a result of that event. (Decreases in size are likely driven by distinct social processes [see [40]], which we do not consider here).

**H2 Event-recruitment:** organizational growth (increased \( s \)) is partly driven by recruitment associated with the production of new events (increased \( k \)), i.e., events lead to recruitment which leads to organizational growth. Mathematically, \( ds/dk > 0 \).

H2 does not imply that growth comes only from violence-related recruitment. So long as recruitment is partly based on the production of violent events, H2 implies a correlation between increases in size and increased event production.

**Frequency Acceleration**

Together, H1 and H2 imply a positive feedback loop in which attacks lead to recruitment which leads to organizational growth and thus an increased group-level production of new attacks. So long as a portion of the growth is allocated to producing additional events, i.e., so long as the militant wing grows with the overall organization, H1 and H2 jointly imply H3.

**H3 Frequency-acceleration:** as an organization carries out more attacks (increased \( k \)), the time between subsequent attacks \( \Delta t \) decreases. Mathematically, \( d\Delta t/dk < 0 \).

That is, H1 predicts \( s \propto 1/\Delta t \) while H2 predicts \( ds/dk > 0 \). Eliminating the common factor of \( s \) yields the prediction that \( d\Delta t/dk < 0 \), in which the continued production of violent events produces a decreasing delay between those events. (This dynamical relationship produces a similar pattern to that observed in “learning” or “progress curves,” in which continued production covaries with lowered production costs or time [36,39,41]. Although the pattern is similar, the mechanism is different).

**Impact of Size on Severity**

Increased size may bring greater access to capital and skilled labor, e.g., experienced professionals, advanced arms, intelligence, etc., and thus more spectacular attacks.

**H4 Severity-increase:** the severity \( x \) of a new attack increases with organizational size \( s \) and, via H2, the number of attacks \( k \). Mathematically, \( dx/ds > 0 \) and \( dx/dk > 0 \), respectively.

Combined with H2, H3 implies that attacks by experienced, larger groups should be consistently and significantly more deadly than those of less experienced or smaller groups.

H4 assumes a tangible benefit for maximizing the severity of attacks, e.g., to gain wider visibility for the organization’s cause or to demonstrate power or resolve. Such incentives are not foregone conclusions: severe attacks may also attract harsh attention from state-level actors, leading to repression, police action or the destruction of physical or financial resources. They may also induce counter-productive effects on potential sympathizers, e.g., due to the shockingness of spectacular events. As a result, we consider the theoretical argument supporting the severity-increase hypothesis to be marginal.

**Results**

**Model of terrorist organizations**

To illustrate these interactions between an organization’s size and the frequency and severity of attacks over its lifetime, we construct a simple model of a terrorist organization’s development (see Figure 1 for a schematic).

Historically, terrorist organizations begin as a small collections of terrorism-inclined individuals [42]. Let this initial collection be composed of roughly \( \eta \) individuals, which denotes the typical or characteristic size of a terrorist cell. The particular value of \( \eta \) is not important, but may depend political ideology, socio-economic context [43], the attack’s target, etc. The cell plans and conducts its first attack, which gains it some visibility, via either traditional media coverage or informal channels. Subsequent recruitment yields a number of additional members \( v \) (H2), and now the organization is larger. Again, the particular value of \( v \) is not important, but likely depends on context-specific factors.

Each cell continues planning and carrying out new attacks, roughly once every \( \tau \) days (H1). Newly recruited members form new cells, of size \( \eta \) (H1) and new cells plan and carry out their own attacks in parallel. It is this parallelism that allows the larger organization to appear to be acting more quickly, even though the planning time \( \tau \) for any particular event remains fixed. An attack by any cell leads to overall organizational growth via recruitment (H2), which in turn increases the organization’s overall production rate of attacks by adding new cells (H3). Finally, as the group grows, the increased manpower also increases its ability to carry out more severe events (H4), e.g., because more supporting roles allow better surveillance, access to better equipment, etc.

Coordinating the activities of these additional individuals, or the development of non-violent initiatives like a political wing or the provision of social services, will draw some members away from
between delay
Finally, the model produces a universal functional relationship
correlation between experience, size and the frequency of events.
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number of cells
size grows exponentially with time, at rate
growth is fast because each event produces at least one new cell.
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of the organization's militant wing. When
for three choices of the ratio
simulating event severities.
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subsequent attacks
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organizations. Here, we are interested in how the delay between
draw a delay \( \tau \) from a fixed distribution. (In
generally, our results hold so long as the distribution of \( \tau \) is well-
behaved and stationary with respect to \( k \).) Specification details and
computer code for the simulation are given in Text S1.

