No Time to Die: The Effect of Lethality and Alliances on Terrorist Group Survival

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ABSTRACT
There is a consensus within existing literature in the terrorism field that cooperation between terrorist groups increases their survival. Such a consensus is lacking where lethality is concerned, in no small part due to lethality rarely being studied as a primary explanatory variable for survival. Furthermore, existing literature does not use statistical network methods to examine survival as a dependent variable. This article uses network analysis to examine the effect that both lethality and alliances have on terrorist group survival. I find that the consensus regarding cooperation holds; even when taking network dependencies into account, cooperation leads to longer survival. I also find support for lethality having a curvilinear effect on survival.

1. Introduction

How does a terrorist group survive? Extant literature has studied a number of factors that may extend group survival, such as their funding sources, their orientation, and their alliances (e.g. Acosta 2014; Choi, Choi, and Yang 2024; Gaibulloev and Sandler 2013; Hou, Gaibulloev, and Sandler 2020; Milton and Price 2020; Olzak 2016; Phillips 2015; Piazza 2018, 2021; Price 2019; Young and Dugan 2014). In this paper, I build from this literature in two ways. First, I theorize about how lethality contributes to or undermines terrorist group survival. Currently, research in the terrorism field has included different measures of lethality as confounding variables but results are ambiguous, with some studies finding that lethality increases survival, others finding that it decreases survival, and others finding insignificant results (Blomberg, Engel, and Sawyer 2010; Blomberg, Gaibulloev, and Sandler 2011; Gaibulloev and Sandler 2013; Hao 2022; Olzak 2022). I contribute not only by researching lethality as the primary explanatory variable but also by incorporating the network of terrorist group alliances. I follow the idea of lethality as a signal of capacity and I present a theory as to why I expect that the effect of lethality on longevity is curvilinear, with the longest survival expected for groups that have low levels of lethality and groups that have high levels of lethality. This, I expect, is because the signal that groups send at low levels of lethality is weak and does not promote urgency in a state response, while at high levels of lethality, groups have the capacity to evade state attempts at elimination.

Second, I re-examine theories about alliances and survival. Extant literature is not in disagreement; most research on the effect of alliances on terrorist group survival agree that alliances extend longevity. However, the literature currently does not use network analysis methods, instead continuing the use of traditional regression models that treat groups as independent, when merely having an alliance inherently means that groups are not independent. This paper is one of the first to examine terrorist group survival as a dependent variable while using statistical network methods. The contribution here is not only the use of network methods; incorporating the alliance network also allows the exploration of lethality while accounting for network dependence.

In my analysis, I employ techniques that enable me to examine how both lethality and alliances affect survival; these techniques allow me to test the nonlinear effect of lethality on survival and at the same time test the impact of alliances on survival. The statistical network method that I use is a stochastic actor-oriented model, which models the co-evolution of a network and a behavior. I use data on network alliances in order to model the co-evolution of the global terrorist alliance network and terrorist group survival. I do this with an extension of the Siena model first presented as a diffusion model (Greenan 2015). Typically, this technique is used to model diffusion of an actor-level variable through a network, such as how adolescent drinking or smoking diffuses through a friendship network (Greenan 2015; Light et al. 2013, 2019). However, because the diffusion model reduces to a proportional hazards model, I use it instead to model survival. I pair this with an accelerated failure time model to account for any shortcomings with the Siena diffusion model. I find support for both of my hypotheses.

The rest of the paper is as follows. I review literature on lethality, capacity, and survival and theorize about how lethality affects survival. I then review the literature on cooperation and survival and present a hypothesis about how alliances affect survival. This is followed by the research design, wherein I explain the process of collecting the network data, an explanation of the stochastic actor-oriented model and how it will be implemented, and an explanation of how the accelerated failure time model will be implemented. This is followed with a discussion of the results for each type of model. I end with a discussion of the next steps.

2. Lethality and Survival

How does a terrorist group's capacity for violence affect its survival? The effect of overall lethality of terrorist organizations on their survival has rarely been studied as a primary explanatory variable, but organizational lethality has often been included as a control variable in studies of terrorist group longevity. As a control variable, lethality or the amount of violence that a group does has been conceptualized in different ways. In some studies, lethality is measured as the number of casualties or fatalities (Blomberg, Engel, and Sawyer 2010; Blomberg, Gaibulloev, and Sandler 2011; Hao 2022; Olzak 2022) or the number of casualties per million people in the base country (Gaibulloev, Hou, and Sandler 2020). In other studies, lethality is measured as a number of attacks (Carter 2012; Hao 2022), and it has even been measured as casualties per attack (Gaibulloev and Sandler 2013).

Findings when these various conceptualizations of lethality have been included as control variables have been mixed. In some studies, an increase in lethality is associated with an increase in survival (Blomberg, Engel, and Sawyer 2010). In other studies, an increase in lethality is associated with a decrease in survival (Blomberg, Gaibulloev, and Sandler 2011; Gaibulloev and Sandler 2013). And still other research finds insignificant results for the respective measure(s) of violence, suggesting no evidence that lethality affects terrorist group survival (Acosta 2014, 2016; Hao 2022). Young and Dugan (2014) take a more direct approach at examining lethality. They create a variable for "top dog" groups, measured as the terrorist organizations that committed the most attacks in their primary country, and they find that top dog groups are less likely to end.

A few pieces of extant literature examine distinct ways that terrorist groups end, treating these as competing risks. Carter (2012) examines internal splintering and ending by force. The primary variable of interest is safe havens, but a count of attacks is included as a control variable, and he finds that a count of attacks increases the likelihood of ending by force. Gaibulloev and Sandler (2014) use competing risk analysis to explore different ways that terrorist groups end, including by military or police force, splintering, and victory or joining the political process. Their analysis includes only transnational attacks and as such, they measure lethality as the number of transnational attacks per million people. They find no evidence that the number of attacks affects the different ways of ending, but they do find that a higher number of attacks makes groups that began after 1990 more likely to end overall. They suggest that this is because increased attacks engenders a stronger state response. Olzak (2022) studies two ways of ending: ending by joining politics and ending by military force, splintering, merging, or fading away. The main explanatory variable of interest is ideological ambiguity, and the number of civilian deaths is included as a control variable.[1] She finds that causing a higher number of civilian deaths decreases the risk of ending by military force, splintering, merging, or fading away, but the effect is substantively small.

In this paper, I attempt to reconcile these ambiguous findings. I do so by adopting the idea that lethality aligns with capacity. Capacity denotes a group's access to material resources and information (Asal and Rethemeyer 2008), and access to resources should in turn enable a group to increase lethality. Bueno de Mesquita (2005) links resources to capacity by arguing that terrorist organizations devote their limited resources to the most skilled members, and with more skilled members, the groups devote more resources to violence.

Much of the extant literature demonstrates that increased capacity engenders increased lethality. The clandestine nature of terrorist organizations makes it inherently difficult to assess their capacity, but many studies focus on proxies for organizational capacity or strength. These proxies, such as size, tactical diversity, or territorial control, are often found to increase lethality, whether conceptualized as fatalities (Asal and Rethemeyer 2008; Fisher and Asal 2021; Hou, Gaibulloev, and Sandler 2020; Olzak 2022) or attacks (Clauset and Gleditsch 2012; Mierau 2015). Asal et al. (2018) look specifically at insurgent groups and argue that insurgent groups need a certain level of capacity to be able to withstand state repression by turning to the targeting of civilians. It has even been argued that organizational capacity is the best determinant of lethality (Fisher and Asal 2021), and Robinson and Malone (2024) argue that the violence of splinter groups depends on their capacity.

In addition to the research which finds that organizational capacity leads to an increase in organizational lethality, other research argues that lethality is a conceptualization of capacity in and of itself. Overgaard (1994) and Lapan and Sandler (1993), for example, show that attacks signal to the government the amount of resources that a group has, and Overgaard (1994) in particular argues that the first attack that a group commits should be destructive enough to indicate that they have high resource levels even if they do not actually have high resource levels. In other words, groups' initial attacks should be lethal enough to signal high capacity. Horowitz and Potter (2014) contend that lethality itself represents capacity, and in a similar vein, Blair and Potter (2022) argue that violent attacks are a demonstration of capacity.

[1] In Olzak (2022), the number of civilian deaths also serves as a dependent variable in part of the analysis.

If lethality functions as capacity, then it seems logical that groups with higher lethality should last longer. However, I expect that the relationship is not so straightforward and it is precisely because lethality is a signal of capacity that groups with very low lethality will also last longer. This is because lethality sends a signal of the destruction that a group is willing to do (Lapan and Sandler 1993; Overgaard 1994), and I theorize that at low levels of lethality, the signal is not strong enough to warrant urgency from the state, nor enough to leverage the state into making concessions.

I also expect that groups with high levels of lethality will last longer. This is because at high levels of lethality, groups have undermined their own bargaining power, so they are less likely to be granted concessions (Abrahms 2006, 2012). In civil wars, for example, groups that kill more civilians are less likely to receive concessions or achieve their goals (Fortna 2015; Stanton 2020; Wood and Kathman 2015). In fact, research has shown that high levels of lethality or high-lethality tactics bring about a backlash in which the government becomes more resolved to eliminate the group (Abrahms 2013; Acosta 2014). Yet, at the same time, if lethality correlates with capacity or functions as capacity, even as the state pursues the group with increased intensity, the groups that have high levels of lethality will have the capacity to avoid detection and elimination. Thus, I expect that there is a middle level of lethality at which terrorist groups are more likely to terminate. This argument can be restated as the following hypothesis:

$H1$: *Terrorist groups that exhibit moderate levels of lethality are more likely to end.*

3. Cooperation and Survival

One of the ways that terrorist groups increase their capacity is through alliances. Terrorist groups cooperate with other groups in order to overcome organizational deficiencies (Bacon 2018a). Doing so allows for resources pooling so that groups gain skills, recruits, weapons, funding, and even tactical information (Asal and Rethemeyer 2008; Asal and Shkolnik 2024; Byman 2014; Horowitz and Potter 2014; Moghadam 2017; Phillips 2019; Plapinger and Potter 2017; Price 2012). For instance, by forming network ties, Al-Qaeda was able to specialize within the Iraq market, brand outside it, legitimize itself within the network, and gain access to donors, logistics, and propaganda capacities (Byman 2014). Bacon (2018b) argues that certain groups become alliance hubs in that many groups try to ally with them to improve their own capacity.

The increase in capacity is shown in that terrorist groups and insurgencies with allies have increased lethality. Some studies have found this when considering the number of allies that a group has (Asal and Rethemeyer 2008; Asal and Shkolnik 2024; Olzak 2022). Others find that it is not the *number* of allies that a group has but rather the connectedness of the allies or even the overall network of groups that matters (Asal, Phillips, and Rethemeyer 2022; Horowitz and Potter 2014; Olzak 2016; Pearson, Akbulut, and Lounsbery 2017). Organizations with allies have also been able to turn to more lethal tactics or more difficult targets (Asal, Phillips, and Rethemeyer 2022; Asal, Ackerman, and Rethemeyer 2012; Horowitz 2010).

As groups increase their capacity, they gain access to material and informational resources which contribute to their survival. Lethality notwithstanding, terrorist groups that have alliances tend to last longer (Acosta 2016, 2014; Choi, Choi, and Yang 2024; Hou, Gaibulloev, and Sandler 2020; Milton and Price 2020; Phillips 2015; Price 2012, 2019). Phillips (2014) proposes that the connectedness of allies is what matters for survival, but he does not find support for this hypothesis and instead finds that the number of alliances matter. However, Milton and Price (2020) find that the connectedness of allies matters. Still other research finds that allies or the connectedness of allies matters not for terrorist groups ending in general but for specific kinds of endings (Olzak 2016, 2022).

What the studies on alliances and organizational longevity have in common is that they use traditional regression methods that treat groups as independent. However, having alliances inherently means that groups are not independent, but rather exist in a network. Even though terrorist groups exist in a network, the use of social network analysis (SNA) in terrorism literature is still rare. Even research that collects original data on terrorist or insurgent relationships still uses traditional regression methods that assume independence (Acosta 2016; Balcells, Chen, and Pischedda 2022; Blair et al. 2021). Those that do use statistical network methods do so primarily to model the formation of alliances or rivalries rather than how these relationships affect the groups themselves (Asal et al. 2016; Asal, Phillips, and Rethemeyer 2022; Balcells, Chen, and Pischedda 2022; Blair et al. 2021; Gade et al. 2019).

I re-examine the idea that cooperation leads to longevity, but I use network methods to do so. This enables me to take the entire network into account when exploring how cooperation affects terrorist group survival, and it additionally allows me to account for dependence while examining the hypothesis on lethality (H1). Thus, I restate my expectations for cooperation and group longevity in the following hypothesis:

> $H2$: *Terrorist groups that are more embedded in the network of terrorist groups will survive longer.*

4. Research Design

4.1. *Network Data*

I use both yearly alliance network data and group-year time-series cross-sectional data. I began with the sample of 760 groups from 1970 to 2016 contained in Extended Data on Terrorist Groups (EDTG; Hou, Gaibulloev, and Sandler 2020). I chose this as the foundation because it is based on the Global Terrorism Database (GTD; START 2020) but the curators did extensive cleaning to account for misspellings and aliases.

The network data are intended to capture cooperative relationships including joint attacks, joint planning, training together, providing funding and weapons, or sharing members, similar to the definition of cooperation/alliance used by Acosta (2016); Bapat and Bond (2012); Horowitz and Potter (2014); Phillips (2019). Verbal support such as announcing support of another group's attack or pledging allegiance to a group are not included as relationships in the data. The relationship data is a binary variable coded at a dyad-year level.

I used existing datasets in order to code the alliance data. The main dataset that I used for cooperative relationships was the Militant Group Alliances and Relationships (MGAR; Blair et al. 2021) dataset. I chose this because it is the most widely encompassing militant relationship dataset and includes groups that are in the GTD. However, it includes many aliases and fronts as distinct groups, so I extensively cleaned it to ensure that I was capturing the correct relationships and ensuring that no relationships were missed by virtue of groups having a different name or being listed multiple times under different names within the MGAR data. MGAR includes several types of relationships ranging from concrete, material support to rhetorical support.

