Cultures of Violence and Acts of Terror: Applying a Legitimation–Habituation Model to Terrorism

Christopher W. Mullins and Joseph K. Young

Abstract

Although uniquely positioned to provide insight into the nature and dynamics of terrorism, overall the field of criminology has seen few empirically focused analyses of this form of political violence. This article seeks to add to the understanding of terror through an exploration of how general levels of violence within a given society influence the probability of political dissidents within that society resorting to terror as a form of political action. Drawing on the legitimation–habituation thesis, the authors explore whether general levels of legitimate and illegitimate violence within a society predict terrorist violence (both internal and external in direction) within that society. To do so, the authors use zero-inflated negative binomial regression models to perform time series cross-sectional analysis on predictors of terrorist events from the Global Terrorism Database. The authors find support for their core hypothesis and provide a discussion of the implications for the findings within their data and for future criminological research on terrorism.

Keywords

terrorism, homicide, cultures of violence, comparative criminology

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Introduction

What can explain the cross-national variance in states generating terror events? Political scientists claim that the type of regime matters. States that limit opportunities for political participation should encourage terror, systems where policy is deadlocked should generate more terror events, and other political institutional factors help explain this puzzle (Crenshaw, 1981; Li, 2005; Young & Dugan, 2008). However, there are assuredly factors relevant to this question that go beyond the nature of state constitution and behavior. Criminology, especially a sociologically informed criminology, is positioned to add to our understanding of this question, but application of theories that might explain why some states are terror prone is rare (Lafree & Dugan, 2004). Criminologists have generally acknowledged the lack of research on terrorism in our field, as well as our unique position to contribute to this academic discourse (i.e., LaFree, 2007; Rosenfeld, 2002). As scholars devoted to the explanation of crime, we should be equipped to explain terrorism not only as a criminal behavior but also as a form of violence. Yet little has been done in response to this call, with most empirical studies of terrorism being done in political science, economics, and other fields (notable exceptions include Dugan, LaFree, & Piquero, 2005; Greenbaum, Dugan, & LaFree, 2007). Mostly because of data constraints, few criminologists provide statistical tests of specific criminological theories. Recently, however, the Global Terrorism Database (GTD) has been made public, offering criminologists an opportunity to engage in the study of this form of violent political crime.

We conceptualize terrorism as the threat or use of violence to achieve a political goal by attacking a target in the hope of coercing a third party.1 As Schmid (1984) notes, there are more than 100 ways terrorism has been defined by scholars. But as Victoroff (2003) suggests,

two common elements are usually found in contemporary definitions: (1) that terrorism involves aggression versus noncombatants and (2) that the terrorist action in itself is not expected by its perpetrator to accomplish a political goal but instead to influence a target audience. (p. 4)

To be clear, the act of terrorism itself is not meant to achieve a goal. According to Lake (2002), the act is often used “to provoke the target into a disproportionate response that radicalizes moderates . . . expanding supporters and allies” (p. 16) for the cause of the group using terrorism. Our definition incorporates both these elements, conceptually separating who receives the violence (the victims) from the broader target of the violence (the audience). Additionally, we identify the goals of terror groups as political (even if their
motivations may be religious, economic, or social) as well as incorporate the use of threats in addition to actual actions. Threats of violence are as important as the actual use of violence; kidnappers, hijackers, and other terrorists often threaten force to coerce the other side rather than to simply implement violence. Because the goal of the terror group is coercion, threats are as useful as actual implementation of force. Finally, this definition is consistent with the way that coders of the GTD conceptualize and identify terror incidents.

As mentioned, criminologists have infrequently published on terrorism. Empirically, Dugan et al. (2005) found support for a rational choice–based model, which predicted airline hijackings, and Greenbaum et al. (2007), drawing on some assumptions of community-based theories, found that terror events did influence business climates within Italian communities. Otherwise, most of the criminological work on terror and terror groups has been largely conceptual and drawn on subculture theories (Hamm, 2002, 2004), interactionist theories of identity (Arena & Arrigo, 2004), or social learning theories (Akers & Silverman, 2004). Such models suggest that various levels of exposure to terror groups or their ideologies combined with other individual-level characteristics can predict whether or not a given individual adopts these attitudes and then goes on to engage in terrorist behavior. The historical strength of learning theories within the discipline suggests that these experiences and processes are important in the overall explanation of terrorism. However, the lack of available micro-level data prevents systematic tests of these hypotheses. Although the GTD data lack information on individual offenders and individual-level characteristics, this is not the only way to test basic predictions of learning or cultural models. Although learning processes indeed occur on the micro level, the influences of learning are often active on meso and macro levels. Here, we draw on prior work on macro-level associations between legitimate violence and illegitimate violence (e.g., Archer & Gartner, 1984; Ember & Ember, 1993, 1994; Gartner, 1990; Landau & Pfeffermann, 1988) to explore basic patterns of the distribution of terrorism across states. Although previous political science approaches focus on formal institutions, we argue that states that have cultures of violence are more prone to generating terrorism.