Each simulated terrorist organization generates a unique
sequence of events representing the collective behavior of its cells
er over time, and we extract the generic behavior by computing
quantiles over variables of interest for many such simulated
organizations. Here, we are interested in how the delay between
subsequent attacks \( \Delta t \) varies with cumulative number of events \( k \)
(H3), and how the size of the organization, measured by the
number of cells \( s/\eta \) varies with calendar time \( t \) from the first event
(H2). H4 predicts that event severity correlates with organization
size and thus no additional information is gained by explicitly
simulating event severities.

Figure 2 shows the results for 10,000 simulated organizations,
for three choices of the ratio \( v/\eta \), which represents the growth rate
of the organization's militant wing. When \( v/\eta < 1 \) regime,
organizational growth is slow because multiple events are required
to establish a new terrorist cell; but, when \( v/\eta > 1 \), organizational
growth is fast because each event produces at least one new cell.

The generic behavior of our model is clear: (i) organizational
size grows exponentially with time, at rate \( v/\eta \), and (ii) the
feedback between size and production rate induces a strong
correlation between experience, size and the frequency of events.
Finally, the model produces a universal functional relationship
between delay \( \Delta t \) and cumulative production \( k \) of the form
\( \Delta t \propto k^{-1} \), and this relationship is independent of the growth rate
\( v/\eta \).

This latter point is worth reiterating: so long as each new event
leads to some marginal increase in the overall production rate
(H2), a positive feedback loop between size and event production
will exist. This feedback will be linear \( \Delta t \propto k^{-1} \) if the growth rate
\( v/\eta \) does not vary with experience \( k \). If the militant wing is a
decreasing fraction of the overall organization (\( v/\eta \) decreases over
time), the feedback will be sub-linear and \( k^{-\beta} \) with \( \beta < 1 \), while if
it increases with time, the feedback will be super-linear and \( \beta > 1 \).
These properties imply that if a growing organization does
provokes responses from state-level actors, these responses will not
break the feedback loop unless they succeed in both limiting the
growth and reducing the size of the organization, a point to which
we will return later.

These quantitative predictions can be tested with empirical data
by examining \( \Delta t \) as a function of \( k \) across many organizations. If
\( \Delta t \propto k^{-1} \) holds in the data, we have strong evidence for precisely
the size-mediated feedback loop described here.

Empirical data
Organizational size data were drawn from the Big Allied And
Dangerous (BAAD) data set [8], which offers the currently best
available size estimates for terrorist organizations worldwide.
Other sources of size data lack the breadth or temporal resolution
for accurate analysis. For instance, the START program and the
MIPT database previously held a small number of estimates of uncertain accuracy, generated by Detica, Inc., a British defense
contractor, and [44] compiled a database of information on 649
terrorist groups that included only estimates of the maximum size
over a group's entire lifetime. The BAAD data were generated by
a survey of domain experts at the Monterey Institute of
International Studies (MIIS) who estimated the rough order of
sonnel) of the maximum size achieved by each of 381 groups,
over a group's entire lifetime. The BAAD data were generated by
endorsing their BAAD data set [8], which offers the currently best
available size estimates for terrorist organizations worldwide.

To ensure good compatibility with this organization list, event
data were drawn from the MIPT Terrorism Knowledge Base [45],
which contained 33,668 terrorism events, of which 13,274 resulted
in at least one fatality, as of 29 January 2008. (Other sources of
event data include the Global Terrorism Database [46], the
Worldwide Incident Tracking System [47] and the ITERATE
data [48]. We note that neither these nor the MIPT database
provide complete and consistent worldwide coverage.) For the
period 1968–1997, the MIPT database includes mainly interna-
tional events involving actors from at least two countries, while for
1998–2008 it includes both domestic and international events
from much of the world. (The MIPT data were originally drawn
from the RAND Terrorism Chronology 1968–1997, the RAND-
MIPT Terrorism Incident database (1998–Present), the Terrorism
Indictment database (University of Arkansas & University of

Figure 1. A model of terrorist organizations. A schematic illustrating the feedback loop relationship between size \( s \) and the frequency and severity of attacks: the delay between subsequent attacks \( \Delta t \) is inversely related to an organization’s size \( s \) while the severity of subsequent attacks \( x \) grows with \( s \); new events lead to recruitment which leads to growth, which increases the size variable \( s \).
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Figure 2. Simulated development of a terrorist organization. (A) Median event delay $\Delta t$ vs. cumulative number of events $k$, for 10,000 simulated terrorist organizations and three choices of the number of cells $v/n$ added per event. Dashed line shows the function $\Delta t \sim k^{-1}$, from Eq. (1). (B) Median size (number of terrorist “cells” $s/v$) vs. calendar time from the first event, showing exponential growth with rate set by $v/n$.