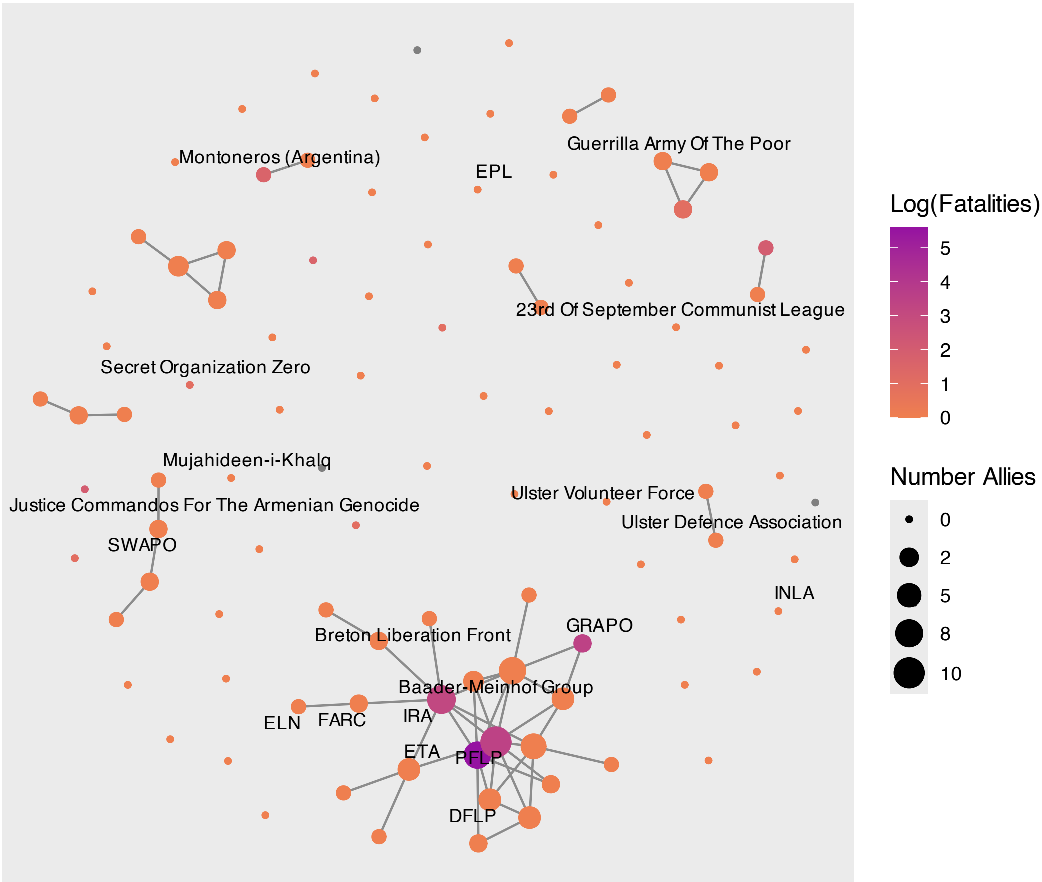

Figure 1. 1975 Terrorist Alliance Network

I included all cooperative relationships coded in MGAR so long as they rose above the level of merely verbally supportive relationships. In the MGAR data, this includes financial, material, training, operations, or territorial support, which are all coded as their own categories.

I also used data from Balcells, Chen, and Pischedda (2022), the Revolutionary and Militant Organizations Dataset (REVMOD; Acosta 2019), UCDP's Georeferenced Event Dataset (Davies et al. 2024), and UCDP's External Support Dataset (Meier et al. 2022). There are caveats to the data collection. MGAR contains an extensive amount of groups, including groups in the GTD, and as mentioned, this is why it was used as the main source of relationship data. However, the aliases and misspellings led some groups from the EDTG base sample of groups to not be included in the MGAR data. The other datasets were used to fill these gaps. UCDP data include insurgencies, and as such, smaller, lesser known terrorist organizations do not appear in the UCDP data. This is a limitation. REVMOD ends in 2014 while EDTG ends in 2016. For groups that had a cooperative relationship in REVMOD from 2011-2014, I made the assumption that this relationship continued into 2015 and 2016.[2]

Figure 1 shows the 1975 alliance network with groups sizes scaled by the number of alliances and colored according to the fatality count.

[2] If other datasets showed fighting between the groups in 2015 and 2016, I did not code a cooperative relationship, even if REVMOD had a cooperative relationship coded for 2011-2014.

4.2. *Siena*

I use two modeling strategies. The first is the stochastic actor oriented model, implemented with the RSiena package in R (Snijders et al. 2024a,b). Stochastic actor oriented models implemented with RSiena are called Siena models. Siena models allow for jointly modeling the evolution of a longitudinal network and a behavior. Here, I use Siena models to jointly model the evolution of the alliance network of terrorist groups and terrorist group failure.

Siena models assume that networks are states that gradually change over time (as opposed to being comprised of quickly changing events). Because of this stability, Siena models assume that changes to the network come from a Markov process such that the network at any time point is determined by the network at the immediate previous time point and not by information further in the past (Snijders, van de Bunt, and Steglich 2010). The Siena model assumes a continuous time process but takes data in the form of discrete time points, called *waves* — which in this paper are years — and the model simulates the network process in the *periods* between the waves. In the periods between the waves, the Siena model does agent-based simulations of "ministeps" in order to simulate how the network state in one observed time wave transitions to the network state at the next observed time wave (Snijders, van de Bunt, and Steglich 2010; Snijders et al. 2024a). The ministeps are sequential such that only one tie is made or dissolved at a ministep, and it is assumed that an actor's choice to create or dissolve a tie is based on the simulated network (Snijders et al. 2024a). Many ministeps happen within one period.

In the case of this paper, a terrorist network may exist in, for example, 2010 and 2011. The network may look different between the two years because terrorist groups may have stopped cooperating, started cooperating, ended and dropped out of the network, or new groups may have sprung up. Having the observed network data for 2010 and 2011, Siena would then simulate many ministeps taken between 2010 and 2011 in order to get from the observed 2010 network to the observed 2011 network.

In the Siena model that models co-evolution of a network and a behavior, both the network and behavior are governed by their own rate function and evaluation function. In a traditional Siena model, the rate function models the frequency by which actors have the opportunity to make a change (Snijders, Steglich, and Schweinberger 2007; Snijders et al. 2024a). For the network, this is the frequency by which actors can create or dissolve a tie. For the behavior, it is the frequency by which actors can make a change to the behavior. The evaluation function, on the other hand, models whether a choice will be made (Snijders, Steglich, and Schweinberger 2007; Snijders et al. 2024a). Put another way, the rate function models whether an actor has the opportunity to change, and the evaluation function models whether they will make the change once receiving the opportunity. In the traditional Siena model, explanatory variables typically are included in the respective network and behavior evaluation functions so that the explanatory variables affect the probability of an actor making a change to the network or behavior, respectively, once given the opportunity.

Rather than using this traditional Siena model, I use the Siena diffusion of innovations model. (Greenan 2015) extends the Siena co-evolution model by using a behavior variable that cannot decrease and by including covariates in the behavior rate function instead of the evaluation function. She shows that this causes the model to become a survival process, so that while the network changes still follow the traditional SAOM, the rate function models the hazard of a behavior change rather than the frequency of opportunities of a behavior change. Greenan's diffusion model extension is usually used to study how an actor-level variable diffuses through a network, but because it reduces to a proportional hazards model, I use it to model survival. It is not a model of diffusion of group ending across a network because once the group ends, it drops out of the network.

4.2.1. Siena Implementation

My data span 1970–2016. While there is no set amount of waves that can be modeled by Siena, the modeling procedure has typically been used for a smaller amount of waves, such as less than 10 (e.g. Greenan 2015; Hopp, Stoeger, and Ziegler 2020; Light et al. 2013, 2019; Snijders, van de Bunt, and Steglich 2010), and a high number of waves can bring about difficulty with model convergence or time heterogeneity (Snijders 2018, 2022b). I therefore split my data into 1970–1985, 1985–2000, and 2000–2016 such that each interval contains 16-17 waves,[3] and I run separate models for each of the three time intervals where the waves are years and the periods are the time in between each discrete year time point. There are 203 groups in the 1970–1985 interval, 313 in the 1985–2000 interval, and 482 in the 2000–2016 interval.

Siena takes two dependent variables: the network and the behavior variable. The dependent network variable is the longitudinal network of terrorist group alliances as described above. The dependent behavior variable is terrorist group end. This comes from EDTG. It is a binary variable coded 1 for the last year a group is active and 0 otherwise. The explanatory variables used in a Siena model are called *effects*.

I include dyadic and structural effects for the network part of the model. Geometrically-weighted edgewise shared partnerships (gwesp) is a way to account for triadic closures, which is the idea of "the friend of my friend is my friend," but rather than a straightforward count of triangles, which can make convergence difficult, gwesp allows for decreasing importance of triadic closures as more triadic closures are added. It is important to account for transitivity; as Asal, Phillips, and Rethemeyer (2022) show, militant groups are more likely to form alliances with allies of their allies. The degree activity plus popularity effect accounts for "the rich get richer," or in other words, groups that gain more ties simply because they already have many ties. A homophily effect for region is included in order to account for groups in the same region being more likely to cooperate. Finally, I include an ego effect for duration, which is simply the effect that duration has on a group forming ties. This is included because groups that have been active longer may have more ties by virtue of having had more opportunity to form them. Table 1 lists the network effects.

For the behavior variable, the first primary effect of interest is the fatalities caused by a group. This comes from EDTG and I log it in base 2. I also include a squared term (also logged) because I hypothesize an inverted-U shaped relationship. The second primary effect of interest is network embeddedness, which I capture with a degree effect in the rate function. This will model whether a terrorist group's number of allies affects its survival. This is currently the only way of capturing network embeddedness within the behavior rate function.

My control variables come from EDTG. It is recommended to have few effects in a Siena model (Snijders, van de Bunt, and Steglich 2010) and I therefore do not include many of the control variables that are often included in terrorism literature. I include a binary variable indicating whether a group has a religious orientation because groups

[3] 1985 and 2000 are included in two intervals so that the 1985–1986 and 2000–2001 periods are modeled. If an interval ends in 1985 and the next starts in 1986, then the shift from the 1985 wave to the 1986 wave is never modeled.

with a religious ideology have been shown to have extended longevity (Blomberg, Gaibulloev, and Sandler 2011; Gaibulloev, Piazza, and Sandler 2023; Piazza and Piazza 2020; Tokdemir 2021) and another binary variable indicating whether a group has a territory goal. As a way of capturing strength, I include a binary measure of whether a group has a base in more than one country.[4] I also include a few base country effects, which also come from EDTG. These include population (logged), GDP per capita (logged), and polity. Finally, I include duration as an effect since I split the 1970–2016 time period into three intervals. All of these effects are included in the rate model. [5]

Table 1. RSiena Network Effects

Effect	**Interpretation**
Degree (density)	Tendency of network to have ties. Functions as an intercept
GWESP	Triadic closures. *Friend of my friend is my friend* effect
Degree activity + popularity	*Rich get richer effect*
Same region	Models whether alliances are more likely between groups in the same region
Ego effect for duration	Models whether duration affects the number of alliances a group makes

4.3. *Accelerated Failure Time Models*

The advantage of RSiena is that it allows for modeling a dependent variable of interest while accounting for network dependence. There are drawbacks, however, including not being able to include many time waves or covariates. I also found time heterogeneity that I was unable to unable to completely solve by including time dummy interactions nor by modeling fewer periods of time, which will be discussed further in the results section. Nevertheless, Siena offers a major advantage by modeling not only the full network, but also how the evolution of this network affects survival and in turn how survival affects the network.

To balance the drawbacks that come with using RSiena, I also include accelerated an failure time (AFT) model. This is a more traditional survival model. The disadvantage is that network dependence is not modeled and groups are assumed to be independent. The main advantage is that different measures intended to capture network embeddedness can be included, as well as a number of potentially confounding variables. Although the Siena diffusion model reduces to a proportional hazards model, I use AFT models instead of Cox proportional hazards models because the time heterogeneity within the Siena models strongly suggests that the proportional hazards assumption will not hold. The log-normal distribution is used The distribution of the maximum survival of each group in the dataset is shown in Figure 2

To capture lethality, I again use the fatalities caused by a terrorist group (logged in base 2 due to outliers). I include the squared version, also logged, because I expect a curvilinear relationship. I use three measures of network embeddedess. The first is degree centrality, which is a straightforward count of a terrorist group's allies. The second measure is eigenvector centrality, which is a measure of an actor's centrality

[4]Models using attack diversity or share of transnational attacks out of total attacks did not converge.

[5]Within the longitudinal network, there are groups that enter late or leave early, called joiners and leavers in RSiena. These are represented by structural zeroes in the network. Per (Snijders et al. 2024a), I include a dummy variable for these "missing" actors fixed at a large negative rate in order to stop the model from estimating behavior changes at ministeps for groups that are not in the network during the period being modeled.

that takes into the importance of its allies account (Bonacich 1987; Borgatti and Everett 2006). A group connected to five groups that each have five other connections will have a higher eigenvector centrality than a group connected to five groups that each have one other connection. Notably, eigenvector centrality considers the entire network, and not just the immediate connections. The third measure that I use for network embeddedness is the ego network at order two. This is a count of a group, its direct allies, and its allies' direct allies. I also include the local clustering coefficient, or local transitivity, as a control variable in order to capture some network dependence.

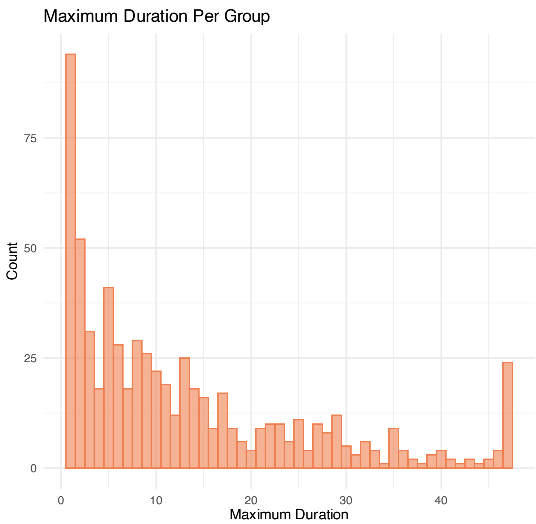

Figure 2. Maximum duration distribution

Figure 3 shows the distribution of yearly alliance counts and logged fatalities per group in the dataset.

Several group or group-year control variables are included. The data come from EDTG. I control for group orientation, categorized as left, right, nationalist, or religious, with religious as the reference category. I also control for group goals, which are regime change, territory goals, policy goals, or maintaining the status quo, with status quo as the reference category. Attack diversity is included because groups that are able to shift tactics may evade detection and last longer (Blomberg, Gaibulloev, and Sandler 2011; Gahramanov, Gaibulloev, and Younas 2024; Gaibulloev, Piazza, and Sandler 2023; Gaibulloev, Hou, and Sandler 2020). The share of transnational attacks is the proportion of a group's attacks that are transnational. Attacking transnationally has been shown to affect survival (e.g. Gahramanov, Gaibulloev, and Younas 2024; Gaibulloev, Piazza, and Sandler 2023; Kim and Sandler 2021; Olzak 2022; Young and Dugan 2014). Third, a binary indicator for multiple bases is included. Groups that have multiple bases may strong and more capable of evading detection (Gaibulloev and Sandler 2013).