This article seeks to add to our understanding of terror through an exploration of how general levels of violence within a given society influence the probability of political dissidents resorting to terror as a form of political action. Drawing on the legitimation–habituation thesis, we explore whether general levels of legitimate and illegitimate violence within a society predict terrorist violence (both internal and external in direction) within that society. To do so, we use zero-inflated negative binomial regression models to perform time series cross-sectional analysis on predictors of terrorist events from the GTD.
A culture of violence can affect which states generate terrorism through three separate pathways. First, prior experience with violence can generate future uses of violence by members of society. If there is a truism within the social sciences, it is that past behavior is the best predictor of future behavior. Second, states and leaders can generate an elite culture that sanctions violence against civilians. This can produce terror either as retaliation to such a culture or as a mirroring of it. Third, violent citizen behavior can spill over into uses of violent political behavior—especially in the form of terrorism.

Theoretical explanations linking crime to explicit or implicit value structures are not new in the field (e.g., Sellin, 1938; Sutherland, 1939). Lately, most work in this area has focused on subcultural approaches to explaining urban violence. For example, Anderson’s (1999) work on the “code of the street” thoroughly examines a normative structure extolling violence as a mechanism of dispute resolution nested within structural experiences of concentrated disadvantage. Similarly, other ethnographic work has charted the cognitive map of embedded offenders participating in street life subculture. Focusing on a hedonistic culture of desperate partying that structures the experience of habitual offenders, crime is contextualized within broader network-based values and experiences of marginality (see Shover & Henderson, 1995; Shover & Honaker, 1992; Wright & Decker, 1994, 1996). Through experiences within street life subculture, embedded offenders adopt and have reinforced values that promote criminal behavior as core problem-solving actions, including violent responses to personal affronts that jeopardize their reputation (see Jacobs & Wright, 2006, 2008). Qualitatively, these scholars have provided a cognitive map of violent cultural terrain that is beginning to be confirmed via quantitative analysis (e.g., Baumer, Horney, Felson, & Lauritsen, 2003; Stewart & Simons, 2006). However, before this focus on subcultural values, a body of interdisciplinary criminological scholarship made headway into linking macro rates of violence to macro-level cultural values and experiences.

Consistent correlations of violent crime rates in a society with levels of legitimized violence make us look to broader aspects of social experiences and cultures when trying to explain terrorism. The legitimation–habituation hypothesis identifies a strong link between the amount of legitimated violence within a society and the amount of criminal violence. Extant studies find that (a) a society’s experiences of international conflict, (b) the number of causalities in that conflict, (c) the presence of capital punishment, and (d) the amount of justifiable homicide are strongly associated with the homicide rates within a society. Typically,
Criminologists have interpreted this to be reflective of a broad learning process. Social actors witness widespread legitimate violence, then they model this behavior within other social interactions (Archer & Gartner, 1984; Ember & Ember, 1993, 1994; Gartner, 1990; Landau & Pfeffermann, 1988). In essence, we see this as a spillover effect, where standards of behavior drawn from one social situation are applied to another social situation, regardless of their acceptability in that second interactional context.

From this standpoint, it is logical to assume that such a spillover effect could also influence the likelihood of terrorism within a given society. Simply put, terrorism is a violent form of political dissent. If a society is more likely to produce various forms of violent behavior generally because of a cultural/structural condition, it could be more likely to produce terrorism specifically. We suggest that one important social force is the general acceptability of violence within the society itself. As many scholars have shown, violence and toleration of violence varies widely among societies (Archer & Gartner, 1984; Ember & Ember, 1993, 1994). If a dissident group occupies a society that has a greater cultural toleration of violence, we suggest that the likelihood of their resorting to terrorism over other forms of dissent expression is higher. If the state (or other key institutions) models violence as a solution to interactional difficulties (be they international such as war or communal such as capital punishment), then the probability that dissident groups will resort to terror is higher than when legitimate models of violence are weaker or absent.

The general theoretical arguments have focused on legitimate violence, be it warfare, execution, and so on, generating a broader cultural acceptance of violence. This, in turn, increases the amount of criminal violence a society experiences. Typically, this is explained via a combination of exposure to wide-scale violence and its legitimating functioning to both model violent behavior as legitimate as well as desensitizing individuals to the use and experience of violence. As subcultural work has shown, illegitimate violence can serve the same function. Decades ago, scholars established the link between legitimate externally directed violence (i.e., warfare) and illegal internally directed violence (i.e., homicide). As Ember and Ember (1993, 1994) have shown in cross-cultural data, violence in one social arena is strongly related to violence in others. In their data, wars generally increase violence within a society that is not related to the war itself. As individuals are exposed to widespread legitimate violence, they become more likely to adopt more permissive norms toward violence. Because of generational effects of socialization, even once the war was over, these societies had higher levels of interpersonal violence. Cohorts raised during wartime exhibited higher levels of aggression across their life course. Ember and Ember (1994, p. 643) highlight that although rooted in the
need to produce courageous warriors . . . high rates of homicide are and assault are inadvertent . . once you learn to kill an enemy, you may find it easier to hurt or kill anyone . . . [additionally] war may be a direct cause of more violence because war legitimizes violence. (p. 643)

Although their data are primarily drawn from tribal cultures, these mechanisms should apply to more developed societies in a similar fashion.