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Regression models

Before analyzing the evolution of attacks by individual organizations we conduct static or cross-sectional regression analysis at the level of individual organizations. We examine the relationship between group size and attack patterns, in particular the delay between attacks, the experience of a group in terms of number of events, and the severity of attacks.

To recap, we expect larger groups to generate a larger number of attacks, have shorter delays between attacks (H1), and generate more severe attacks even accounting for other attack patterns (H4). We can evaluate H1 by comparing maximum group size $s$ from BAAD and the minimum delay between attacks $\Delta t$ in MIPT. We can assess H4 by comparing size and the maximum severity $x$ of attacks. Finally, H2 implies that larger groups should have higher maximum experience $k$ or cumulative number of events. (H3, postulating a declining delay with subsequent attack, cannot be evaluated with static data; we return to this point later).

Although group size should predict attack patterns, individual measures such as maximum severity will be at least in part a function of the total number of attacks. That is, for any distribution of severities, an increased production rate (sampling intensity) will naturally inflate the maximum severity over a fixed time period, even if the distribution is stationary. Thus, in order to examine the partial relationship between size and the related attack variables–or their independent predictive value on size once we take into account the other attack pattern characteristics–it is more convenient to consider to what extent we can account for size as function of the attack measures.

We use an ordered logit regression model of size since the BAAD data give order-of-magnitude estimates of maximum size. As the BAAD data pertain to the time period 1998–2005, we restrict our attack pattern measures to attacks during this same time period. Since the distributions of minimum delay, maximum experience, and maximum severity are all highly skewed we take the natural logarithm, adding 1 to severity to prevent taking the log of 0 in the case of non-fatal events. We report the empirical intensity) will naturally inflate the maximum severity over a fixed time period. Thus, in order to examine the partial relationship between size and the related attack variables–or their independent predictive value on size once we take into account the other attack pattern characteristics–it is more convenient to consider to what extent we can account for size as function of the attack measures.

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The results display a significant negative relationship between fatal attack delay and group size, consistent with our claim that larger groups will have shorter delays between attacks (H1). We also find a positive relationship between group size and experience, consistent with our claim that larger groups generate a higher number of attacks (H2). Finally, the maximum severity of the attacks is not significantly related to group size, once we have controlled for delay and experience variables. This contradicts the hypothesis that larger groups are systematically more likely to generate severe attacks (H4). Overall, the model places 58.75% of all the groups in the correct bins for group size. Only 5% of the observations are badly mis-classified, with predictions off by more than one order of magnitude. By contrast, a null model predicting all groups to have the modal size category (100–1000) only classified 43.75% of the observations correctly. (We considered a number of alternative specifications. Severity remains an insignificant predictor of group size when we consider combinations of...
delay and experience for both deadly and non-deadly attacks. Using a linear regression model rather than ordered logit does not change our substantive conclusions).

Since the BAAD data cover only about half of the identifiable organizations in the MIPT database over a restricted time span (1998–2005), we conduct a supplementary analysis with the full MIPT dataset, where we consider how a group’s total experience can be accounted for by differences in minimum delay and maximum attack severity. (We limit the analysis to MIPT dataset, where we consider how a group’s total experience can be accounted for by differences in minimum delay and maximum attack severity. We instrument a common timeline using organizational criteria.) These static analyses provide substantial preliminary evidence for the frequency-acceleration (H3) and attack-severity hypotheses (H4) predictions. However, the specific factors associated with particular organizations may obscure the generic tendency embodied by our hypothesis. To investigate these, we examine the average trajectory across many organizations by tabulating the conditional distribution $Pr(\Delta t|k)$ of delays, for a specified level of experience $k$. Thus, an organization that has carried out $k^*$ events contributes to each of the $k \leq k^*$ conditional distributions. This approach provides a strong test of the frequency-acceleration (H3) and attack-severity hypotheses (H4) predictions.