I also control for aspects of the base country. When a group has multiple base countries, the measures are averaged. These measures include population logged in base 2, GDP per capita logged in base 2, region – with MENA as the reference category, and V-Dem's electoral democracy index and a squared version of the democracy index. V-dem is used in the AFT models even though polity is used in the Siena models because V-dem is the preferred measurement but caused convergence issues when included in the Siena models.

5. Results

5.1. *Siena*

As explained in section 4.2.1, I break up the 1970–2016 data into three time intervals and run the model separately for each time interval. Each model models the ministeps taken between each year for all the years in that time interval. The results are seen in Table 2. Model 1 covers 1970 through 1985, model 2 covers 1985 through 2000, and

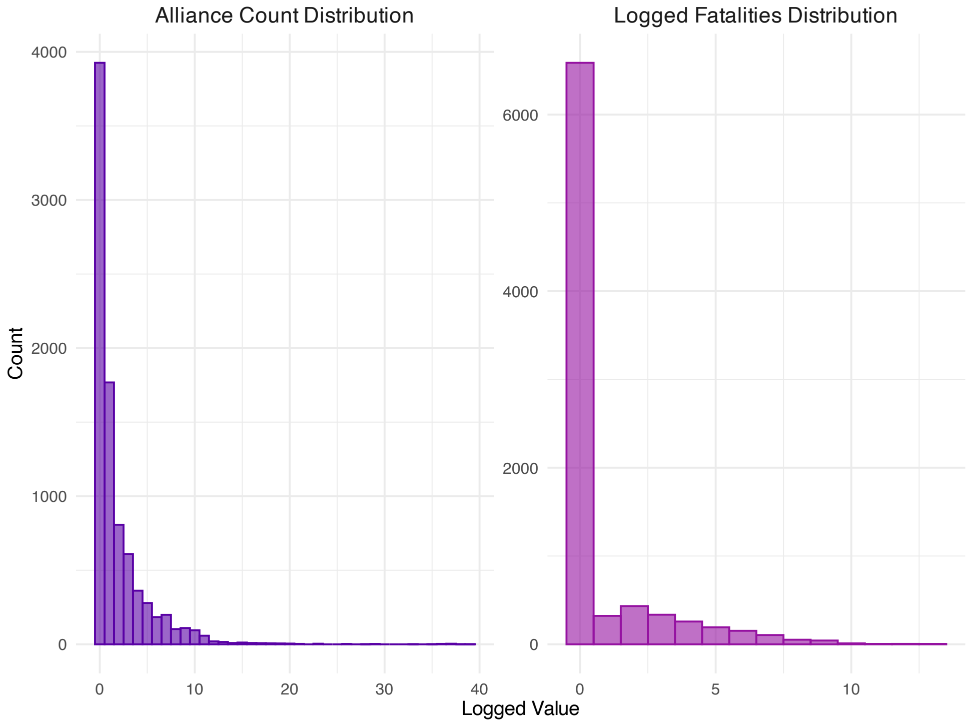

Figure 3. Independent Variable Distribution

model 3 covers 2000 through 2016. The network dynamics were included as part of the evaluation function and the coefficients can be interpreted as log-probability ratios (Snijders et al. 2024a). It is log-probability rather than log-odds because the model is multinomial; the actors decide between many potential partners as well as the option not to make a tie rather than just deciding to form a tie or not form a tie (Snijders et al. 2024a; Snijders 2022a). The behavior dynamics were included as part of the rate function and the estimates can be interpreted as effects on the hazard of group end. I will first interpret the effects of Table 2 but there is a caveat that the third time interval (model 3 of Table 2) has time heterogeneity for many of the parameters during many periods, and a number of steps are taken in order to attempt to address this, discussed further below.

5.1.1. Network Dynamics

The degree (density) effect represents the tendency of the network to have ties and functions as an intercept. The parameter is negative, suggesting that the probability of having ties is low. The GWESP effect in model 1 has a coefficient of 1.064, meaning that the probability of a group creating or maintaining an alliance that closes a triangle is $e^{1.064} = 2.898$ times higher than creating or maintaining a tie that does not close a triangle, all else being equal. The effect is similar in models 2 and 3.

The degree activity plus popularity effect is insignificant and substantially almost nonexistent in model 1, meaning that between 1970 and 1985, there is no evidence that groups with a higher number of alliances are more likely to create or form alliances than groups that do not have a high number of alliances. In models 2 and 3, the coefficient is significant but the exponentiated coefficient is close to 1 in both models,

Table 2. Main Siena Models

Effect	(1) 1970–1985 est.	(s.e.)	(2) 1985–2000 est.	(s.e.)	(3) 2000–2016 est.	(s.e.)
Network Dynamics						
Degree (density)	–2.156***	(0.145)	–2.590***	(0.135)	–2.860***	(0.072)
GWESP (69)	1.064***	(0.187)	1.074***	(0.122)	0.917***	(0.069)
Degree act+pop	0.001	(0.014)	0.034***	(0.010)	0.025***	(0.004)
Same region	1.000***	(0.135)	0.894***	(0.118)	0.850***	(0.072)
Duration ego	–0.006	(0.020)	0.003	(0.009)	0.005	(0.003)
Behaviour Dynamics						
Number of Allies	–0.412**	(0.152)	–0.187*	(0.084)	–0.205***	(0.061)
Fatalities (log)	1.998*	(0.868)	1.284†	(0.705)	0.076	(1.367)
Fatalities sq. (log)	–1.005*	(0.454)	–0.644†	(0.359)	0.052	(0.691)
Territory Goal	–0.554	(0.388)	–1.328***	(0.358)	–0.064	(0.236)
Religious	–0.920	(0.609)	–1.202**	(0.388)	–0.107	(0.256)
Multiple Bases	–0.048	(0.345)	0.095	(0.281)	0.330	(0.262)
Population (log)	0.010	(0.098)	–0.272***	(0.067)	–0.116	(0.072)
GDP per capita (log)	0.492***	(0.134)	0.139*	(0.071)	0.266**	(0.083)
Polity	–0.063*	(0.030)	–0.003	(0.025)	–0.028	(0.022)
Duration	–0.115*	(0.045)	–0.029*	(0.014)	–0.034***	(0.010)

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Convergence t ratios all < 0.05.

Overall maximum convergence ratio Model 1: 0.23; Model 2: 0.19; Model 3: 0.14.

suggesting that groups with a high number of alliances are only very marginally more likely to form or maintain ties than groups that do not have a high number of alliances. The coefficient for same region is positive and significant. In model 1, a terrorist group is $e^{1.000} = 2.718$ more likely to form or maintain alliances with groups in the same region than with groups in different regions. The effect is similar in models 2 and 3. The effect of duration is very small and insignificant in all three models, meaning that there is no evidence that older groups are more likely to form or maintain alliances.

5.1.2. Behavior Dynamics

In models 1 and 2, the effect fatalities is positive and significant. Fatalities is logged in base 2, so a doubling of fatalities leads to a $(e^{1.998} - 1) * 100 = 637.4\%$ increase in the hazard of ending in model 1 and the effect is 261.1% in model 2. These effects seem quite large, but the significant and negative effect when fatalities is squared means that each time fatalities is doubled, its effect on the hazard of ending is decreased more and more until the relationship changes signs, resulting in an inverted-U shape whereby the hazard of ending is highest at an intermediate level of fatalities. In model 1, the effect of fatalities is reduced by $(1 - e^{-1.005}) * 100 = 63.4\%$ for the first doubling of fatalities, and this reduction grows quadratically. In model 2, the initial reduction in the effect of fatalities is 47.5%. In model 3, the effects are not significant, and the quadratic effect is not in the expected direction. However, testing for time heterogeneity revealed substantial time heterogeneity. I take measure to account for this heterogeneity, discussed below.

The degree effect on the hazard of ending is negative and significant in all three models of Table 2. In model one, the effect of degree is that having one more ally decreases a group's hazard of ending by $(1 - e^{-0.412}) * 100 = 33.8\%$. In model 2, each additional ally decreases the hazard of ending by 17.1%, and in model 3, each additional ally decreases the hazard of ending by 18.5%. While the substantive decrease in the hazard of ending caused by having one additional ally is different across the models, the significant negative effects suggest strong support for H2.

Being based in a country with a higher GDP per capita appears to increase the hazard of ending. This is likely because GDP per capita captures some aspects of state capability. In model 1, a doubling of the base country's GDP per capita leads to a $(e^{0.492} - 1) * 100 = 63.6\%$ increase in the hazard of ending. In model 2, this effect is 14.9%, and in model 3, this effect is 30.5%. A higher duration appears to decrease the hazard of ending across all three models. A one year increase in age leads to a group's hazard of ending being $(1 - e^{-0.115}) * 100 = 10.9\%$ lower. This decrease is much smaller in model 2 (2.9%) and 3 (3.3%).

5.1.3. Time Heterogeneity

I tested the three main models for time heterogeneity. The 1970–1985 model had no changes in period 8 (the shift from 1977 to 1978) and period 9 (the shift from 1978 to 1979) so to be able to run the time tests, I first reran the model for the 1970–1985 interval by having one model for 1970–1977 and a second model for 1979–1985. Siena models are complex and as such can become overloaded with parameters; for this reason, I dropped the control variables when modeling these smaller intervals. These results for these models are reported in Table A1 in the appendix. The significance and magnitude of the network dynamics are not dramatically different than from the main model in Table 2. For the behavior dynamics, the degree effect on the hazard of ending still has significant results that suggest a decrease in the hazard of ending, but between the 1970–1977 model and 1979–1985, the magnitude of the effects is different. The effect of fatalities is of a similar magnitude and retains significance, but fatalities squared loses significance in the 1970-1977 model. This may be due to removing control variables.

Results of the time tests are reported in Appendix A.1. The tests show whether the null hypothesis of no time heterogeneity can be rejected separately for each period of each parameter. Little to no time heterogeneity is suggested by these tests for 1970–2000. For the 2000–2016 interval (model 3 of Table 2), the null hypothesis of no time heterogeneity can be rejected many periods of many parameters, particularly the network dynamics. This is tricky to deal with. Time heterogeneity is typically accounted for by incorporating a time dummy for the parameter and period for which there is time heterogeneity. RSiena models are prone to becoming overloaded with effects, which has the result of making all estimates appear insignificant. Therefore, adding so many time dummies would overload the model.

However, when testing for time heterogeneity, period 1 is left out as a baseline. In this case, period 1 includes wave 2000 and wave 2001. I therefore considered that rather than time heterogeneity existing for a majority of periods, it instead may exist in period 1. This is supported by Asal, Phillips, and Rethemeyer (2022), who find that the insurgent network varied greatly before and after 9-11. I therefore reran the model for that time period but with 2000 and 2001 removed. The results can be seen in Table 3. Here, the estimates for fatalities and fatalities squared are in the expected direction, which is a change from the initial model, but they remain insignificant. Testing for time heterogeneity in this new model revealed that there was still time heterogeneity

Table 3. Siena Model 2002–2016

Effect	est.	(s.e.)
Network Dynamics		
Degree (density)	–2.877***	(0.075)
GWESP (69)	0.852***	(0.072)
Degree act+pop	0.026***	(0.004)
Same region	0.832***	(0.075)
Duration ego	0.005	(0.003)
Behaviour Dynamics		
Number of Allies	–0.174**	(0.062)
Fatalities (log)	0.473	(0.957)
Fatalities sq. (log)	–0.190	(0.483)
Territory Goal	0.035	(0.263)
Religious	0.074	(0.272)
Multiple Bases	0.371	(0.301)
Population (log)	–0.092†	(0.055)
GDP per capita (log)	0.160*	(0.064)
Polity	–0.027	(0.024)
Duration	–0.036**	(0.011)

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

convergence t ratios all < 0.05.

Overall maximum convergence ratio 0.12.

for too many parameters in too many periods to be able to include time dummies in the model.

Therefore, the next strategy that I tried was splitting the models into smaller time intervals, so I modeled an interval of 2000–2008 and another of 2008–2016. The initial results are reported in Appendix A.1. I tested these models for time heterogeneity and reran the models with time dummies; the results are shown in Table 4. With some time heterogeneity accounted for, the effects of fatalities and fatalities squared on the hazard of ending are in the expected direction for 2008–2016, but remain insignificant. The effects of these variables for 2000–2008 are still in the opposite direction from what was expected. Together, this aligns with the effects being in the expected direction in the 2002–2016 model, and provides more evidence that 2000 and 2001 are abnormal waves. Additionally, duration loses significance for the 2000–2008 model, but did not lose significance in the 2008–2016 model nor in the 2002–2016 model, which again lightly suggests that 2000 and 2001 are abnormal years. Moreover, the very large standard errors suggest that there is potentially new time heterogeneity revealed when time in some periods is controlled for and indeed the tests for this, the results of which are reported in Appendix A.1, reveal that there is quite a bit of new time heterogeneity, but to control for further periods would overload the model.

Overall, the Siena results show moderate support for H1. When modeling 1970 through 2000, the results for fatalities and the squared effect are significant and in the expected direction. When attempting to account for time heterogeneity, results are insignificant but in the expected direction when 2000 and 2001 are not included. The insignificance is likely due to leftover time heterogeneity that is not accounted for. This points to terrorist group lethality having an inverted-U shaped relationship with terrorist group end, suggesting some support for H1. Meanwhile, there is strong support for H2. The effect of having another ally is significant decreases the hazard of ending

Table 4. Siena Models for Third Time Interval with Time Dummies

Effect	(1) 2000-2008 est.	(s.e.)	(2) 2008-2016 est.	(s.e.)
Network Dynamics				
Degree (density)	–2.779***	(0.116)	–2.908***	(0.106)
GWESP (69)	0.874***	(0.124)	0.957***	(0.114)
Degree act+pop	0.029***	(0.006)	0.019***	(0.006)
Same region	0.910***	(0.113)	0.800***	(0.106)
Duration ego	0.011†	(0.006)	0.007	(0.005)
Dummy2 ego x GWESP (69)	0.619†	(0.364)	.	.
Dummy3 ego x GWESP (69)	.	.	1.172**	(0.438)
Dummy4 ego x GWESP (69)	–1.488**	(0.486)	.	.
Dummy6 ego x GWESP (69)	–0.067	(0.207)	–0.538†	(0.278)
Dummy7 ego x GWESP (69)	–0.388	(0.308)	–0.029	(0.382)
Dummy8 ego x GWESP (69)	–1.108**	(0.358)	.	.
Dummy3 ego x Degree act+pop	–0.038**	(0.013)	–0.030	(0.023)
Dummy7 ego x Degree act+pop	–0.020†	(0.011)	–0.054*	(0.024)
Dummy3 ego x Same region	.	.	0.116	(0.416)
Dummy6 ego x Same region	.	.	–0.298	(0.195)
Dummy7 ego x Same region	–0.308	(0.236)	.	.
Dummy8 ego x Same region	–0.089	(0.241)	.	.
Dummy3 ego	.	.	0.025	(0.440)
Dummy7 ego	.	.	0.241	(0.213)
Behaviour Dynamics				
Number of Allies	–0.249**	(0.076)	–0.003	(0.075)
Fatalities (log)	–0.431	(1.371)	0.278	(1.328)
Fatalities sq. (log)	0.295	(0.693)	–0.135	(0.671)
Duration	–0.015	(0.012)	–0.073**	(0.024)

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Convergence t ratios all < 0.07.