Another indirect influence that warfare may have on broader violence rates involves its influence on the structure of the state. Gurr (1988, p. 48) argues that “[o]ne specific consequence of recurring involvement in war, internal or external is the development of specialized organizations ready to fight future wars.” An important implication is that leaders who have secured power via force “are disposed to respond violently to future challenges” (p. 49). This, in turn, generates an elite culture that favors the use of violence in political disputes. Gurr (1988, p. 51) refers to this development of a violent elite culture as the garrison state and claims that these states “maintain large-scale military and/or internal security apparatus establishments, and [their] elite political culture sanctions the use of extreme coercion.” Once established, these state structures should continue to have a strong direct and indirect socialization and legitimating influence on citizens’ perceptions and uses of violence.

Drawing on modern cross-national data, Archer and Gartner (1984) found that after major wars domestic homicides increased. Testing a number of potential models for this effect,2 they found that a legitimation model was the only one consistent with their data. Drawing on a social–psychological modeling argument, they suggest that government serves as a very powerful agent of socialization for youth and adults, especially vis-à-vis violence. In later work, Gartner (1990) found an association between battle deaths and homicide rates for all ages, grades, and sexes within a population. As Ghabrah, Huth, and Russett (2003; p. 192) also note, “Gerosi and King (2002) report a significant rise in homicides and suicides, transportation deaths, and other unintentional injuries (both the latter are likely to include misclassified suicides) in the U.S. population immediately following the Korean and Vietnam wars.” Thus studies strongly suggest a spillover effect from legitimate war-related violence to other interactional contexts.

Studying Israel, Landau and Pfeffermann (1988) found that the amount of war violence experienced (operationalized in terms of casualty counts) was strongly related to the number of civilian homicides. Controlling for economic, population, and other variables, their work found that out-group directed legitimate violence (war) indeed predicted future homicide rates. This effect was not found in acquisitive crimes, even violent acquisitive crimes such as robbery,
which was better predicted by economic variables (i.e., unemployment). This work leads us to the following hypothesis:

**Hypothesis 1:** States that have recently experienced externally directed state-organized and supported violence, especially in the form of warfare, will have higher rates of terrorism than states that do not have recent experiences with externally directed violence.

States can also legitimize violence through the use of capital punishment. Although there is still a contested literature on the precise size and influence of the brutalization effect, numerous studies have found a positive association between the practice of capital punishment and homicide rates (e.g., Bowers, 1984; Cheatwood, 1993; Gartner, 1990). Whether or not capital punishment generates a general deterrent effect is not of interest to our study here (and we do not seek to enter this debate). Rather, for our purposes, execution, like warfare, represents legitimate violence carried out by the state. As Bowers (1984, p. 274) simply states, “[e]xecutions demonstrate that it is correct and appropriate to kill those who have gravely offended us.” The violence takes on a moralistic dimension and is justified as righting a prior wrongdoing. The moralistic nature of street violence is something that qualitative researchers have recently begun to examine (Jacobs & Wright, 2006, 2008); the moralistic nature of terrorist violence from the perspective of the terrorist has also been well documented (see Hoffman, 1998, p. 43). Thus, in determining the level of toleration and acceptance of violence within a society, this represents an important measure. If the state uses violence morally to redress wrongs, individuals should be more likely to do the same. This leads us to the following hypothesis:

**Hypothesis 2:** States that practice capital punishment will have higher rates of terrorism committed by their population than states that do not practice capital punishment.

A third source of violence modeling comes from the broader existence of violence within a community itself. Although indeed the state can be a strong model for social actor behavior, much of learning theory and subculture theory within criminology points to peers and neighborhood conditions as important agents within this process. Exposure to violent values, direct and vicarious experiences of violence, and weakened mainstream institutions of socialization can all contribute to a greater likelihood of the use of violence (e.g., Akers, 1998; Anderson, 1999; Shaw & McKay, 1942; Sutherland, 1939;
Wolfgang & Ferracuti, 1982). Williams and Flewelling (1988) showed that nonstate, legitimate, lethal violence (measured as the rate of justifiable homicides) within an urban community strongly predicted the amount of homicides. The relationship was stronger when the rates were disaggregated and only conflict homicides were analyzed. They conclude that this represents the culture of violence theory, especially as it shows individuals more likely to draw on lethal violence when there are more instances of legitimate homicide in their immediate environment (here, city-based data). This mirrors our theoretical predictions about the use of terror being more likely in cultural contexts that have higher levels of violence. If violence is perceived as acceptable in interpersonal disputes, it should also then have a higher likelihood of being perceived as an acceptable form of political expression. Yet this violence need not be legal to act as a modeling influence. Illegitimate violence of one form (i.e., individualized assault or homicide) can also be seen as a model for other types of illegitimate violence (for our purposes, terrorism). This finding has been documented in several studies (e.g., Archer & Gartner, 1984; Gartner, 1990; Ross 1985). However, if we postulate a modeling effect then we should also consider the surrounding amounts of violence in total. Subculture theory shows that violence need not necessarily be state sanctioned to function as a model (Anderson, 1999; Wolfgang & Ferracuti, 1982). A society’s general homicide rate serves as a reasonable measure for overall violence within the society as a whole, as patterns of aggravated assault tend to mirror homicide trends. Thus, we can hypothesize the following:

**Hypothesis 3:** A state’s homicide rate is positively related to the amount of terrorism used by its members.

In this article, we evaluate these hypotheses using cross-national time series data including measures of terrorism from the GTD. Next, we turn to a discussion of operationalization. We then discuss how we dealt with missing data in the GTD. We then explore issues of estimation using terrorism data. After the estimation section, we present and discuss our findings. We conclude with an overall examination of the significance of this article for studies of violence in general and terrorism more specifically.