**Developmental dynamics.** A development curve is a statistical tool that measures the evolution of organization behavioral variables along a common quantitative timeline [22]. It is similar in structure and use to the “experience”, “learning” and “progress curves” sometimes used in management science [36,39] to quantify the relationship between per-item production cost (or time) and “experience” (cumulative item production). Because we study behavioral variables rather than the costs of production, and to explicitly avoid implying learning-based mechanisms, we choose a distinct term. The analysis of these developmental curves facilitates direct comparisons of the behaviors of different groups at similar points in their life histories, which is useful for testing our hypotheses.

We instrument a common timeline using organizational experience $k$, defined as the cumulative number of events produced by or associated with a particular organization, and we compare the delay $\Delta t$ between the $k$th and $(k+1)$th events, or the severity $x$ of the $k$th attack, across all organizations in our sample. For each of the 910 organizations, we extract from the MIPT event data an ordered sequence of coordinates $\{(1,z_1),(2,z_2),\ldots\}$, which represent the group’s behavioral trajectory on the variable $z$ over its lifetime. The visualization of such trajectory is typically made using double-logarithmic axes, as illustrated in our simulation results in Figure 2. Although the curve construction itself ignores details such as the date of an organization’s first attack, its location, ideology, etc., these variables can be used for subsequent analysis, e.g., comparing the trajectories across covariates.

### Table 1. Ordered logit regression of group size, by fatal attack patterns.

| Variable | $\hat{\beta}$ | SE($\hat{\beta}$) |
|----------|---------------|-------------------|
| Delay: $\ln(\Delta t)$ | $-0.351$ | $0.119$ |
| Experience: $\ln(\max(k))$ | $0.707$ | $0.193$ |
| Severity: $\ln(\max(x))$ | $0.150$ | $0.159$ |
| $\alpha_0$ | $0.163$ | $0.840$ |
| $\alpha_1$ | $2.652$ | $0.895$ |
| $\alpha_2$ | $5.039$ | $1.056$ |

$N = 80, LR \chi^2 = 41.42, df = 3, 58.73\%$ correctly classified. doi:10.1371/journal.pone.0048633.t001

### Table 2. Linear regression of experience, by attack delay and severity.

| Variable | $\hat{\beta}$ | SE($\hat{\beta}$) | $\hat{\beta}$ | SE($\hat{\beta}$) |
|----------|---------------|-------------------|---------------|-------------------|
| Delay: $\ln(\Delta t)$ | $-0.119$ | $0.042$ | $-0.110$ | $0.040$ |
| Experience: $\ln(\max(k))$ | $-0.778$ | $0.110$ | $-0.795$ | $0.105$ |
| Delay $\times$ Severity | $0.074$ | $0.017$ | $0.073$ | $0.016$ |
| Severity: $\ln(\max(x))$ | $0.100$ | $0.059$ | $0.150$ | $0.056$ |
| $\alpha$ | $3.115$ | $0.236$ | $3.336$ | $0.225$ |

$N = 167, R^2 = 0.545, N = 167, R^2 = 0.565$ |

$R^2$ (severity) = $0.515$ |

$R^2$ (delay) = $0.222$ |

$R^2$ (severity) = $0.546$ |

$R^2$ (delay) = $0.182$ |

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### Developmental Dynamics of Terrorist Organizations

Using a linear regression model rather than ordered logit does not change our substantive conclusions.)
achieve $k = 12$ events, the median total calendar time between the first and twelfth event is 4.4 years. Similar results hold for the timing between deadly attacks.

None of the sampled organizations progressively slowed their attack rate over time, moving from high-frequency to low-frequency. A few unusual groups, such as Al-Qaeda in the Land of Two Rivers, begin and remain in the high-frequency domain. But, Al-Qaeda in the Land of Two Rivers is an interesting case because it is well-known to have operated under a different name prior to 2004 [49]; thus, their initial high-frequency behavior can be interpreted as support for the labor-constraint hypothesis (H1) because their initial larger size–a hold over from their previous identity–allowed them to “begin” life $(k = 1)$ at a relatively high initial production rate of attacks.

### Statistical model for the frequency of attacks

Quantifying the dynamical relationship between delays and experience allows us to go beyond our static analyses. To do this, we statistically model the conditional distribution $\Pr(\Delta t|k)$ from which delays are drawn and how this distribution varies with experience.

For these data, a truncated log-normal distribution, with the following mathematical form

$$\Pr(\Delta t|k) \propto \exp\left[\frac{-(\log \Delta t + \beta \log k - \mu)^2}{2\sigma^2}\right], \quad (1)$$

provides an excellent fit to the empirical delay data for all organizations. Here, $\sigma^2$ is the variance in delays at a given $k$, $\mu$ is related to the characteristic delay between attacks and $\beta$ controls the rate at which that delay decreases with increased experience $k$. That is, $\beta$ governs the strength of the feedback loop between organizational experience and the production of new events. To include the effect of the minimum timing resolution $\Delta t \geq 1$ present in the empirical data, we force $\Pr(\Delta t|k) = 0$ for $\Delta t < 1$ day.