Overall maximum convergence ratio Model 1: 0.20; Model 2: 0.22.

in all models except the 2008–2016 model. This strongly supports the hypothesis that terrorist groups that are more embedded within the network last longer.

5.2. *Accelerated Failure Time Models*

I use a second modeling strategy due to the time heterogeneity within the Siena models. I use AFT models because the Siena models as implemented reduce to a proportional hazards model, but the excess time differences suggests that the proportional hazards assumption may not hold, and AFT models allow for non-constant effects over time. Of note is that whereas the Siena model showed the effect of the covariates on the hazard of ending, the AFT model shows the effect of the covariates on survival time. This means that while H1 posits an inverted-U shaped relationship between lethality and survival in the Siena model, here H1 posits a U-shaped relationship (in which groups with the lowest and highest levels of lethality survive longer).

AFT models were run using the Eha package in R (Broström 2020). I ran the models using the log-normal, Weibull, log-logistic, and extreme value distributions. AIC and BIC are best with the log-normal distribution, so results from this model are discussed. Results from the log-logistic and extreme value distributions are included in the appendix. There is not a major change in substantive results between the different distributions.

There is the possibility that network dependence is not entirely being captured by the centrality and clustering terms. I therefore employ shared frailty models with the same terms but with a yearly frailty effect. A frailty is a random effect for survival models; a yearly frailty means that all groups in a given year will be affected by the same unobserved factor. While not accounting for network dependence directly, it does create and account for dependence between the groups by correlating their hazards. For the frailty models, I use Weibull hazards with a gamma frailty distribution.[6] The Weibull models with and without frailty are reported in Table 6. The frailty parameter was small and insignificant, which means that there is no evidence that there is unobserved heterogeneity across different years. Additionally, the coefficients do not substantively change when frailty is included, and the estimates from the Weibull models with and without frailty are very similar to the log-normal model. I therefore discuss the results for the log-normal model because it was the best fitting model.

The main results can be seen in Table 5. Model 1 uses degree centrality for network embeddedness, model 2 includes eigenvector centrality, and model 3 includes the neighborhood of order 2. The regression coefficients are exponentiated and standard errors have been transformed using the Delta method.[7] AFT models act directly on the time to event; the exponentiated coefficients can be interpreted as the factor by which the survival time is increased or decreased.[8]

Looking to Table 5, the effect of fatalities is in the expected direction and significant. Fatalities is logged in base 2 so that the effect can be interpreted as the effect that a twofold increase in fatalities has on the time to event. A doubling of fatalities multiplies the survival time by a factor close to 0.35 in all three models, which reduces the time to termination by about 65%, or accelerates the time to termination by a factor of $1/0.35 = 2.86$. However, the exponentiated coefficient for fatalities squared is about

[6] Weibull models with a log-normal frailty distribution were run and the frailty parameter was significant, but AIC was very poor, so these are not reported.

[7] P-Values come from the original set of coefficients and standard errors before transformation.

[8] I used the "lifeExp" parameter when running the models in R so that an exponentiated coefficient below 1 decreases life expectancy or accelerates the time to event, and an exponentiated coefficient above 1 increases life expectancy or decelerates the time to event.

1.5 and significant in all three models. This suggests that the increase in time to event associated with fatalities becomes less strong with each doubling of fatalities until the relationship changes signs. This provides strong support for H1.

Table 5.: Accelerated Failure Time Models, Log-Normal Distribution

	(1)	(2)	(3)
Fatalities (log)	0.358**	0.352**	0.358**
	(0.145)	(0.145)	(0.147)
Fatalities Sq. (log)	1.523**	1.580**	1.553**
	(0.311)	(0.329)	(0.323)
Number of Allies	1.294***		
	(0.065)		
EV Centrality		1.015**	
		(0.007)	
Neighborhood			1.024***
			(0.010)
Clustering	0.865	1.603*	1.365
	(0.244)	(0.443)	(0.395)
Left	0.648*	0.625*	0.698
	(0.154)	(0.155)	(0.175)
Right	0.377***	0.333***	0.374***
	(0.134)	(0.124)	(0.140)
Nationalist	0.592**	0.561**	0.613**
	(0.134)	(0.131)	(0.144)
Regime	0.524*	0.512*	0.495**
	(0.177)	(0.181)	(0.175)
Policy	0.431**	0.408**	0.401**
	(0.149)	(0.147)	(0.144)
Territory	0.965	1.054	1.012
	(0.331)	(0.377)	(0.361)
Attack Diversity	6.741***	7.421***	7.632***
	(3.153)	(3.593)	(3.679)
Share Trans. Terr.	0.250***	0.248***	0.256***
	(0.038)	(0.039)	(0.040)
Multiple Bases	0.918	0.999	0.970
	(0.165)	(0.185)	(0.180)
Pop (log)	1.039	1.039	1.032
	(0.045)	(0.046)	(0.046)
GDP/Pop (log)	0.954	0.952	0.958
	(0.064)	(0.067)	(0.067)

Democracy	0.732	0.853	0.791
	(0.273)	(0.328)	(0.305)
East Asia & Pacific	1.749*	1.728*	1.782*
	(0.520)	(0.528)	(0.546)
Europe & Central Asia	0.861	0.767	0.803
	(0.209)	(0.191)	(0.200)
Latin Am. & Caribbean	0.993	0.935	0.948
	(0.275)	(0.269)	(0.272)
North America	1.315	1.159	1.244
	(0.465)	(0.425)	(0.457)
South Asia	1.389	1.312	1.419
	(0.472)	(0.460)	(0.497)
Sub-Saharan Africa	2.364***	2.074**	2.269**
	(0.787)	(0.715)	(0.785)
log(scale)	3.353**	3.520***	3.473**
	(1.311)	(1.361)	(1.359)
log(shape)	-0.253***	-0.294***	-0.289***
	(0.046)	(0.047)	(0.047)
Observations	7,777	7,777	7,777
AIC	2049.981	2077.055	2074.463
BIC	2216.995	2244.069	2241.478
Log Likelihood	−1,000.990	−1,014.528	−1,013.232
Note:	*p<0.1; **p<0.05; ***p<0.01		

All three variables intended to capture network embeddedness are above 1 and significant, suggesting that network embeddedness increases survival. The effects are strongest when network embeddedness is measured as the number of allies, or degree centrality, seen in model 1. Having one more ally increases the time to termination by a factor of 1.294, or a 29.4% increase from the baseline in the time it takes for a group to fail. When network embeddedness is measured as the neighborhood of order 2, or a group, its allies, and its allies' allies, the effect on group termination is significant but weak. Having one more node in the neighborhood increases a group's time to termination by a factor of 1.024, or 2.4%. When network embeddedness is measured as eigenvector centrality — the importance of allies — a one-unit increase in eigenvector centrality increases the time to termination by 1.5%. Overall, this provides support for H2.

The effect of clustering is ambiguous, with the direction and significance of the results changing between the models. Being a left wing group is marginally significant in models 1 and 2 and the exponentiated coefficient is about 0.6, which suggests a decrease in survival by 40%, or an acceleration in the time to termination by a factor of $1/0.6 = 1.67$. In other words, compared to the reference category of religious groups, being a left wing group is associated with a quicker termination. Being a right wing group has a much quicker time to termination than being a religious group and this is significant in all 3 models. The effect of being a nationalist group compared to a religious group is similar to the effect of being a left wing group. This complements the results of the Siena models, which suggest that being religious decreases the hazard of ending, compared with not being religious. Turning to goals, compared to groups with the goal of maintaining the status quo, groups with regime change goals and policy goals see a decrease in survival time. The exponentiated coefficients for having a territory goal are insignificant and close to 1 in all three models, meaning that there is no evidence that having a territory goal affects group termination. The RSiena results showed territory goals as decreasing the hazard of ending, but this was only significant in the 1985-2000 model.

Attack diversity, the share of transnational attacks out of total attacks, and multiple bases were included as different measures of group strength. Attack diversity and the share of transnational attacks have significant effects across all three models, but the effects are in different directions for the two covariates, with an increase in attack diversity leading to an increase in survival, which lends credence to the idea that terrorist groups that can diversity their attacks can evade detection. On the other hand, an increase in the share of transnational attacks shortens survival time. One possibility for this is that groups that attack transnationally have more opportunities to be caught. There is no evidence that having more than one base affects survival.

The models reveal no evidence that population, GDP per capita, or electoral democracy affect survival. Finally, results are significant for only two regions. Compared to the MENA region, having a base in the East Asia and Pacific region increases survival time by a factor of about 1.7, and having a base in Sub-Saharan Africa increases survival time by a factor of more than 2.

Table 6.: Accelerated Failure Time Models: Weibull Models with and without Frailty

	No Frailty			With Frailty		
	(1)	(2)	(3)	(4)	(5)	(6)
Fatalities (log)	0.397**	0.411**	0.403**	0.398**	0.415**	0.407**
	(0.164)	(0.172)	(0.169)	(0.166)	(0.181)	(0.167)
Fatalities Sq. (log)	1.464*	1.484*	1.491*	1.463*	1.476*	1.483*
	(0.308)	(0.315)	(0.317)	(0.310)	(0.331)	(0.310)
Number of Allies	1.305***			1.298***		
	(0.078)			(0.078)		
EV Centrality		1.015**			1.015**	
		(0.008)			(0.007)	
Neighborhood			1.017*			1.016*
			(0.010)			(0.009)
Clustering	0.679	1.273	1.221	0.685	1.243	1.213
	(0.193)	(0.342)	(0.345)	(0.195)	(0.327)	(0.336)
Left	0.537**	0.537**	0.574**	0.541**	0.544**	0.578**
	(0.130)	(0.133)	(0.145)	(0.133)	(0.132)	(0.141)
Right	0.340***	0.317***	0.340***	0.354***	0.339***	0.360***
	(0.107)	(0.102)	(0.112)	(0.113)	(0.108)	(0.114)
Nationalist	0.602**	0.585**	0.611**	0.601**	0.589**	0.614**
	(0.138)	(0.138)	(0.146)	(0.138)	(0.134)	(0.141)
Regime	0.611	0.602	0.586	0.614	0.610	0.598
	(0.200)	(0.203)	(0.199)	(0.199)	(0.212)	(0.201)
Policy	0.442**	0.425**	0.418**	0.454**	0.448**	0.442**
	(0.150)	(0.147)	(0.146)	(0.152)	(0.160)	(0.153)
Territory	1.013	1.173	1.149	1.013	1.152	1.137
	(0.343)	(0.406)	(0.402)	(0.342)	(0.416)	(0.395)
Attack Diversity	7.755***	8.421***	8.843***	7.423***	7.975***	8.436***

	(3.766)	(4.148)	(4.347)	(3.610)	(4.336)	(4.085)
Share Trans. Terr.	0.219***	0.209***	0.217***	0.232***	0.227***	0.234***
	(0.034)	(0.033)	(0.034)	(0.038)	(0.037)	(0.038)
Multiple Bases	0.855	0.888	0.892	0.844	0.870	0.879
	(0.140)	(0.149)	(0.152)	(0.140)	(0.143)	(0.145)
Pop (log)	1.064	1.055	1.049	1.060	1.049	1.043
	(0.047)	(0.048)	(0.049)	(0.046)	(0.051)	(0.050)
GDP/Pop (log)	0.951	0.962	0.969	0.948	0.958	0.966
	(0.062)	(0.065)	(0.065)	(0.062)	(0.075)	(0.065)
Democracy	0.916	0.963	0.919	0.873	0.913	0.879
	(0.349)	(0.377)	(0.363)	(0.333)	(0.383)	(0.340)
East Asia & Pacific	1.589	1.558	1.588	1.581	1.536	1.562
	(0.491)	(0.491)	(0.505)	(0.489)	(0.468)	(0.481)
Europe & Central Asia	0.960	0.842	0.848	0.986	0.884	0.882
	(0.222)	(0.196)	(0.199)	(0.230)	(0.200)	(0.203)
Latin Am. & Caribbean	0.959	0.899	0.881	0.963	0.908	0.885
	(0.252)	(0.241)	(0.237)	(0.253)	(0.243)	(0.232)
North America	1.309	1.256	1.282	1.330	1.263	1.277
	(0.407)	(0.403)	(0.415)	(0.423)	(0.392)	(0.409)
South Asia	1.341	1.321	1.407	1.345	1.328	1.409
	(0.490)	(0.494)	(0.530)	(0.499)	(0.483)	(0.516)
Sub-Saharan Africa	1.970**	1.769*	1.847*	1.911**	1.703*	1.771*
	(0.632)	(0.579)	(0.614)	(0.622)	(0.569)	(0.576)
Frailty Theta				0.0005	0.0001	0.0000
				(0.0020)	(0.0019)	(0.0000)
log(scale)	3.153**	3.383**	3.372**	3.290	3.617	3.590
	(1.294)	(1.352)	(1.361)			
log(shape)	0.002	-0.023	-0.028	-0.054	-0.086	-0.081
	(0.049)	(0.050)	(0.050)			
Observations			7,777			
AIC	2072.926	2096.964	2098.343	2073.368	2095.832	2097.762
BIC	2239.94	2263.978	2265.357			
Log Likelihood	-1,012.463	-1,024.482	-1,025.172	-1011.684	-1022.916	-1023.881
Note:						*p<0.1; **p<0.05; ***p<0.01

6. Conclusion

In this article, I explored the ambiguity that has been found with regard to terrorist group lethality on survival and I re-examined existing findings on alliances and lethality in a network context. I used two modeling techniques that complement each other and allow me to explore the effect of both lethality and alliances on longevity. Siena models allowed me to model the co-evolution of the terrorist alliance network, the effect of this network on survival, and — as groups terminated and dropped out — the effect of survival in turn on the network. AFT models allowed me to use different measures of network embeddedness to test my hypothesis on group alliances and survival while also examining the curvilinear effect of lethality on survival, and additionally provided a robustness check for the Siena models.

Even with time heterogeneity in the Siena models, the results of the Siena models and AFT model taken together support the hypothesis that lethality has a curvilinear relationship with survival whereby groups with intermediate levels of lethality are most likely to end. The models showed strong support for the hypothesis that network embeddedness increases survival, which I theorize in this paper is due to the increased capacity that comes from pooling resources and sharing tactical information.