**Research Design**

Building on previous criminological arguments relating certain cultural constellations to violence, we identified several hypotheses amenable to empirical testing.
To evaluate these hypotheses, we use data from 174 countries for the time period from 1970 to 1997. This spatial domain includes a large sample of countries in the world and includes a time period that straddles major world events including the end of the Cold War, the rise of Islamic fundamentalism, and other important events that might affect the number of terror events. Although the temporal domain of the study does not include the time period before 1970 or after 1997, we do not believe that our inferences would change dramatically if we had data that extended backwards to the end of World War II or extend forward to the present. The GTD data are currently being extended forward so further work could evaluate whether terrorism has somehow changed since 9/11. The ITERATE data, which measure only transnational terrorism, find no large changes in the patterns of terrorism since 9/11, suggesting that the underlying reasons for terror in the postwar world are consistent over time (Sandler & Enders, 2006).4

**Dependent Variable**

The dependent variable for our study is a count of fatal terror events in a given country-year. To counter problems in other databases, this includes both domestic and international terror events (though domestic events make up the bulk of events). Although it is impossible to completely separate the data, the GTD has an “entity” variable that allowed us to distinguish domestic events from transnational events as best as possible. We use domestic fatal events in our models as we believe domestic culture is generating these processes. With that said, analyses using both domestic and transnational events are similar.

We are able to disaggregate these events to include measures of terrorism that have slightly different coding rules.5 This allows us to check the robustness of the results over different coding rules for terror events. As mentioned above, these data come from the GTD and range from 1970 to 1997. Before transferring the data from the Pinkerton Group to the University of Maryland, the data from 1993 were lost. We impute the values for 1993 in the models where other data are imputed and exclude 1993 in the models with the nonimputed data. Figure 1 shows the number of attacks in the world by year.

**Independent Variables**

To measure cultures of violence we use several indicators. First, we use indicators of state violence both through judicial processes and extrajudicial processes. Next, we use a measure of citizen violence—the homicide rate. Our final group of indicators relate to a state’s previous experience with violence. We use a measure of whether a state experienced war or civil war in the previous year.
We draw on two different measures of state violence. The first is a dichotomous variable that indicates in any given year whether or not the state practiced execution. Because our theoretical model emphasizes capital punishment’s legitimation effect, we do not see it having an influence on a culture of violence if it is not in practice. Even if a state has laws permitting capital punishment, they are only coded as executors if they practice it. For states that have banned capital punishment, abolished capital punishment for ordinary crimes, or have placed moratoria on executions, we use the last date of execution performance to determine when this state moves from executor to nonexecutor status.6

Our second measure of violence taps into the fact that in many weakened and failing states, standing governments practice extrajudicial executions. In these states, individuals are killed by the state without formal legal procedures. We see this as conceptually similar to execution in that it adds to the general levels of violence within a society as well as serving as a legitimation of violence. Gibney and Dalton (1996) developed a measure of state violence against civilians called the Political Terror Scale (PTS). The PTS ranges measures the level and scope of state-sanctioned killing, torture, disappearances, and political imprisonment in a particular year on a 5-level scale. Another similar measure (CIRI), created by

Figure 1. The number of terrorist attacks in the world by year (Global Terrorism Database: 1970-1997)

Capital Punishment and State Terror

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Cingranelli and Richards (2008), measures the state’s violations of individuals’ personal integrity rights including the above four ways that states may do this. This is an additive index constructed from the Torture, Extrajudicial Killing, Political Imprisonment, and Disappearance indicators. It ranges from 0 (no government respect for these four rights) to 8 (full government respect for these four rights). We use both measures as a proxy for state violence that is outside the formal institutional process. Because the PTS data go back further in time, we use this measure in the estimations on nonimputed data. Results for the PTS and CIRI measures are similar.

To measure citizen violence, we use World Health Organization (WHO) data on homicide rates. This is a measure of the number of homicides per 100,000 people. Although other databases exist, as Messner, Raffalovich, and Shrock (2002, p. 383) note quoting (Kalish, 1988) the WHO data are potentially better because they are “‘based on an actual count of deceased persons’ and thus are not susceptible to biases resulting from intercountry differences in the classification of ‘attempted homicides.’” Ideally, we would include other measures of violence within a society (i.e., sexual or aggravated assaults, armed robberies). Unfortunately, there are no reliable international numbers on these acts to use.