This mathematical structure implies that the typical delay between attacks generically decreases according to a power-law function with increasing experience.

$$\Delta t \approx e^{\beta} k^{-\beta}. \quad (2)$$

(Details of this derivation are given in Text S1.) Thus, if $\beta > 0$, we will observe a transition toward increasingly fast event production, indicating support for H3. In contrast, if $\beta = 0$, production rates do not vary with organizational experience, while if $\beta < 0$, production rates will decrease (larger $\Delta t$) with increasing experience. In the $\beta > 0$ regime predicted by H3, the acceleration effect is dampened as the mean delay asymptotes to the minimum timing resolution at $\Delta t = 1$; this produces slight upward curvature for large values of $k$ (see Text S1).

The particular value of $\beta$ has a strong effect on the material dynamics of the feedback loop between increasing experience and increasing production. If $\beta = 1$, then the feedback loop is linear, as in our simulation model, and increases in organizational experience lead to proportional increases in event production. Linearity implies that the marginal growth associated with a new event is relatively constant over the organization’s lifetime and a roughly constant fraction of new recruits are allocated to increase overall tempo of militant activities.

In contrast, $\beta \neq 1$ implies a non-linear feedback process. Notably, non-linear feedback processes are not common models of social processes (but see the literature on arms-races, particularly [17] and [30]). Traditional models often focus on proportional effects in which increases in one variable cause proportional changes in other variables. In non-linear feedback processes, small increases in one variable can produce dramatic and continuing swings in other variables, leading to highly unpredictable dynamics [51].

When $\beta > 1$, the feedback is super-linear, and one or both of these factors must increase with $k$. That is, either per-event growth in militant activities increases over time or an increasing fraction of growth is allocated to militant activities. When $\beta < 1$, the feedback is sub-linear and the marginal recruitment benefits of new events decrease over time or they are constant but recruits are increasingly allocated toward non-militant activities.

Fitting this model directly to the empirical data on all events, we find that the maximum likelihood estimate is $\hat{\beta} = 1.0 \pm 0.1$ (std. err.), indicating linear feedback. (This approach to estimating the parameter gives weight to the events early in organization’s lifetime that is proportional to the number of such events in our data set; in contrast, a simple regression approach on the mean delays would bias the estimate by giving significant weight to the rare but long-lived groups.) Using a Monte Carlo simulation against a null model with fixed $\beta = 0$ (no acceleration over time)
and with \( \mu, \sigma \) estimated using maximum likelihood given the fixed \( \beta \) value, we find that the value of \( \hat{\beta} \) is highly statistically significant \( (p < 0.001) \). (Fitting to deadly attacks alone yields a highly statistically significant \( \beta = 1.1 \pm 0.2 \), slightly in the super-linear regime, but this value is statistically indistinguishable from \( \beta = 1 \).

A linear feedback implies that the marginal growth from event-driven recruitment does not vary much with organizational size or experience. Furthermore, it implies that organizational learning in terrorist groups [25,38], in which the production rate increases due to improved efficiency of a fixed number of individuals, plays a lesser role in explaining the overall acceleration of event production than do the effects of increasing organizational size, because learning would mimic the effect of super-linear feedback by allowing a constant number of militants to behave identically to an increasing number.

A strong test of the statistical model’s plausibility is its prediction that each of the \( k \) conditional delay distributions \( \Pr (\Delta t|k) \) is a scaled version of the underlying log-normal distribution \( \text{LN}(\mu, \sigma^2) \). To test this prediction, we re-scale the empirical distributions by the predicted factor, i.e., we multiply each delay variable \( \Delta t_i \) by \( k_i^{\hat{\beta}} \), and then plot them against the estimated underlying log-normal distribution. A close alignment of these re-scaled conditional distributions, also called a “data collapse” [52], is strong evidence for the hypothesized data model over a wide range of alternatives. Furthermore, for an alternative model to produce such a data collapse requires that it follows the log-normal form closely enough to be effectively equivalent. Figure 3B shows the results of this test, illustrating an excellent data collapse, with each of the re-scaled log-normal conditional distributions closely aligning with the underlying log-normal form.