This article contributes to the terrorism literature in several ways. First, while many studies include group lethality as a control variable through various measurements in studies of terrorist longevity, few directly examine the effect of lethality on survival. This article contributes by using existing literature to build a novel hypothesis about the effect of lethality on survival. Second, I test the effect of lethality while incorporating network embeddedness. Third, while many studies explore the effect of alliances on survival, few do so in a network context.

Finally, the use of network analysis is still rare within the terrorism literature even though terrorist groups are not independent. I therefore contribute by demonstrating an application of a statistical network model to terrorist group survival. Furthermore, the diffusion extension to the Siena model has thus far been used to explicitly model diffusion of a an innovation through a network; I use it instead to model survival such that groups drop out once adopting the innovation.

Future work can build from this by researching how alliances affect lethality in a network context. Additionally, future work can also bring in data on the rivalry network because just as groups cooperate, they also fight one another. Finally, on the methodological side, while this paper uses a network survival model — something that has not been done in the terrorism literature and in general has rarely been done when using time-varying covariates — extensions to existing survival models should be made in order to account for network dependence so that the RSiena diffusion of innovations extension is not the only method for modeling both survival and the network.

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Appendix A.

A.1. *Time Heterogeneity Tests*

This section includes the estimates from the time heterogeneity tests and the new models that were run for 1970–1977 and 1979–1985. A p-value under 0.05 in the time test means that the null hypothesis of no time heterogeneity cannot be rejected.

Table A1. Siena Models for First Time Interval

Effect	(1) 1970–1977 est.	(s.e.)	(2) 1979–1985 est.	(s.e.)
Network Dynamics				
degree (density)	–3.162***	(0.403)	–1.805***	(0.227)
GWESP (69)	1.078***	(0.313)	0.965***	(0.289)
Degree act+pop	0.097**	(0.036)	–0.040	(0.026)
Same region	1.339***	(0.292)	0.912***	(0.188)
Duration ego	0.174†	(0.094)	0.004	(0.030)
Behaviour Dynamics				
Number of Allies	–1.060*	(0.498)	–0.290†	(0.160)
Fatalities (log	2.515†	(1.386)	2.879**	(1.107)
Fatalities sq. (log)	–1.146	(0.720)	–1.517**	(0.588)
Duration	–0.073	(0.136)	–0.093*	(0.047)

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Convergence t ratios all < 0.06.

Overall maximum convergence ratio Model 1: 0.12; Model 2: 0.16.

Table A2. Siena Models for 2000–2016 Without Time Dummies

Effect	(1) 2000–2008 est.	(s.e.)	(2) 2008–2016 est.	(s.e.)
Network Dynamics				
Degree (density)	–2.775***	(0.107)	–2.923***	(0.099)
GWESP (69)	0.911***	(0.091)	0.873***	(0.106)
Degree act+pop	0.029***	(0.005)	0.022***	(0.005)
Same region	0.905***	(0.105)	0.810***	(0.100)
Duration ego	0.010†	(0.006)	0.006	(0.004)
Behaviour Dynamics				
Number of Allies	–0.252***	(0.075)	–0.002	(0.076)
Fatalities (log)	–0.391	(1.354)	0.272	(1.322)
Fatalities sq. (log)	0.276	(0.685)	–0.132	(0.667)
Duration	–0.015	(0.012)	–0.073**	(0.025)

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Convergence t ratios all < 0.08.

Overall maximum convergence ratio Model 1: 0.21; Model 2: 0.23.

Table A3.: Time Heterogeneity Test for 1970–1977

	One.Step.Est.	p.Value
(*)Dummy2:degree (density)	-2.51	0.73
(*)Dummy3:degree (density)	-2.00	0.26
(*)Dummy4:degree (density)	-3.13	0.03
(*)Dummy5:degree (density)	-3.12	0.09
(*)Dummy6:degree (density)	-3.68	0.21
(*)Dummy7:degree (density)	-5.64	0.11
(*)Dummy2:GWESP (69)	1.53	0.22
(*)Dummy3:GWESP (69)	3.05	0.35
(*)Dummy4:GWESP (69)	2.13	0.10
(*)Dummy5:GWESP (69)	1.34	0.63
(*)Dummy6:GWESP (69)	2.90	0.97
(*)Dummy7:GWESP (69)	3.05	0.00
(*)Dummy2:degree act+pop	-0.19	0.62
(*)Dummy3:degree act+pop	-0.38	0.04
(*)Dummy4:degree act+pop	-0.18	0.07
(*)Dummy5:degree act+pop	-0.21	0.81
(*)Dummy6:degree act+pop	-0.22	0.29
(*)Dummy7:degree act+pop	-0.04	0.00
(*)Dummy2:same region	2.97	0.84
(*)Dummy3:same region	2.79	0.28
(*)Dummy4:same region	2.01	0.00
(*)Dummy5:same region	4.82	0.03
(*)Dummy6:same region	3.36	0.22
(*)Dummy7:same region	5.00	0.00
(*)Dummy2:degree effect on rate endbeh_7077 (rate)	-0.18	0.29
(*)Dummy3:degree effect on rate endbeh_7077 (rate)	0.04	0.64
(*)Dummy4:degree effect on rate endbeh_7077 (rate)	2.91	0.00
(*)Dummy5:degree effect on rate endbeh_7077 (rate)	-0.21	0.46
(*)Dummy6:degree effect on rate endbeh_7077 (rate)	-0.07	0.53
(*)Dummy7:degree effect on rate endbeh_7077 (rate)	0.42	0.70
(*)Dummy2:effect logdeaths on rate endbeh_7077 (rate)	1.21	0.55
(*)Dummy3:effect logdeaths on rate endbeh_7077 (rate)	-0.39	0.66
(*)Dummy4:effect logdeaths on rate endbeh_7077 (rate)	0.68	0.00
(*)Dummy5:effect logdeaths on rate endbeh_7077 (rate)	2.34	0.80
(*)Dummy6:effect logdeaths on rate endbeh_7077 (rate)	0.62	0.52
(*)Dummy7:effect logdeaths on rate endbeh_7077 (rate)	2.69	0.26
(*)Dummy2:effect logdeathssq on rate endbeh_7077 (rate)	-0.40	0.59
(*)Dummy3:effect logdeathssq on rate endbeh_7077 (rate)	0.40	0.69
(*)Dummy4:effect logdeathssq on rate endbeh_7077 (rate)	0.77	0.00
(*)Dummy5:effect logdeathssq on rate endbeh_7077 (rate)	-0.86	0.76
(*)Dummy6:effect logdeathssq on rate endbeh_7077 (rate)	-0.07	0.55
(*)Dummy7:effect logdeathssq on rate endbeh_7077 (rate)	-1.15	0.22

Table A4.: Time Heterogeneity Test for 1979–1985

	One.Step.Est.	p.Value
(*)Dummy2:degree (density)	0.11	0.59

(*)Dummy3:degree (density)	0.38	0.38
(*)Dummy4:degree (density)	0.93	0.00
(*)Dummy5:degree (density)	0.19	0.01
(*)Dummy6:degree (density)	0.60	0.78
(*)Dummy2:GWESP (69)	-1.59	0.01
(*)Dummy3:GWESP (69)	0.31	0.47
(*)Dummy4:GWESP (69)	0.35	0.00
(*)Dummy5:GWESP (69)	1.29	0.00
(*)Dummy6:GWESP (69)	1.47	0.16
(*)Dummy2:degree act+pop	-0.07	0.19
(*)Dummy3:degree act+pop	-0.07	0.20
(*)Dummy4:degree act+pop	-0.21	0.00
(*)Dummy5:degree act+pop	-0.07	0.00
(*)Dummy6:degree act+pop	-0.14	0.72
(*)Dummy2:same region	1.11	0.82
(*)Dummy3:same region	0.10	0.70
(*)Dummy4:same region	0.11	0.01
(*)Dummy5:same region	0.75	0.00
(*)Dummy6:same region	-0.11	0.63
(*)Dummy2:degree effect on rate endbeh_7985 (rate)	0.64	0.89
(*)Dummy3:degree effect on rate endbeh_7985 (rate)	0.52	0.79
(*)Dummy4:degree effect on rate endbeh_7985 (rate)	0.24	0.23
(*)Dummy5:degree effect on rate endbeh_7985 (rate)	0.76	0.22
(*)Dummy6:degree effect on rate endbeh_7985 (rate)	0.50	0.77
(*)Dummy2:effect logdeaths on rate endbeh_7985 (rate)	-4.76	0.10
(*)Dummy3:effect logdeaths on rate endbeh_7985 (rate)	-0.04	0.56
(*)Dummy4:effect logdeaths on rate endbeh_7985 (rate)	-1.78	0.47
(*)Dummy5:effect logdeaths on rate endbeh_7985 (rate)	1.65	0.92
(*)Dummy6:effect logdeaths on rate endbeh_7985 (rate)	0.77	0.94
(*)Dummy2:effect logdeathssq on rate endbeh_7985 (rate)	1.66	0.18
(*)Dummy3:effect logdeathssq on rate endbeh_7985 (rate)	-0.66	0.51
(*)Dummy4:effect logdeathssq on rate endbeh_7985 (rate)	0.45	0.43
(*)Dummy5:effect logdeathssq on rate endbeh_7985 (rate)	-1.53	0.78
(*)Dummy6:effect logdeathssq on rate endbeh_7985 (rate)	-0.99	0.92

Table A5.: Time Heterogeneity Test for 1985–2000

	One.Step.Est.	p.Value
(*)Dummy2:degree (density)	-0.38	0.10
(*)Dummy3:degree (density)	-2.06	0.26
(*)Dummy4:degree (density)	0.82	0.68
(*)Dummy5:degree (density)	-0.60	0.19
(*)Dummy6:degree (density)	-0.04	0.58
(*)Dummy7:degree (density)	-0.92	0.24
(*)Dummy8:degree (density)	-1.01	0.60
(*)Dummy9:degree (density)	-1.59	0.47
(*)Dummy10:degree (density)	-1.70	0.40
(*)Dummy11:degree (density)	-1.45	0.87
(*)Dummy12:degree (density)	-0.95	1.00

(*)Dummy13:degree (density)	-0.39	0.37
(*)Dummy14:degree (density)	-0.76	0.58
(*)Dummy15:degree (density)	-1.13	0.68
(*)Dummy2:GWESP (69)	2.50	0.00
(*)Dummy3:GWESP (69)	0.02	0.09
(*)Dummy4:GWESP (69)	-0.04	0.08
(*)Dummy5:GWESP (69)	0.07	0.46
(*)Dummy6:GWESP (69)	0.16	0.38
(*)Dummy7:GWESP (69)	0.22	0.68
(*)Dummy8:GWESP (69)	0.32	0.43
(*)Dummy9:GWESP (69)	-0.15	0.82
(*)Dummy10:GWESP (69)	-0.31	0.92
(*)Dummy11:GWESP (69)	-0.08	0.77
(*)Dummy12:GWESP (69)	-0.03	0.91
(*)Dummy13:GWESP (69)	-0.27	0.04
(*)Dummy14:GWESP (69)	0.22	0.98
(*)Dummy15:GWESP (69)	-0.27	0.93
(*)Dummy2:degree act+pop	-0.10	0.10
(*)Dummy3:degree act+pop	0.13	0.03
(*)Dummy4:degree act+pop	-0.10	0.07
(*)Dummy5:degree act+pop	-0.01	0.41
(*)Dummy6:degree act+pop	-0.07	0.16
(*)Dummy7:degree act+pop	-0.01	0.31
(*)Dummy8:degree act+pop	0.10	0.16
(*)Dummy9:degree act+pop	0.08	0.86
(*)Dummy10:degree act+pop	0.08	0.57
(*)Dummy11:degree act+pop	0.06	0.45
(*)Dummy12:degree act+pop	0.02	0.90
(*)Dummy13:degree act+pop	-0.02	0.05
(*)Dummy14:degree act+pop	-0.02	0.39
(*)Dummy15:degree act+pop	0.05	0.38
(*)Dummy2:same region	1.08	0.01
(*)Dummy3:same region	1.31	0.15
(*)Dummy4:same region	-0.45	0.23
(*)Dummy5:same region	0.96	0.08
(*)Dummy6:same region	0.43	0.66
(*)Dummy7:same region	0.56	0.41
(*)Dummy8:same region	-0.30	0.48
(*)Dummy9:same region	0.50	0.46
(*)Dummy10:same region	0.70	0.49
(*)Dummy11:same region	0.62	0.90
(*)Dummy12:same region	0.61	0.95
(*)Dummy13:same region	0.49	0.27
(*)Dummy14:same region	0.73	0.92
(*)Dummy15:same region	0.69	0.72
(*)Dummy2:degree effect on rate endbeh_8500 (rate)	0.37	0.47
(*)Dummy3:degree effect on rate endbeh_8500 (rate)	-0.26	0.32
(*)Dummy4:degree effect on rate endbeh_8500 (rate)	-0.37	0.39
(*)Dummy5:degree effect on rate endbeh_8500 (rate)	0.26	0.28
(*)Dummy6:degree effect on rate endbeh_8500 (rate)	-0.10	0.76