Another potential measure for the culture of violence that we claim legitimates the use of terror is whether a state experienced war recently. We use a measure from the Correlates of War project that is coded 1 if war (interstate or intrastate) occurred in the prior year and 0 otherwise. Because war, state violence, and citizen violence may all be indicators of the latent variable, culture of violence, we also performed exploratory factor analysis on measures of these variables to make sure that there is a single factor that explains the covariation among these measures. We found evidence that a single dimension underlies these indicators. We extracted this factor for use in a series of models as a more parsimonious way to represent the culture of violence.

**Control Variables**

We use a series of control variables to make sure that our culture of violence argument is robust to alternative explanations for terrorism. A commonly used measure in the quantitative study of terrorism is population. States with more people should be more likely to generate individuals willing to use violence. We use a logged measure from the World Bank Development Indicators (2003).

Recent research suggests that regime type is important in explaining terror, especially suicide terror events (Lai, 2007; Li, 2005; Pape, 2003) whereas others cast doubt on this assertion (Koch & Cranmer, 2007; Wade & Reiter; 2007;
Young & Dugan, 2008). We control for regime type by including a measure from Gates et al. (2006) that is an indicator that ranges from 0 to 1, with 0 representing the most autocratic states and 1 representing the most democratic states. Their measure is preferable to other measures of democracy that conflate democracy with measures of political violence (Vreeland, 2008). The often used polity measure, as Vreeland (2008, p. 401) notes, has a component that includes “a factional category where political competition is “intense, hostile and frequently violent” (Gurr as cited in Vreeland, 2008, p. 401). To avoid associating regime type of terrorism by fiat, we use the Gates, Hegre, Jones, and Strand (2006) measure.

The level of development of a state may also be important in determining terrorism. Because terrorism is a strategy of weak actors who generally lack support from society (Lake, 2002), terrorism may more likely occur in developed societies. In much of Sub-Saharan Africa, for example, dissidents may use different forms of violence such as civil war to redress grievances. Not surprisingly, this is the area of the world with the most civil wars currently and the least amount of terror events. We use gross domestic product (GDP) from the World Bank Development Indicators to proxy for the level of development.9

**Missing Data**

One of the most difficult aspects of working with cross-national data on violence is the large amount of missing data. Typically, listwise deletion is used to deal with this problem. However, if data are missing because of nonrandom factors, then estimates based on a sample that uses only observations with non-missing data may lead to biased inferences. This bias is especially pernicious as the portion of data with missing values increases (King, Honaker, Joseph, & Scheve, 2001). In our data, of a possible 4,517 observations only 1,097 are complete observations. In other words, more than 3,000 observations have at least one of the covariates missing. If the data are missing completely at random, this may not be a problem. When data are missing at random (MAR), or when they are missing because of some observable factor, then using multiple imputation can reduce this bias. Multiple imputation, as introduced by Rubin (1987), replaces missing values with a combination of simulated values prior to analysis (Schafer & Graham, 2002). In our case, most of the developed countries such as the United States and Canada have complete data whereas some countries such as Afghanistan and Sierra Leone have spotty or missing data. Because GDP and other potential measures may help predict this missingness, we are comfortable assuming the data are MAR.10 As King et al. (2001) note, predicting these values
is not causal . . . To an extent then, the analyst, rather than the world that generates the data, controls the degree to which the MAR assumption fits. It can be made to fit the data by including more variables in the imputation process to predict the pattern of missingness. (p. 51)

To impute values, we include measures beyond our actual estimation model to attempt to fit the MAR assumption.\textsuperscript{11}

We imputed five data sets and estimated models using all five data sets (see Rubin, 1987). We imputed the data using two different approaches. First, we used Royston’s (2005) ICE program in Stata, which uses \textit{chained equations} for imputing missing data. Each variable in this approach was imputed using all other variables as predictors. Then, these values along with the other data were used to predict the missing values for the next variable. One benefit of this approach is that the analyst can specify how to impute each variable. For example, a dichotomous variable can be predicted using logit models, whereas a continuous variable can be predicted using ordinary least squares (OLS). Because this approach is fairly new, Horton and Kleinman (2007) suggest that more work needs to be done to ensure the validity of the results. Honaker and King (2008) have an alternative approach, called Amelia II, which creates an algorithm especially useful for time series cross-sectional data. We also use this approach and compare the results among the three general ways that we deal with missingness: listwise deletion, the ICE imputation model, and the Amelia II imputation model. Tables 1 through 3 offer summary statistics for the three sets of data: the data with missing values (Table 1), the data imputed using ICE (Table 2), and the data imputed using Amelia II (Table 3). Comparing the means of the data from missing data with the imputed data sets reveals some interesting outcomes. First, countries with few terror attacks tend to have the most missing data. These missing data also tend to have lower levels of GDP. It is not surprising that countries with more wealth report better information across our independent variables. Without imputation, selection problems bias the sample. In other words, the missing data tend to select out poorer countries. Because we have GDP data, we can impute the missing values for some of the other data. Again, this is a reasonable strategy as the missingness is likely because of observable factors. Our summary statistics suggest that the imputations for missing values of democracy have a large variance. Although this lessens our confidence in the results for this measure in the models, it should not affect our inferences for the key variables of interest. There were very few missing data on our dependent variable. The difference between the mean of terrorist attacks in the missing data sample and the imputed data reflect the composition of the observations rather than as an artifact of the imputations.
Table 1. Summary Statistics for Models With Missing Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terror attacks</td>
<td>16.824</td>
<td>44.064</td>
<td>0</td>
<td>404</td>
</tr>
<tr>
<td>Government terror</td>
<td>2.167</td>
<td>1.158</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Homicide</td>
<td>6.040</td>
<td>10.241</td>
<td>0</td>
<td>107.872</td>
</tr>
<tr>
<td>War</td>
<td>0.103</td>
<td>0.304</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Death penalty</td>
<td>0.352</td>
<td>0.478</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Democracy</td>
<td>0.712</td>
<td>0.327</td>
<td>0</td>
<td>0.980</td>
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<tr>
<td>Development</td>
<td>7.208</td>
<td>4.673</td>
<td>0.626</td>
<td>26.755</td>
</tr>
<tr>
<td>Culture of violence</td>
<td>-0.027</td>
<td>0.915</td>
<td>-0.899</td>
<td>3.404</td>
</tr>
</tbody>
</table>