These results also hold when we consider the development curves for groups with a common political ideology (see Text S1). [53] divides the political motivations for terrorism into four conventional categories: nationalistic-separatist, reactionary, religious and revolutionary. We coded according to Miller’s criteria the 131 most prolific groups in our sample (all with \( k \geq 10 \) deadly events), which accounts for 85% of events, and fitted Eq. (1) to the data within each ideological category. Organizations with multiple political motivations were placed in multiple categories, which would only lessen any differences between estimated parameters for different categories. Within each of these categories, we observe the same acceleration pattern, with the strongest acceleration \( \{\beta \} \) appearing for religious groups (Table 3).

**Severity of attacks over time.** In contrast to the delay development curve, we find no statistically significant relationship between the severity of attacks and increased experience (Pearson’s \( r = -0.024 \), t-test, \( p = 0.17 \)), indicating no support for the severity-increase hypothesis \((H4)\). Across all organizations in our sample, the average severity of the first deadly event is \( \langle x \rangle = 6.7 \pm 0.9 \), which is only slightly larger than the average severity of deadly events by highly experienced groups (those with \( k > 100 \)) \( \langle x \rangle = 5.1 \pm 0.6 \). Figure 4A shows the composite severity curve for all organizations in our study.

As with the frequency curves, we find that the conditional severity distributions \( \Pr (x|k) \) roughly collapse onto a single, underlying form (Figure 4B), which is similar to the power law observed for all deadly terrorist attacks worldwide from 1968–2008 [20,31]. That is, Richardson’s Law for terrorism appears to hold for both inexperienced and highly experienced groups. Combined with our static analysis of organizational size, this pattern implies a highly counter-intuitive fact: the severity of attacks by larger, more experienced organizations, is not significantly greater than the severity of attacks by small, inexperienced organizations. That is, the common assumption that only experienced groups are capable of such mass destruction [54] is incorrect: inexperienced organizations are just as likely to produce extremely severe events as highly experienced organizations.

However, although more experienced organizations are not systematically more lethal at the individual-event level, the observed frequency-acceleration pattern implies that more experienced groups are significantly more lethal overall. This pattern was observed by [9] in their analysis of the BAAD organizations. Our results thus clarify their results, showing that the observed correlation between greater lethality (total deaths attributed to an organization) and greater organizational size appears because larger, more experienced organizations produce events more quickly than smaller, less experienced organizations. It is the cumulative effect of the many small events that generates an increased lethality, not a systematic increase in the lethality of individual events.

Repeating these analyses on our ideology-coded set of organizations, we find no systematic dependence of severity of attacks on organizational experience within any of the ideological categories (see Text S1). That is, none of the model coefficients are significant, and the average severity of events within each category vary only a little. In short, we find that political ideology has no systematic impact on the severity of events or the trajectory that event severities take over the lifespan of an organization.

### Table 3. Frequency curve parameters for organizations with similar political motivations.

| political motivation | groups | events | \( \mu \) | \( \sigma \) | \( \beta \) | significance |
|----------------------|--------|--------|--------|--------|--------|-------------|
| nationalist-separatist | 55     | 2959   | 5.1(5) | 2.2(1) | 0.9(2) | \( p < 0.001 \) |
| reactionary          | 5      | 143    | 3.2(6) | 1.8(2) | 0.1(3) | \( p < 0.001 \) |
| religious            | 17     | 999    | 5(1)   | 2.4(5) | 1.7(5) | \( p < 0.001 \) |
| revolutionary        | 53     | 2527   | 5.7(4) | 2.3(2) | 1.1(2) | \( p < 0.001 \) |
| all secular          | 883    | 6232   | 5.2(2) | 2.25(9) | 0.9(1) | \( p < 0.001 \) |
| all groups           | 910    | 7231   | 5.1(2) | 2.32(9) | 1.0(1) | \( p < 0.001 \) |

Note: statistical significance estimated via Monte Carlo simulation of a two-tail test against a null model with \( \beta = 0 \) (no frequency acceleration), using the sum-of-squared errors (SSE). Values in parentheses indicate bootstrap standard uncertainty in the last digit.

**Discussion**

Although details and circumstances vary widely across terrorist organizations, the generic nature of our results suggests general conclusions. In particular, we find strong evidence for a positive feedback loop among organizational size (number of personnel), experience (cumulative number of events) and the frequency at which that organization launches new events. Small and inexperienced organizations tend to produce events slowly, while larger and more experienced organizations tend to produce events sometimes hundreds of times more frequently.