(*)Dummy7:degree effect on rate endbeh_8500 (rate)	-0.05	0.42
(*)Dummy8:degree effect on rate endbeh_8500 (rate)	-0.44	0.97
(*)Dummy9:degree effect on rate endbeh_8500 (rate)	-0.44	0.47
(*)Dummy10:degree effect on rate endbeh_8500 (rate)	-0.76	0.75
(*)Dummy11:degree effect on rate endbeh_8500 (rate)	0.29	0.07
(*)Dummy12:degree effect on rate endbeh_8500 (rate)	-0.17	0.88
(*)Dummy13:degree effect on rate endbeh_8500 (rate)	-0.42	0.95
(*)Dummy14:degree effect on rate endbeh_8500 (rate)	-0.59	0.49
(*)Dummy15:degree effect on rate endbeh_8500 (rate)	-0.33	0.23
(*)Dummy2:effect logpop on rate endbeh_8500 (rate)	0.49	0.09
(*)Dummy3:effect logpop on rate endbeh_8500 (rate)	0.30	0.22
(*)Dummy4:effect logpop on rate endbeh_8500 (rate)	0.01	0.94
(*)Dummy5:effect logpop on rate endbeh_8500 (rate)	-0.16	0.89
(*)Dummy6:effect logpop on rate endbeh_8500 (rate)	-0.10	0.87
(*)Dummy7:effect logpop on rate endbeh_8500 (rate)	0.07	0.99
(*)Dummy8:effect logpop on rate endbeh_8500 (rate)	-0.58	0.40
(*)Dummy9:effect logpop on rate endbeh_8500 (rate)	0.00	0.84
(*)Dummy10:effect logpop on rate endbeh_8500 (rate)	-0.45	0.29
(*)Dummy11:effect logpop on rate endbeh_8500 (rate)	-0.00	0.60
(*)Dummy12:effect logpop on rate endbeh_8500 (rate)	-0.10	0.62
(*)Dummy13:effect logpop on rate endbeh_8500 (rate)	-0.24	0.57
(*)Dummy14:effect logpop on rate endbeh_8500 (rate)	-0.43	0.60
(*)Dummy15:effect logpop on rate endbeh_8500 (rate)	0.08	0.45
(*)Dummy2:effect loggdppc on rate endbeh_8500 (rate)	-0.22	0.08
(*)Dummy3:effect loggdppc on rate endbeh_8500 (rate)	-0.22	0.98
(*)Dummy4:effect loggdppc on rate endbeh_8500 (rate)	-0.21	0.76
(*)Dummy5:effect loggdppc on rate endbeh_8500 (rate)	-0.72	0.96
(*)Dummy6:effect loggdppc on rate endbeh_8500 (rate)	-0.58	0.55
(*)Dummy7:effect loggdppc on rate endbeh_8500 (rate)	-0.37	0.75
(*)Dummy8:effect loggdppc on rate endbeh_8500 (rate)	-1.33	0.47
(*)Dummy9:effect loggdppc on rate endbeh_8500 (rate)	-0.56	0.54
(*)Dummy10:effect loggdppc on rate endbeh_8500 (rate)	-0.38	0.94
(*)Dummy11:effect loggdppc on rate endbeh_8500 (rate)	-0.67	0.38
(*)Dummy12:effect loggdppc on rate endbeh_8500 (rate)	-0.50	0.37
(*)Dummy13:effect loggdppc on rate endbeh_8500 (rate)	-0.01	0.91
(*)Dummy14:effect loggdppc on rate endbeh_8500 (rate)	-0.33	0.43
(*)Dummy15:effect loggdppc on rate endbeh_8500 (rate)	-0.37	0.94
(*)Dummy2:effect logdeaths on rate endbeh_8500 (rate)	4.09	0.87
(*)Dummy3:effect logdeaths on rate endbeh_8500 (rate)	0.24	0.42
(*)Dummy4:effect logdeaths on rate endbeh_8500 (rate)	1.96	0.85
(*)Dummy5:effect logdeaths on rate endbeh_8500 (rate)	0.85	0.76
(*)Dummy6:effect logdeaths on rate endbeh_8500 (rate)	3.43	0.32
(*)Dummy7:effect logdeaths on rate endbeh_8500 (rate)	7.55	0.07
(*)Dummy8:effect logdeaths on rate endbeh_8500 (rate)	14.28	0.57
(*)Dummy9:effect logdeaths on rate endbeh_8500 (rate)	11.62	1.00
(*)Dummy10:effect logdeaths on rate endbeh_8500 (rate)	12.91	0.13
(*)Dummy11:effect logdeaths on rate endbeh_8500 (rate)	4.57	0.25
(*)Dummy12:effect logdeaths on rate endbeh_8500 (rate)	6.71	0.58
(*)Dummy13:effect logdeaths on rate endbeh_8500 (rate)	5.45	0.01
(*)Dummy14:effect logdeaths on rate endbeh_8500 (rate)	6.95	0.97

(*)Dummy15:effect logdeaths on rate endbeh_8500 (rate)	3.78	0.40
(*)Dummy2:effect logdeathssq on rate endbeh_8500 (rate)	-2.02	0.86
(*)Dummy3:effect logdeathssq on rate endbeh_8500 (rate)	-0.07	0.46
(*)Dummy4:effect logdeathssq on rate endbeh_8500 (rate)	-0.77	0.78
(*)Dummy5:effect logdeathssq on rate endbeh_8500 (rate)	-0.37	0.86
(*)Dummy6:effect logdeathssq on rate endbeh_8500 (rate)	-1.67	0.35
(*)Dummy7:effect logdeathssq on rate endbeh_8500 (rate)	-3.44	0.09
(*)Dummy8:effect logdeathssq on rate endbeh_8500 (rate)	-7.01	0.67
(*)Dummy9:effect logdeathssq on rate endbeh_8500 (rate)	-5.87	0.83
(*)Dummy10:effect logdeathssq on rate endbeh_8500 (rate)	-6.14	0.16
(*)Dummy11:effect logdeathssq on rate endbeh_8500 (rate)	-2.41	0.24
(*)Dummy12:effect logdeathssq on rate endbeh_8500 (rate)	-3.22	0.65
(*)Dummy13:effect logdeathssq on rate endbeh_8500 (rate)	-2.01	0.01
(*)Dummy14:effect logdeathssq on rate endbeh_8500 (rate)	-3.37	0.94
(*)Dummy15:effect logdeathssq on rate endbeh_8500 (rate)	-1.85	0.45
(*)Dummy2:effect polity on rate endbeh_8500 (rate)	0.09	0.06
(*)Dummy3:effect polity on rate endbeh_8500 (rate)	-0.09	0.80
(*)Dummy4:effect polity on rate endbeh_8500 (rate)	-0.12	0.22
(*)Dummy5:effect polity on rate endbeh_8500 (rate)	0.14	0.46
(*)Dummy6:effect polity on rate endbeh_8500 (rate)	0.06	0.95
(*)Dummy7:effect polity on rate endbeh_8500 (rate)	0.01	0.59
(*)Dummy8:effect polity on rate endbeh_8500 (rate)	0.36	0.42
(*)Dummy9:effect polity on rate endbeh_8500 (rate)	0.02	0.59
(*)Dummy10:effect polity on rate endbeh_8500 (rate)	-0.05	0.78
(*)Dummy11:effect polity on rate endbeh_8500 (rate)	-0.01	0.54
(*)Dummy12:effect polity on rate endbeh_8500 (rate)	-0.03	0.24
(*)Dummy13:effect polity on rate endbeh_8500 (rate)	-0.12	0.46
(*)Dummy14:effect polity on rate endbeh_8500 (rate)	0.13	0.32
(*)Dummy15:effect polity on rate endbeh_8500 (rate)	-0.02	0.67

Table A6.: Time Heterogeneity Test for 2000–2016

	One.Step.Est.	p.Value
(*)Dummy2:degree (density)	0.98	0.01
(*)Dummy3:degree (density)	0.79	0.99
(*)Dummy4:degree (density)	-0.09	0.86
(*)Dummy5:degree (density)	0.98	0.02
(*)Dummy6:degree (density)	0.95	0.00
(*)Dummy7:degree (density)	1.00	0.13
(*)Dummy8:degree (density)	0.21	0.29
(*)Dummy9:degree (density)	1.07	0.00
(*)Dummy10:degree (density)	0.46	0.89
(*)Dummy11:degree (density)	0.49	0.25
(*)Dummy12:degree (density)	0.40	0.01
(*)Dummy13:degree (density)	0.69	0.31
(*)Dummy14:degree (density)	0.74	0.00
(*)Dummy15:degree (density)	0.87	0.00
(*)Dummy16:degree (density)	-0.16	0.02
(*)Dummy2:GWESP (69)	1.92	0.00
(*)Dummy3:GWESP (69)	0.49	0.68
(*)Dummy4:GWESP (69)	-1.00	0.01

(*)Dummy5:GWESP (69)	0.60	0.05
(*)Dummy6:GWESP (69)	0.95	0.00
(*)Dummy7:GWESP (69)	0.35	0.03
(*)Dummy8:GWESP (69)	-0.34	0.01
(*)Dummy9:GWESP (69)	0.93	0.00
(*)Dummy10:GWESP (69)	0.30	0.67
(*)Dummy11:GWESP (69)	1.60	0.00
(*)Dummy12:GWESP (69)	-0.06	0.00
(*)Dummy13:GWESP (69)	1.10	0.46
(*)Dummy14:GWESP (69)	-0.16	0.00
(*)Dummy15:GWESP (69)	0.16	0.00
(*)Dummy16:GWESP (69)	0.39	0.30
(*)Dummy2:degree act+pop	-0.10	0.01
(*)Dummy3:degree act+pop	-0.11	0.28
(*)Dummy4:degree act+pop	-0.02	0.73
(*)Dummy5:degree act+pop	-0.08	0.03
(*)Dummy6:degree act+pop	-0.09	0.00
(*)Dummy7:degree act+pop	-0.09	0.03
(*)Dummy8:degree act+pop	-0.04	0.79
(*)Dummy9:degree act+pop	-0.08	0.02
(*)Dummy10:degree act+pop	-0.08	0.78
(*)Dummy11:degree act+pop	-0.10	0.30
(*)Dummy12:degree act+pop	-0.08	0.01
(*)Dummy13:degree act+pop	-0.11	0.14
(*)Dummy14:degree act+pop	-0.06	0.12
(*)Dummy15:degree act+pop	-0.11	0.00
(*)Dummy16:degree act+pop	-0.04	0.97
(*)Dummy2:same region	-1.48	0.02
(*)Dummy3:same region	-0.65	0.42
(*)Dummy4:same region	-0.27	0.86
(*)Dummy5:same region	-1.24	0.09
(*)Dummy6:same region	-1.23	0.00
(*)Dummy7:same region	-1.44	0.04
(*)Dummy8:same region	-0.83	0.42
(*)Dummy9:same region	-1.29	0.03
(*)Dummy10:same region	-0.66	0.43
(*)Dummy11:same region	-0.90	0.17
(*)Dummy12:same region	-0.83	0.07
(*)Dummy13:same region	-1.09	0.51
(*)Dummy14:same region	-1.52	0.00
(*)Dummy15:same region	-1.35	0.00
(*)Dummy16:same region	-0.72	0.10
(*)Dummy2:duration ego	0.03	0.02
(*)Dummy3:duration ego	-0.02	0.57
(*)Dummy4:duration ego	-0.02	0.55
(*)Dummy5:duration ego	-0.05	0.06
(*)Dummy6:duration ego	-0.02	0.90
(*)Dummy7:duration ego	0.01	0.13
(*)Dummy8:duration ego	0.02	0.02
(*)Dummy9:duration ego	-0.04	0.20
(*)Dummy10:duration ego	0.02	0.13
(*)Dummy11:duration ego	0.01	0.08
(*)Dummy12:duration ego	0.00	0.68
(*)Dummy13:duration ego	-0.02	0.15
(*)Dummy14:duration ego	-0.03	0.02
(*)Dummy15:duration ego	0.01	0.88
(*)Dummy16:duration ego	-0.00	0.66
(*)Dummy2:degree effect on rate endbeh_0016 (rate)	-0.09	0.29
(*)Dummy3:degree effect on rate endbeh_0016 (rate)	-0.09	0.19

(*)Dummy4:degree effect on rate endbeh_0016 (rate)	0.05	0.59
(*)Dummy5:degree effect on rate endbeh_0016 (rate)	0.23	0.26
(*)Dummy6:degree effect on rate endbeh_0016 (rate)	0.12	0.93
(*)Dummy7:degree effect on rate endbeh_0016 (rate)	0.22	0.23
(*)Dummy8:degree effect on rate endbeh_0016 (rate)	-0.25	0.36
(*)Dummy9:degree effect on rate endbeh_0016 (rate)	-0.01	0.76
(*)Dummy10:degree effect on rate endbeh_0016 (rate)	-0.11	0.62
(*)Dummy11:degree effect on rate endbeh_0016 (rate)	0.00	0.49
(*)Dummy12:degree effect on rate endbeh_0016 (rate)	0.25	0.40
(*)Dummy13:degree effect on rate endbeh_0016 (rate)	0.02	0.73
(*)Dummy14:degree effect on rate endbeh_0016 (rate)	0.35	0.74
(*)Dummy15:degree effect on rate endbeh_0016 (rate)	1.23	0.07
(*)Dummy16:degree effect on rate endbeh_0016 (rate)	2.58	0.01
(*)Dummy2:effect logpop on rate endbeh_0016 (rate)	-0.61	0.63
(*)Dummy3:effect logpop on rate endbeh_0016 (rate)	-0.32	0.83
(*)Dummy4:effect logpop on rate endbeh_0016 (rate)	-0.05	0.08
(*)Dummy5:effect logpop on rate endbeh_0016 (rate)	-0.72	0.11
(*)Dummy6:effect logpop on rate endbeh_0016 (rate)	-0.44	0.99
(*)Dummy7:effect logpop on rate endbeh_0016 (rate)	-0.37	0.95
(*)Dummy8:effect logpop on rate endbeh_0016 (rate)	-1.26	0.21
(*)Dummy9:effect logpop on rate endbeh_0016 (rate)	-0.51	0.59
(*)Dummy10:effect logpop on rate endbeh_0016 (rate)	-0.29	0.94
(*)Dummy11:effect logpop on rate endbeh_0016 (rate)	-0.42	0.76
(*)Dummy12:effect logpop on rate endbeh_0016 (rate)	-0.49	0.93
(*)Dummy13:effect logpop on rate endbeh_0016 (rate)	-0.67	0.54
(*)Dummy14:effect logpop on rate endbeh_0016 (rate)	-0.50	0.81
(*)Dummy15:effect logpop on rate endbeh_0016 (rate)	0.16	0.18
(*)Dummy16:effect logpop on rate endbeh_0016 (rate)	-0.14	0.73
(*)Dummy2:effect loggdppc on rate endbeh_0016 (rate)	-0.65	0.43
(*)Dummy3:effect loggdppc on rate endbeh_0016 (rate)	-0.25	0.29
(*)Dummy4:effect loggdppc on rate endbeh_0016 (rate)	-0.27	0.73
(*)Dummy5:effect loggdppc on rate endbeh_0016 (rate)	-0.45	0.28
(*)Dummy6:effect loggdppc on rate endbeh_0016 (rate)	-0.51	0.94
(*)Dummy7:effect loggdppc on rate endbeh_0016 (rate)	-0.65	0.45
(*)Dummy8:effect loggdppc on rate endbeh_0016 (rate)	-1.48	0.01
(*)Dummy9:effect loggdppc on rate endbeh_0016 (rate)	-0.24	0.45
(*)Dummy10:effect loggdppc on rate endbeh_0016 (rate)	-0.34	0.70
(*)Dummy11:effect loggdppc on rate endbeh_0016 (rate)	-1.18	0.14
(*)Dummy12:effect loggdppc on rate endbeh_0016 (rate)	-0.47	0.73
(*)Dummy13:effect loggdppc on rate endbeh_0016 (rate)	-1.07	0.12
(*)Dummy14:effect loggdppc on rate endbeh_0016 (rate)	-0.92	0.39
(*)Dummy15:effect loggdppc on rate endbeh_0016 (rate)	-1.50	0.18
(*)Dummy16:effect loggdppc on rate endbeh_0016 (rate)	-1.08	0.98
(*)Dummy2:effect logdeaths on rate endbeh_0016 (rate)	-1.19	0.43
(*)Dummy3:effect logdeaths on rate endbeh_0016 (rate)	-1.05	0.30
(*)Dummy4:effect logdeaths on rate endbeh_0016 (rate)	-1.16	0.82
(*)Dummy5:effect logdeaths on rate endbeh_0016 (rate)	5.92	0.12
(*)Dummy6:effect logdeaths on rate endbeh_0016 (rate)	0.89	0.48
(*)Dummy7:effect logdeaths on rate endbeh_0016 (rate)	0.86	0.01
(*)Dummy8:effect logdeaths on rate endbeh_0016 (rate)	28.58	0.03
(*)Dummy9:effect logdeaths on rate endbeh_0016 (rate)	6.10	0.17
(*)Dummy10:effect logdeaths on rate endbeh_0016 (rate)	8.82	0.65
(*)Dummy11:effect logdeaths on rate endbeh_0016 (rate)	0.29	0.88
(*)Dummy12:effect logdeaths on rate endbeh_0016 (rate)	0.42	0.57
(*)Dummy13:effect logdeaths on rate endbeh_0016 (rate)	8.51	0.86
(*)Dummy14:effect logdeaths on rate endbeh_0016 (rate)	-0.74	0.93
(*)Dummy15:effect logdeaths on rate endbeh_0016 (rate)	-3.69	0.23
(*)Dummy16:effect logdeaths on rate endbeh_0016 (rate)	-10.16	0.41
(*)Dummy2:effect logdeathssq on rate endbeh_0016 (rate)	0.78	0.41