NOTE: Number of observations = 1,040.

Table 2. Summary Statistics for Imputed Data Using ICE

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Error of the Mean</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terror attacks</td>
<td>7.818</td>
<td>0.455</td>
<td>4,331</td>
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<tr>
<td>Government terror</td>
<td>2.452</td>
<td>0.026</td>
<td>4,331</td>
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<tr>
<td>Homicide</td>
<td>5.480</td>
<td>0.163</td>
<td>4,331</td>
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<tr>
<td>War</td>
<td>0.153</td>
<td>0.006</td>
<td>4,331</td>
</tr>
<tr>
<td>Death penalty</td>
<td>0.565</td>
<td>0.008</td>
<td>4,331</td>
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<tr>
<td>Democracy</td>
<td>-29.027</td>
<td>9.283</td>
<td>4,331</td>
</tr>
<tr>
<td>Population</td>
<td>9.024</td>
<td>0.032</td>
<td>4,331</td>
</tr>
<tr>
<td>Development</td>
<td>4.321</td>
<td>0.076</td>
<td>4,331</td>
</tr>
<tr>
<td>Culture of violence</td>
<td>-0.003</td>
<td>0.014</td>
<td>4,331</td>
</tr>
</tbody>
</table>

Table 3. Summary Statistics for Imputed Data Using Amelia

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Error of the Mean</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terror attacks</td>
<td>7.818</td>
<td>0.455</td>
<td>4,331</td>
</tr>
<tr>
<td>Government terror</td>
<td>2.458</td>
<td>0.021</td>
<td>4,331</td>
</tr>
<tr>
<td>Homicide</td>
<td>5.491</td>
<td>0.307</td>
<td>4,331</td>
</tr>
<tr>
<td>War</td>
<td>0.146</td>
<td>0.005</td>
<td>4,331</td>
</tr>
<tr>
<td>Death penalty</td>
<td>0.563</td>
<td>0.008</td>
<td>4,331</td>
</tr>
<tr>
<td>Democracy</td>
<td>-28.716</td>
<td>2.866</td>
<td>4,331</td>
</tr>
<tr>
<td>Population</td>
<td>9.002</td>
<td>0.025</td>
<td>4,331</td>
</tr>
<tr>
<td>Development</td>
<td>4.339</td>
<td>0.073</td>
<td>4,331</td>
</tr>
<tr>
<td>Culture of violence</td>
<td>-0.001</td>
<td>0.012</td>
<td>4,331</td>
</tr>
</tbody>
</table>
Estimation

Because the dependent variable, or number of terror attacks in a given country-year is a count, most quantitative studies of terror use either Poisson or negative binomial regression models (NBRM). Because the Poisson model is based on the assumption that the mean count is the same as the variance, it rarely fits the real data. Fortunately, NBRM relaxes this assumption and allows for overdispersion, or when the variance of the counts exceeds the mean. Many recent studies of terrorism use this strategy (Koch & Cranmer, 2007; Lai, 2007; Li, 2005). As Drakos and Gofas (2006) and Young and Dugan (2008) argue, terror data are not only characterized by overdispersion but also by two types of zeroes. Some countries never experience terror whereas some countries have no terror events in this year but may have had terror events last year. This suggests a process that generates a group of countries that never experience terror and some that do not have terror now but may experience it in the past or future. To model this process, Drakos and Gofas (2006) and Young and Dugan (2008) use zero-inflated negative binomial models (ZINB) and show that a Vuong test confirms this approach is preferable to the NBRM. We also estimate ZINB models along with NBRM models to make sure our results our robust to the different modeling assumptions embedded in these estimators. In Table 4, we report estimates from the ZINB models; we report the NBRM models in the appendix. We also clustered standard errors on country to adjust for within panel correlations.