Within this feedback loop, new attacks lead to organizational growth and the corresponding increase in size leads to faster production of new events because a larger size means more terrorist cells are operating in parallel, not because events themselves are planned more quickly. The result of this feedback
loop is a generic “developmental” trajectory: as an organization ages, it tends to produce violent events more and more quickly.

The typical form of this relationship can be mathematically modeled by a power-law function, in which the delay $\Delta t$ between consecutive events decreases roughly like $\Delta t \propto k^{-\beta}$ where $k$ counts the cumulative number of events and $\beta$ describes the strength and direction of the feedback loop. The implication of the power-law pattern is that large organizations are very much like “scaled up” versions of small organizations, and in particular that size and experience are coupled in a positive feedback loop.

Across all organizations in our sample, we estimate $\beta = 1.0 \pm 0.1$, indicating a linear feedback loop, which implies that an organization’s overall size is strongly correlated with the size of its militant wing. This pattern is strongest for small or inexperienced organizations, e.g., those with $k \leq 10$ events, which covers 87% of the 910 organizations in our sample. In contrast, highly experienced organizations seem to saturate their event production rates at the daily or weekly level, which may be indicative of a tendency of large organizations to engage in multiple types of activities, e.g., the provision of social services, criminal activities, etc., continuing to grow their militant wings.

The mathematical precision of this relationship is striking, as is the ability of our computer simulation to reproduce it. Except for Richardson’s Law for the frequency and severity of wars, few statistical relationships in the study of political violence exhibit such regularity.

The power-law relation between organizational experience and production rate is both conceptually and mathematically similar to the relationship between cost and cumulative production observed in manufacturing [36] or organizational learning [37,39], where decreases in per-item production costs or time can be described by a power law in the cumulative number of items produced. That a similar patterns appears in the production of terrorist events is surprising, and it may not be superficial to describe terrorist organizations as a special type of manufacturing firm whose principal product is political violence and whose overall production of violence is fundamentally constrained by its size.

The implication is that terrorism is inherently non-amenable to mass production, i.e., it is not a scalable enterprise, perhaps because each event must be humanly conceived and planned around a particular target, tactic or environment, and there is a limit to how much this process can be automated. One implication of this conclusion for cyber-terrorism is that even there, despite the great potential for automating attacks, these too will likely not be scalable without advances in general artificial intelligence.

In the language of economics, we say that terrorism capital and labor are not freely substitutable with respect to producing new events. If the day-to-day work of event production does not require specialized skills, then the growth potential of an organization be extremely large because it may draw on the largest possible pool of potential recruits. This point suggests that conflict-level event production rates should ultimately be responsive to policy and counter-terrorism efforts that target the size and mobility of the pool of potential recruits. That is, successful “hearts and minds” strategies [55] are likely to lead directly to lower incident rates by both restricting the growth and reducing the size of terrorist organizations. They may not, however, eliminate the possibility of spectacular attacks as these do not depend on organizational size.

Recently, following our original work on progress curves in terrorism [22], Johnson et al. [25] analyzed the timing of events in the Iraq and Afghanistan conflicts, finding similar power-law like acceleration curves in the delay between events. They argue that this pattern is caused by a kind of “red queen” effect—a concept borrowed from arms races in evolutionary biology [56]—in which two sides of the conflict race through some abstract space, and the timing between events is given by how far “ahead” the insurgent side is in the race. In practice, however, this explanation is difficult to validate because the connection is not specified as to how real-world events and structures drive the dynamics of the abstract race. In contrast, our explanation of the phenomena is both tangible, general and testable: we argue that the size of the insurgency or the terrorist group sets the tempo of the conflict. The more people there are fighting, the more frequently we will observe events. This explanation makes direct and testable predictions about the relationship of organizational size and frequency of events, which we show are upheld by empirical data on organizational sizes. (As a technical note, in the language of physics, the “size” of an organization or insurgency is an extensive variable of the conflict system, much like area and number of particles are for physical systems [57]; this fact makes additional testable predictions of our theory.) The implication for the Iraq and Afghanistan conflicts is that the number of insurgents active in the various provinces is the primary determinant of the frequency of events observed there.

Although the acceleration is remarkably strong, the vast majority of organizations do not achieve high levels of experience (only 23% of groups are associated with $k > 10$ events) or fast...
production rates. The progressive loss of organizations could be due to high rates of organizational death, e.g., from counter-terrorism activities or internal conflicts [44,58], shifts away from violence, or a right censoring effect on young and still active organizations. Significantly, the particular mode of organizational demise seems not to have a strong impact on the production time of events, suggesting that the transition from development (growth) to death may happen very quickly, so that the experience curve does not bend upward but rather simply halt. Further exploration of the death of organizations [44,58], and how it impacts the production of violence, is an interesting avenue for future work.