(*)Dummy3:effect logdeathssq on rate endbeh_0016 (rate)	0.58	0.33
(*)Dummy4:effect logdeathssq on rate endbeh_0016 (rate)	0.70	0.79
(*)Dummy5:effect logdeathssq on rate endbeh_0016 (rate)	-3.04	0.11
(*)Dummy6:effect logdeathssq on rate endbeh_0016 (rate)	-0.50	0.50
(*)Dummy7:effect logdeathssq on rate endbeh_0016 (rate)	-0.01	0.01
(*)Dummy8:effect logdeathssq on rate endbeh_0016 (rate)	-14.08	0.04
(*)Dummy9:effect logdeathssq on rate endbeh_0016 (rate)	-2.73	0.19
(*)Dummy10:effect logdeathssq on rate endbeh_0016 (rate)	-4.25	0.70
(*)Dummy11:effect logdeathssq on rate endbeh_0016 (rate)	-0.13	0.89
(*)Dummy12:effect logdeathssq on rate endbeh_0016 (rate)	-0.00	0.56
(*)Dummy13:effect logdeathssq on rate endbeh_0016 (rate)	-4.25	0.80
(*)Dummy14:effect logdeathssq on rate endbeh_0016 (rate)	0.34	0.90
(*)Dummy15:effect logdeathssq on rate endbeh_0016 (rate)	1.53	0.24
(*)Dummy16:effect logdeathssq on rate endbeh_0016 (rate)	4.67	0.42
(*)Dummy2:effect duration on rate endbeh_0016 (rate)	-0.00	0.82
(*)Dummy3:effect duration on rate endbeh_0016 (rate)	-0.04	0.23
(*)Dummy4:effect duration on rate endbeh_0016 (rate)	0.01	0.38
(*)Dummy5:effect duration on rate endbeh_0016 (rate)	0.07	0.00
(*)Dummy6:effect duration on rate endbeh_0016 (rate)	-0.01	0.95
(*)Dummy7:effect duration on rate endbeh_0016 (rate)	-0.03	0.45
(*)Dummy8:effect duration on rate endbeh_0016 (rate)	-0.00	0.95
(*)Dummy9:effect duration on rate endbeh_0016 (rate)	-0.01	0.78
(*)Dummy10:effect duration on rate endbeh_0016 (rate)	-0.05	0.23
(*)Dummy11:effect duration on rate endbeh_0016 (rate)	-0.09	0.31
(*)Dummy12:effect duration on rate endbeh_0016 (rate)	0.04	0.36
(*)Dummy13:effect duration on rate endbeh_0016 (rate)	-0.02	0.58
(*)Dummy14:effect duration on rate endbeh_0016 (rate)	-0.04	0.51
(*)Dummy15:effect duration on rate endbeh_0016 (rate)	-0.05	0.77
(*)Dummy16:effect duration on rate endbeh_0016 (rate)	-0.09	0.61

Table A7.: Time Heterogeneity Test for 2002–2016

	One.Step.Est.	p.Value
(*)Dummy2:degree (density)	-0.95	0.93
(*)Dummy3:degree (density)	0.13	0.01
(*)Dummy4:degree (density)	0.18	0.00
(*)Dummy5:degree (density)	0.23	0.33
(*)Dummy6:degree (density)	-0.70	0.52
(*)Dummy7:degree (density)	0.35	0.00
(*)Dummy8:degree (density)	-0.29	0.63
(*)Dummy9:degree (density)	-0.22	0.14
(*)Dummy10:degree (density)	-0.31	0.04
(*)Dummy11:degree (density)	-0.03	0.55
(*)Dummy12:degree (density)	-0.15	0.01
(*)Dummy13:degree (density)	-0.05	0.00
(*)Dummy14:degree (density)	-0.96	0.04
(*)Dummy2:GWESP (69)	-1.64	0.03
(*)Dummy3:GWESP (69)	0.07	0.02
(*)Dummy4:GWESP (69)	0.42	0.00
(*)Dummy5:GWESP (69)	-0.15	0.12
(*)Dummy6:GWESP (69)	-0.82	0.05
(*)Dummy7:GWESP (69)	0.45	0.00
(*)Dummy8:GWESP (69)	-0.24	0.95

(*)Dummy9:GWESP (69)	1.13	0.00
(*)Dummy10:GWESP (69)	-0.58	0.01
(*)Dummy11:GWESP (69)	0.58	0.25
(*)Dummy12:GWESP (69)	-0.69	0.00
(*)Dummy13:GWESP (69)	-0.23	0.00
(*)Dummy14:GWESP (69)	-0.47	0.52
(*)Dummy2:degree act+pop	0.09	0.54
(*)Dummy3:degree act+pop	0.04	0.01
(*)Dummy4:degree act+pop	0.02	0.00
(*)Dummy5:degree act+pop	0.01	0.08
(*)Dummy6:degree act+pop	0.07	0.50
(*)Dummy7:degree act+pop	0.02	0.01
(*)Dummy8:degree act+pop	0.02	0.98
(*)Dummy9:degree act+pop	0.00	0.18
(*)Dummy10:degree act+pop	0.02	0.03
(*)Dummy11:degree act+pop	0.00	0.26
(*)Dummy12:degree act+pop	0.05	0.27
(*)Dummy13:degree act+pop	-0.01	0.00
(*)Dummy14:degree act+pop	0.07	0.74
(*)Dummy2:same region	0.48	0.66
(*)Dummy3:same region	-0.52	0.04
(*)Dummy4:same region	-0.58	0.00
(*)Dummy5:same region	-0.78	0.11
(*)Dummy6:same region	-0.20	0.70
(*)Dummy7:same region	-0.67	0.01
(*)Dummy8:same region	0.05	0.28
(*)Dummy9:same region	-0.28	0.09
(*)Dummy10:same region	-0.22	0.15
(*)Dummy11:same region	-0.50	0.77
(*)Dummy12:same region	-0.85	0.00
(*)Dummy13:same region	-0.45	0.01
(*)Dummy14:same region	-0.18	0.18
(*)Dummy2:duration ego	0.00	0.59
(*)Dummy3:duration ego	-0.03	0.06
(*)Dummy4:duration ego	0.00	0.97
(*)Dummy5:duration ego	0.03	0.11
(*)Dummy6:duration ego	0.04	0.01
(*)Dummy7:duration ego	-0.02	0.24
(*)Dummy8:duration ego	0.04	0.10
(*)Dummy9:duration ego	0.03	0.07
(*)Dummy10:duration ego	0.02	0.86
(*)Dummy11:duration ego	-0.00	0.20
(*)Dummy12:duration ego	-0.00	0.04
(*)Dummy13:duration ego	0.02	0.94
(*)Dummy14:duration ego	0.03	0.54
(*)Dummy2:degree effect on rate endbeh_0216 (rate)	0.11	0.48
(*)Dummy3:degree effect on rate endbeh_0216 (rate)	0.24	0.44
(*)Dummy4:degree effect on rate endbeh_0216 (rate)	0.24	0.83
(*)Dummy5:degree effect on rate endbeh_0216 (rate)	0.28	0.41
(*)Dummy6:degree effect on rate endbeh_0216 (rate)	0.00	0.33

(*)Dummy7:degree effect on rate endbeh_0216 (rate)	0.06	0.92
(*)Dummy8:degree effect on rate endbeh_0216 (rate)	-0.01	0.51
(*)Dummy9:degree effect on rate endbeh_0216 (rate)	0.03	0.48
(*)Dummy10:degree effect on rate endbeh_0216 (rate)	0.28	0.46
(*)Dummy11:degree effect on rate endbeh_0216 (rate)	0.13	0.69
(*)Dummy12:degree effect on rate endbeh_0216 (rate)	0.30	0.84
(*)Dummy13:degree effect on rate endbeh_0216 (rate)	1.06	0.10
(*)Dummy14:degree effect on rate endbeh_0216 (rate)	1.62	0.02
(*)Dummy2:effect logpop on rate endbeh_0216 (rate)	0.23	0.08
(*)Dummy3:effect logpop on rate endbeh_0216 (rate)	-0.21	0.12
(*)Dummy4:effect logpop on rate endbeh_0216 (rate)	-0.10	0.98
(*)Dummy5:effect logpop on rate endbeh_0216 (rate)	-0.09	0.89
(*)Dummy6:effect logpop on rate endbeh_0216 (rate)	-0.68	0.23
(*)Dummy7:effect logpop on rate endbeh_0216 (rate)	-0.17	0.66
(*)Dummy8:effect logpop on rate endbeh_0216 (rate)	-0.07	0.92
(*)Dummy9:effect logpop on rate endbeh_0216 (rate)	-0.30	0.74
(*)Dummy10:effect logpop on rate endbeh_0216 (rate)	-0.12	0.93
(*)Dummy11:effect logpop on rate endbeh_0216 (rate)	-0.19	0.58
(*)Dummy12:effect logpop on rate endbeh_0216 (rate)	-0.04	0.86
(*)Dummy13:effect logpop on rate endbeh_0216 (rate)	0.26	0.16
(*)Dummy14:effect logpop on rate endbeh_0216 (rate)	-0.00	0.76
(*)Dummy2:effect loggdppc on rate endbeh_0216 (rate)	-0.04	0.60
(*)Dummy3:effect loggdppc on rate endbeh_0216 (rate)	-0.14	0.18
(*)Dummy4:effect loggdppc on rate endbeh_0216 (rate)	-0.35	0.83
(*)Dummy5:effect loggdppc on rate endbeh_0216 (rate)	-0.38	0.50
(*)Dummy6:effect loggdppc on rate endbeh_0216 (rate)	-1.38	0.01
(*)Dummy7:effect loggdppc on rate endbeh_0216 (rate)	-0.06	0.37
(*)Dummy8:effect loggdppc on rate endbeh_0216 (rate)	-0.12	0.61
(*)Dummy9:effect loggdppc on rate endbeh_0216 (rate)	-1.04	0.13
(*)Dummy10:effect loggdppc on rate endbeh_0216 (rate)	-0.22	0.62
(*)Dummy11:effect loggdppc on rate endbeh_0216 (rate)	-0.56	0.13
(*)Dummy12:effect loggdppc on rate endbeh_0216 (rate)	-0.35	0.43
(*)Dummy13:effect loggdppc on rate endbeh_0216 (rate)	-0.59	0.19
(*)Dummy14:effect loggdppc on rate endbeh_0216 (rate)	-0.44	0.94
(*)Dummy2:effect logdeaths on rate endbeh_0216 (rate)	-0.66	0.84
(*)Dummy3:effect logdeaths on rate endbeh_0216 (rate)	3.46	0.11
(*)Dummy4:effect logdeaths on rate endbeh_0216 (rate)	0.34	0.45
(*)Dummy5:effect logdeaths on rate endbeh_0216 (rate)	1.50	0.01
(*)Dummy6:effect logdeaths on rate endbeh_0216 (rate)	19.22	0.02
(*)Dummy7:effect logdeaths on rate endbeh_0216 (rate)	3.89	0.17
(*)Dummy8:effect logdeaths on rate endbeh_0216 (rate)	6.01	0.67
(*)Dummy9:effect logdeaths on rate endbeh_0216 (rate)	0.61	0.85
(*)Dummy10:effect logdeaths on rate endbeh_0216 (rate)	0.69	0.59
(*)Dummy11:effect logdeaths on rate endbeh_0216 (rate)	5.51	0.87
(*)Dummy12:effect logdeaths on rate endbeh_0216 (rate)	-0.73	0.94
(*)Dummy13:effect logdeaths on rate endbeh_0216 (rate)	-4.56	0.23
(*)Dummy14:effect logdeaths on rate endbeh_0216 (rate)	-5.40	0.40
(*)Dummy2:effect logdeathssq on rate endbeh_0216 (rate)	0.40	0.81
(*)Dummy3:effect logdeathssq on rate endbeh_0216 (rate)	-1.85	0.10
(*)Dummy4:effect logdeathssq on rate endbeh_0216 (rate)	-0.24	0.47

(*)Dummy5:effect logdeathssq on rate endbeh_0216 (rate)	-0.42	0.01
(*)Dummy6:effect logdeathssq on rate endbeh_0216 (rate)	-9.40	0.03
(*)Dummy7:effect logdeathssq on rate endbeh_0216 (rate)	-1.75	0.19
(*)Dummy8:effect logdeathssq on rate endbeh_0216 (rate)	-2.94	0.72
(*)Dummy9:effect logdeathssq on rate endbeh_0216 (rate)	-0.28	0.87
(*)Dummy10:effect logdeathssq on rate endbeh_0216 (rate)	-0.24	0.57
(*)Dummy11:effect logdeathssq on rate endbeh_0216 (rate)	-2.79	0.81
(*)Dummy12:effect logdeathssq on rate endbeh_0216 (rate)	0.31	0.91
(*)Dummy13:effect logdeathssq on rate endbeh_0216 (rate)	2.08	0.24
(*)Dummy14:effect logdeathssq on rate endbeh_0216 (rate)	2.30	0.41
(*)Dummy2:effect polity on rate endbeh_0216 (rate)	0.04	0.27
(*)Dummy3:effect polity on rate endbeh_0216 (rate)	0.03	0.79
(*)Dummy4:effect polity on rate endbeh_0216 (rate)	0.09	0.51
(*)Dummy5:effect polity on rate endbeh_0216 (rate)	0.11	0.84
(*)Dummy6:effect polity on rate endbeh_0216 (rate)	0.27	0.39
(*)Dummy7:effect polity on rate endbeh_0216 (rate)	0.06	0.47
(*)Dummy8:effect polity on rate endbeh_0216 (rate)	-0.01	0.88
(*)Dummy9:effect polity on rate endbeh_0216 (rate)	0.25	0.66
(*)Dummy10:effect polity on rate endbeh_0216 (rate)	0.09	0.75
(*)Dummy11:effect polity on rate endbeh_0216 (rate)	-0.06	0.24
(*)Dummy12:effect polity on rate endbeh_0216 (rate)	-0.10	0.07
(*)Dummy13:effect polity on rate endbeh_0216 (rate)	-0.12	0.22
(*)Dummy14:effect polity on rate endbeh_0216 (rate)	-0.26	0.05