Findings

Table 4 provides results from the ZINB models estimated using data that are listwise deleted (Model 1), imputed using ICE (Model 2), and imputed using Amelia II (Model 3). In the ZINB, there are two estimation stages. The first stage estimates the probability of being in the “always zero” group. In this case, this means that the variables predict the likelihood of being in the “never experienced” terrorism group. Negative signs mean that the variable reduces the likelihood of being in the “always zero” group. In other words, negative signs indicate the factors are likely to produce at least one terror event. In Model 1, Homicide, Government Terror, War, Democracy, and Development all have a negative sign. In this group, War, Homicide, and Government are significant. Because the coefficients in the inflation equation are not easily interpretable, we predicted the percentage change in expected odds for a unit increase in the dependent variables. The presence of war decreases the odds of being in the “never experienced” terror group by 89%, making it likely that war in the previous year leads to future terror. A unit increase in the Government Terror measure increases the
Additionally, a unit increase in the homicide rate leads to, on average, a 14% increase in the odds of being in the group of states that experience at least one terror event holding other variables constant. Because Democracy and Development do not meet statistical significance criteria, we cannot be sure that their effect differs from zero. Population and Death Penalty have a positive sign and are statistically significant, suggesting that both reduce the likelihood that a state will generate at least one terror event. A one unit increase in the percentage of the

<table>
<thead>
<tr>
<th>Count equation</th>
<th>Model 1, Nonimputed Data</th>
<th>Model 2, Imputed Data (ICE)</th>
<th>Model 3, Imputed Data (Amelia)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Government terror</td>
<td>0.825*** (0.163)</td>
<td>0.701*** (0.124)</td>
<td>0.651*** (0.121)</td>
</tr>
<tr>
<td>Homicide</td>
<td>-0.008 (0.009)</td>
<td>0.009 (0.008)</td>
<td>0.017** (0.007)</td>
</tr>
<tr>
<td>War</td>
<td>0.948*** (0.312)</td>
<td>0.864*** (0.260)</td>
<td>0.776*** (0.270)</td>
</tr>
<tr>
<td>Death penalty</td>
<td>-0.823*** (0.232)</td>
<td>-1.380*** (0.219)</td>
<td>-1.357*** (0.220)</td>
</tr>
<tr>
<td>Democracy</td>
<td>0.574 (0.687)</td>
<td>-0.001 (0.000)</td>
<td>-0.001* (0.000)</td>
</tr>
<tr>
<td>Population</td>
<td>0.582*** (0.156)</td>
<td>0.562*** (0.078)</td>
<td>0.574*** (0.081)</td>
</tr>
<tr>
<td>Development</td>
<td>0.028 (0.037)</td>
<td>0.081*** (0.026)</td>
<td>0.077*** (0.026)</td>
</tr>
<tr>
<td>Inflated equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Government terror</td>
<td>-2.721** (1.374)</td>
<td>-0.189 (0.225)</td>
<td>-0.078 (0.219)</td>
</tr>
<tr>
<td>Homicide</td>
<td>-0.156* (0.078)</td>
<td>-0.051* (0.027)</td>
<td>-0.071*** (0.022)</td>
</tr>
<tr>
<td>War</td>
<td>-2.176*** (0.937)</td>
<td>-2.268*** (0.890)</td>
<td>-2.423*** (0.898)</td>
</tr>
<tr>
<td>Death penalty</td>
<td>4.396*** (2.101)</td>
<td>0.864* (0.461)</td>
<td>0.792* (0.424)</td>
</tr>
<tr>
<td>Democracy</td>
<td>-20.121 (17.121)</td>
<td>0.004 (0.006)</td>
<td>0.006 (0.011)</td>
</tr>
<tr>
<td>Population</td>
<td>1.334*** (0.641)</td>
<td>-0.012 (0.177)</td>
<td>-0.028 (0.182)</td>
</tr>
<tr>
<td>Development</td>
<td>-0.133 (0.083)</td>
<td>-0.514*** (0.218)</td>
<td>-0.520*** (0.205)</td>
</tr>
</tbody>
</table>

Number of observations = 1,040
Zero observations = 358
Vuong test z = 3.17

Number of observations = 4,331
Imputations = 5
Vuong test z = 3.17
Pr > z 0.001

NOTE: Coefficients are presented with standard errors clustered on country in parentheses.
*p < .10. **p < .05. ***p < .01.
population of a country is expected to decrease the odds that a terror event will occur by 280%, and the presence of the Death Penalty has nearly the opposite effect of War, thus reducing the odds of generating at least one terror event to almost zero. As mentioned above, these results from Table 4, Model 1, should be taken with care as so many observations are lost because of missing data.

The count equation represents the second stage of the model. In this stage, we estimate an equation that is conditional on the first results. In short, estimates from this equation answer the following question: Given that at least one terror event occurred in a state, what is the expected number of terror events? The covariates in this stage increase or decrease the expected count of terror events. Government Terror, War, Democracy, Population, and Development increase the expected count of terror events, and only Democracy and Development’s effects are not statistically significant. A one unit increase in the PTS scale of government terror leads to, on average, a 128% increase in the expected count for terror events holding other variables at their mean. The presence of war the previous year increases the expected count for terror events by 158%. On average, a 1% increase in the population of a country leads to a 120% increase in expected counts. Surprisingly, the Homicide Rate and the Death Penalty measures have negative signs. The Homicide Rate is not significant, which is likely because of a strong association among the Homicide Rate, Government Terror, and War. The correlation among the variables ranges from .41 to .45, suggesting a solid positive association. When a state uses the death penalty, it reduces the expected count of terror events by more than 56%, holding other variables at their mean. Given the missingness problem identified above, do these results hold when imputing data?