Regardless of the reason, we do not expect the feedback loop to continue as $k \to \infty$. If an organization succeeds in becoming large enough to produce new events each day, it may function more like a stable or mature social institution, with fundamentally different constraints and incentives on the production of violence. Large size and stability may also pose special risks, e.g., leading to larger or longer conflicts. On the other hand, non-violent activities, e.g., engagement with political processes, may also become more attractive with increased size. Exploring these possibilities is an interesting avenue for future work.

Unlike the production of events, we find no evidence of any relationship with the severity of attacks (H4). Rather, Richardson’s Law—a power-law distribution in the frequency of severe events—characterizes the severity of events at all levels of organizational size or experience, and independent of the organization’s political ideology.

This fact clarifies ongoing efforts to identify the underlying social, political or physical mechanism that generates Richardson’s Law in terrorism. Several existing explanations assume or predict a severity-size relationship, e.g., the aggregation-disintegration model of Johnson et al. [23] and [35], but these seem increasingly unlikely given our results here, because they assume the maximum severity of an event is proportional to the organization’s size $N$; thus, if $N$ is small, the severity of events $x$ will also be small. That is, in their existing form, these models predict a severity-size relationship that does not appear in the data. Of course, these models may be adapted to produce the observed size-independence pattern, but doing so requires additional assumptions and additional validation that may not be warranted.

In contrast, two plausible explanations are not ruled out: (i) the explanation proposed in [20], which posits a coevolutionary competition between states and terrorists in which event planning time and severity are strongly related, and (ii) the explanation proposed in [24], in which population densities are broad-scaled and terrorists preferentially target high-density locations. Both of these explanations do not assume any relation between the severity of an attack and the size of an organization.

Together, our results suggest that the total lethality of larger and more mature groups observed by Asal and Rethemeyer [8] is the product of violence, or a right-censoring effect on young and still active organizations. Significantly, the particular mode of organizational demise seems not to have a strong impact on the production time of events, suggesting that the transition from development (growth) to death may happen very quickly, so that the experience curve does not bend upward but rather simply halt. Further exploration of the death of organizations [44,58], and how it impacts the production of violence, is an interesting avenue for future work.

The most productive targets of such policies will be large, established organizations with long histories of producing terrorist attacks. By virtue of their size, these organizations are likely to be well-known players in their particular conflicts and thus easy targets for specific policies. Because small organizations are equally likely to produce severe events, policies aimed specifically at large, well-known organizations may not limit the overall risk of severe events from all sources. For small and potentially unknown organizations, the most effective policies may be those aimed at preventing their formation in the first place, i.e., policies that curtail the acquisition of the means for and resort to violence. Lacking this, once such a terrorist cell carries out its first attack and begins its developmental trajectory, the best action by a government may be an “overwhelming response” to encourage through various means the dissolution of the nascent organization and the truncation of its growth trajectory. This policy is not without risk to the state, however, as certain countermeasures may serve the terrorist’s goals [39,60].

In closing, we point out that the acceleration in the frequency of terrorist events is independent of many commonly studied factors associated with terrorism, including geographic location, time period, international vs. domestic targets, ideological motivations (religious, national-separatist, reactionary, etc.), and political context. Our results thus demonstrate that some aspects of terrorism are not nearly as contingent or unpredictable as is often assumed and the actions of terrorists may be constrained by processes unrelated to strategic tradeoffs among costs, benefits and preferences. Identifying and understanding these processes offers a complementary approach to the traditional rational-actor framework, and a new way to understand what regularities exist, why they exist, what they imply for long-term social and political stability, e.g., large-scale violent conflicts like civil and interstate wars.

Supporting Information

Text S1 Supplementary Text. 1. Additional analysis of organizational sizes and their event frequency and severity. 2. Frequency and severity development curves for four highly prolific organizations. 3. Specification and code for the simulation model. 4. Mathematical details of generic pattern in event frequencies versus experience. 5. Robustness checks of the frequency-acceleration pattern. 6. Analysis of developmental trajectories of organizations by political ideology. (PDF)

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Author Contributions

Conceived and designed the experiments: AC KSG. Performed the experiments: AC KSG. Analyzed the data: AC KSG. Contributed reagents/materials/analysis tools: AC KSG. Wrote the paper: AC KSG.

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