Table A8.: Time Heterogeneity Test for 2000–2008 Model with Time Dummies

	One.Step.Est.	p.Value
(*)Dummy2:degree (density)	0.66	0.22
(*)Dummy3:degree (density)	0.48	0.60
(*)Dummy4:degree (density)	-0.43	0.63
(*)Dummy5:degree (density)	0.67	0.59
(*)Dummy6:degree (density)	0.62	0.20
(*)Dummy7:degree (density)	0.74	0.57
(*)Dummy8:degree (density)	-0.40	0.66
(*)Dummy2:GWESP (69)	0.97	1.00
(*)Dummy3:GWESP (69)	0.24	0.74
(*)Dummy4:GWESP (69)	-0.14	1.00
(*)Dummy5:GWESP (69)	0.40	0.55
(*)Dummy6:GWESP (69)	0.71	0.99
(*)Dummy7:GWESP (69)	0.46	0.99
(*)Dummy8:GWESP (69)	0.51	0.99
(*)Dummy2:degree act+pop	-0.09	0.22
(*)Dummy3:degree act+pop	-0.05	0.99
(*)Dummy4:degree act+pop	0.00	0.17
(*)Dummy5:degree act+pop	-0.05	0.60
(*)Dummy6:degree act+pop	-0.06	0.10
(*)Dummy7:degree act+pop	-0.06	0.99
(*)Dummy8:degree act+pop	-0.03	0.25

(*)Dummy2:same region	-1.14	0.18
(*)Dummy3:same region	-0.36	0.40
(*)Dummy4:same region	0.02	0.36
(*)Dummy5:same region	-0.98	0.42
(*)Dummy6:same region	-0.93	0.14
(*)Dummy7:same region	-0.91	1.00
(*)Dummy8:same region	-0.31	0.99
(*)Dummy2:duration ego	0.04	0.23
(*)Dummy3:duration ego	-0.02	0.48
(*)Dummy4:duration ego	-0.02	0.48
(*)Dummy5:duration ego	-0.06	0.01
(*)Dummy6:duration ego	-0.02	0.16
(*)Dummy7:duration ego	0.01	0.13
(*)Dummy8:duration ego	0.03	0.04
(*)Dummy2:degree effect on rate endbeh_0008 (rate)	-0.18	0.33
(*)Dummy3:degree effect on rate endbeh_0008 (rate)	-0.15	0.21
(*)Dummy4:degree effect on rate endbeh_0008 (rate)	-0.05	0.70
(*)Dummy5:degree effect on rate endbeh_0008 (rate)	0.28	0.07
(*)Dummy6:degree effect on rate endbeh_0008 (rate)	0.11	0.81
(*)Dummy7:degree effect on rate endbeh_0008 (rate)	0.18	0.11
(*)Dummy8:degree effect on rate endbeh_0008 (rate)	-0.38	0.40
(*)Dummy2:effect logdeaths on rate endbeh_0008 (rate)	-1.35	0.64
(*)Dummy3:effect logdeaths on rate endbeh_0008 (rate)	0.00	0.29
(*)Dummy4:effect logdeaths on rate endbeh_0008 (rate)	0.16	0.88
(*)Dummy5:effect logdeaths on rate endbeh_0008 (rate)	5.01	0.15
(*)Dummy6:effect logdeaths on rate endbeh_0008 (rate)	0.92	0.42
(*)Dummy7:effect logdeaths on rate endbeh_0008 (rate)	1.98	0.01
(*)Dummy8:effect logdeaths on rate endbeh_0008 (rate)	30.28	0.02
(*)Dummy2:effect logdeathssq on rate endbeh_0008 (rate)	0.86	0.62
(*)Dummy3:effect logdeathssq on rate endbeh_0008 (rate)	0.05	0.31
(*)Dummy4:effect logdeathssq on rate endbeh_0008 (rate)	0.07	0.86
(*)Dummy5:effect logdeathssq on rate endbeh_0008 (rate)	-2.53	0.14
(*)Dummy6:effect logdeathssq on rate endbeh_0008 (rate)	-0.48	0.43
(*)Dummy7:effect logdeathssq on rate endbeh_0008 (rate)	-0.66	0.01
(*)Dummy8:effect logdeathssq on rate endbeh_0008 (rate)	-14.78	0.03

Table A9.: Time Heterogeneity Test for 2008–2016 Model with Time Dummies

	One.Step.Est.	p.Value
(*)Dummy2:degree (density)	-0.65	0.65
(*)Dummy3:degree (density)	-0.63	0.98
(*)Dummy4:degree (density)	-0.72	0.03
(*)Dummy5:degree (density)	-0.43	0.52
(*)Dummy6:degree (density)	-0.45	0.35
(*)Dummy7:degree (density)	-0.41	0.99
(*)Dummy8:degree (density)	-1.33	0.05
(*)Dummy2:GWESP (69)	-0.68	0.78
(*)Dummy3:GWESP (69)	-0.56	0.99

(*)Dummy4:GWESP (69)	-1.05	0.00
(*)Dummy5:GWESP (69)	0.11	0.34
(*)Dummy6:GWESP (69)	-0.79	0.99
(*)Dummy7:GWESP (69)	-0.54	0.98
(*)Dummy8:GWESP (69)	-0.68	0.41
(*)Dummy2:degree act+pop	0.00	0.78
(*)Dummy3:degree act+pop	0.01	0.98
(*)Dummy4:degree act+pop	0.01	0.01
(*)Dummy5:degree act+pop	-0.02	0.13
(*)Dummy6:degree act+pop	0.03	0.12
(*)Dummy7:degree act+pop	0.00	0.99
(*)Dummy8:degree act+pop	0.05	0.92
(*)Dummy2:same region	0.77	0.26
(*)Dummy3:same region	0.37	0.98
(*)Dummy4:same region	0.52	0.14
(*)Dummy5:same region	0.27	0.79
(*)Dummy6:same region	0.02	1.00
(*)Dummy7:same region	0.04	0.66
(*)Dummy8:same region	0.59	0.21
(*)Dummy2:duration ego	0.06	0.15
(*)Dummy3:duration ego	0.06	0.35
(*)Dummy4:duration ego	0.04	0.68
(*)Dummy5:duration ego	0.02	0.11
(*)Dummy6:duration ego	0.02	0.28
(*)Dummy7:duration ego	0.06	0.06
(*)Dummy8:duration ego	0.05	0.63
(*)Dummy2:degree effect on rate endbeh_0816 (rate)	-0.01	0.41
(*)Dummy3:degree effect on rate endbeh_0816 (rate)	-0.05	0.53
(*)Dummy4:degree effect on rate endbeh_0816 (rate)	0.10	0.76
(*)Dummy5:degree effect on rate endbeh_0816 (rate)	-0.00	0.61
(*)Dummy6:degree effect on rate endbeh_0816 (rate)	0.07	0.99
(*)Dummy7:degree effect on rate endbeh_0816 (rate)	0.41	0.30
(*)Dummy8:degree effect on rate endbeh_0816 (rate)	0.77	0.11
(*)Dummy2:effect logdeaths on rate endbeh_0816 (rate)	0.91	0.63
(*)Dummy3:effect logdeaths on rate endbeh_0816 (rate)	-3.26	0.88
(*)Dummy4:effect logdeaths on rate endbeh_0816 (rate)	-3.90	0.59
(*)Dummy5:effect logdeaths on rate endbeh_0816 (rate)	0.76	0.91
(*)Dummy6:effect logdeaths on rate endbeh_0816 (rate)	-4.66	0.89
(*)Dummy7:effect logdeaths on rate endbeh_0816 (rate)	-5.25	0.24
(*)Dummy8:effect logdeaths on rate endbeh_0816 (rate)	-8.19	0.42
(*)Dummy2:effect logdeathssq on rate endbeh_0816 (rate)	-0.58	0.67
(*)Dummy3:effect logdeathssq on rate endbeh_0816 (rate)	1.48	0.89
(*)Dummy4:effect logdeathssq on rate endbeh_0816 (rate)	1.85	0.56
(*)Dummy5:effect logdeathssq on rate endbeh_0816 (rate)	-0.60	0.85
(*)Dummy6:effect logdeathssq on rate endbeh_0816 (rate)	2.19	0.85
(*)Dummy7:effect logdeathssq on rate endbeh_0816 (rate)	2.28	0.26
(*)Dummy8:effect logdeathssq on rate endbeh_0816 (rate)	3.68	0.44

Appendix B.

B.1. *Alternate Distributions for AFT Models*

Table B1.: Accelerated Failure Time Models, Log-Logistic Distribution

	(1)	(2)	(3)
Fatalities (log)	0.448**	0.448**	0.452**
	(0.169)	(0.172)	(0.174)
Fatalities Sq. (log)	1.380*	1.412*	1.402*
	(0.265)	(0.275)	(0.274)
Number of Allies	1.312***		
	(0.070)		
EV Centrality		1.019**	
		(0.007)	
Neighborhood			1.018**
			(0.009)
Clustering	0.743	1.297	1.291
	(0.194)	(0.326)	(0.342)
Left	0.667*	0.653*	0.695
	(0.155)	(0.156)	(0.172)
Right	0.437**	0.391**	0.417**
	(0.154)	(0.143)	(0.155)
Nationalist	0.602**	0.588**	0.610**
	(0.136)	(0.138)	(0.145)
Regime	0.589	0.584	0.576
	(0.201)	(0.206)	(0.205)
Policy	0.466**	0.444**	0.442**
	(0.162)	(0.159)	(0.159)
Territory	1.169	1.303	1.281
	(0.411)	(0.473)	(0.467)
Attack Diversity	6.878***	7.781***	8.146***
	(2.991)	(3.473)	(3.647)
Share Trans. Terr.	0.297***	0.287***	0.297***
	(0.043)	(0.042)	(0.044)
Multiple Bases	0.828	0.893	0.885
	(0.147)	(0.162)	(0.163)
Pop (log)	1.033	1.029	1.022
	(0.045)	(0.047)	(0.047)
GDP/Pop (log)	0.938	0.950	0.953

	(0.061)	(0.064)	(0.065)
Democracy	0.584	0.635	0.612
	(0.209)	(0.235)	(0.228)
East Asia & Pacific	1.883**	1.888**	1.950**
	(0.554)	(0.569)	(0.596)
Europe & Central Asia	0.879	0.776	0.810
	(0.208)	(0.188)	(0.198)
Latin Am. & Caribbean	0.918	0.875	0.864
	(0.239)	(0.235)	(0.234)
North America	1.404	1.205	1.260
	(0.487)	(0.434)	(0.459)
South Asia	1.447	1.426	1.525
	(0.500)	(0.511)	(0.550)
Sub-Saharan Africa	2.116**	1.908*	2.003**
	(0.683)	(0.637)	(0.679)
log(scale)	3.612***	3.718***	3.752***
	(1.296)	(1.351)	(1.361)
log(shape)	0.296***	0.256***	0.249***
	(0.051)	(0.051)	(0.051)
Observations	7,777	7,777	7,777
AIC	2057.237	2083.36	2086.747
BIC	2224.251	2250.374	2253.761
Log Likelihood	−1,004.618	−1,017.680	−1,019.373
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B2.: Accelerated Failure Time Models, Extreme Value Distribution

	(1)	(2)	(3)
Fatalities (log)	0.373**	0.401**	0.383**
	(0.162)	(0.176)	(0.168)
Fatalities Sq. (log)	1.505*	1.506*	1.530*
	(0.334)	(0.336)	(0.341)
Number of Allies	1.291***		
	(0.082)		
EV Centrality		1.013*	
		(0.007)	
Neighborhood			1.017*
			(0.010)
Clustering	0.657	1.257	1.183
	(0.191)	(0.343)	(0.339)
Left	0.449***	0.454***	0.488***
	(0.110)	(0.113)	(0.123)
Right	0.293***	0.276***	0.297***
	(0.086)	(0.083)	(0.091)
Nationalist	0.643*	0.617**	0.649*
	(0.148)	(0.145)	(0.155)
Regime	0.738	0.704	0.678
	(0.228)	(0.221)	(0.215)
Policy	0.490**	0.459**	0.446**
	(0.159)	(0.151)	(0.148)
Territory	1.047	1.198	1.170
	(0.337)	(0.390)	(0.386)
Attack Diversity	9.996***	9.450***	9.954***
	(5.248)	(4.949)	(5.195)
Share Trans. Terr.	0.179***	0.168***	0.175***
	(0.029)	(0.027)	(0.028)
Multiple Bases	0.900	0.919	0.936
	(0.132)	(0.138)	(0.143)
Pop (log)	1.090**	1.080*	1.074
	(0.047)	(0.048)	(0.048)
GDP/Pop (log)	0.953	0.969	0.978
	(0.058)	(0.061)	(0.061)
Democracy	1.223	1.236	1.177
	(0.469)	(0.482)	(0.465)

East Asia & Pacific	1.503	1.399	1.408
	(0.456)	(0.433)	(0.440)
Europe & Central Asia	1.075	0.940	0.924
	(0.240)	(0.211)	(0.207)
Latin Am. & Caribbean	1.093	1.044	1.011
	(0.269)	(0.263)	(0.255)
North America	1.262	1.281	1.293
	(0.359)	(0.374)	(0.381)
South Asia	1.206	1.227	1.298
	(0.446)	(0.457)	(0.489)
Sub-Saharan Africa	1.864**	1.737*	1.783*
	(0.555)	(0.524)	(0.549)
log(scale)	2.869**	3.087**	3.077**
	(1.92)	(1.259)	(1.269)
log(shape)	-0.242***	-0.253 ***	-0.261***
	(0.051)	(0.052)	(0.051)
Observations	7,777	7,777	7,777
AIC	2088.286	2109.561	2110.403
BIC	2255.3	2276.575	2277.417
Log Likelihood	−1,020.143	−1,030.781	−1,031.201
Note:			*p<0.1; **p<0.05; ***p<0.01