Models 2 and 3 in Table 1 provide estimates using five imputed data sets. Although the estimates from the inflated equation are similar across the three models, a few interesting differences emerge. First, the Government Terror variable is not significant in both Models 2 and 3, suggesting that the results for this measure are more fragile than for Homicide or War. Democracy in both imputed models has a different coefficient than in Model 1. It, however, is not significant when using any of the data. Population is also unstable when looking across the three data sets. Finally, the more developed a state is, the less likely it will be in the “never experienced” terror group in the imputed data, but the effect cannot be distinguished from zero in the data with missing values. In the imputed model, this effect is both larger and significant. This is a piece of corroborating evidence that excluding observations from the estimation through listwise deletion may bias some of the estimates at this stage in the model. In the count equation, the results are also similar with some notable differences across the three models. The Government Terror measure is consistently positive and significant across
the three models. Homicide becomes positive, as expected, when using imputed data but is only significant using the Amelia II data. Although the coefficient is similar, Development also becomes significant using both imputed models.

Models 4, 5, and 6 provide estimates using a factor score for *Cultures of Violence* based on the measures of Government Terror, Homicide, and War (Table 5). The other covariates from Models 1 through 3 remain the same. Across Models 4 through 6, we find strong support for the hypothesis relating Cultures of Violence to more terrorism. In Model 4, a one unit increase in the Culture of Violence measure on average leads to an 88% reduction in the odds of a country never experiencing terror holding other variables constant. This effect is even larger in the models using imputed data. Given that a country experiences at least

Table 5. Effects of Cultures of Violence Factor Score on Terrorism Events Using a Zero-Inflated Negative Binomial Model, 1970-1997

<table>
<thead>
<tr>
<th></th>
<th>Model 4, Nonimputed Data</th>
<th>Model 5, Imputed Data (ICE)</th>
<th>Model 6, Imputed Data (Amelia)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Culture of violence</td>
<td>1.049*** (0.169)</td>
<td>1.104*** (0.122)</td>
<td>1.101*** (0.112)</td>
</tr>
<tr>
<td>Death penalty</td>
<td>-0.960*** (0.271)</td>
<td>-1.494*** (0.235)</td>
<td>-1.465*** (0.243)</td>
</tr>
<tr>
<td>Democracy</td>
<td>0.338 (0.813)</td>
<td>-0.001** (0.000)</td>
<td>-0.001** (0.000)</td>
</tr>
<tr>
<td>Population</td>
<td>0.632*** (0.173)</td>
<td>0.608*** (0.077)</td>
<td>0.612*** (0.079)</td>
</tr>
<tr>
<td>Development</td>
<td>0.026 (0.043)</td>
<td>0.093*** (0.027)</td>
<td>0.088*** 0.028</td>
</tr>
<tr>
<td>Inflated equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Culture of violence</td>
<td>-2.108** (1.051)</td>
<td>-1.489*** (0.454)</td>
<td>-1.614*** (0.513)</td>
</tr>
<tr>
<td>Death penalty</td>
<td>2.659* (1.512)</td>
<td>0.843 (0.579)</td>
<td>0.722 (0.628)</td>
</tr>
<tr>
<td>Democracy</td>
<td>-7.207* (4.064)</td>
<td>0.003 (0.005)</td>
<td>0.010 (0.012)</td>
</tr>
<tr>
<td>Population</td>
<td>0.410 (0.596)</td>
<td>0.095 (0.203)</td>
<td>0.131 (0.220)</td>
</tr>
<tr>
<td>Development</td>
<td>-0.164 (0.138)</td>
<td>-0.778** (0.347)</td>
<td>-0.830** (0.410)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>N = 4,331</td>
<td>N = 4,331</td>
<td></td>
</tr>
<tr>
<td>Zero observations</td>
<td>358</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonzero observations</td>
<td>676</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zero observations &amp; Imputations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vuong test z</td>
<td>2.68</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pr &gt; z</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NOTE: Coefficients are presented with standard errors clustered on country in parentheses.

*p < .10. **p < .05. ***p < .01.
one terror event, a one unit increase in the Culture of Violence measure increases expected counts on average by 186%. This coefficient is very similar across Models 4, 5, and 6.

Although coefficients vary to a small degree, the general inferences remain the same for the control variables. Democracy’s effect on terror counts is minimal and is not stable across the models. The more people a state has, the more likely it is to generate terror. Development is also positively associated with terror in Models 5 and 6 but misses criteria of statistical significance in Model 4, or where missing data are problematic. The Death Penalty seems to affect whether a country is in the “never experiences” terror group (Inflate Equation) in Model 4 but not in Models 5 and 6. The death penalty decreases expected counts among countries that generate at least some terror across all three models. In Model 4, the presence of the death penalty leads to an average reduction in terror counts of 62%.

Discussion and Conclusion

This study was designed to draw on time series cross-sectional data to test a legitimation–habituation model in an attempt to predict the macro-level distribution of terror incidents. Using the GTD data, we estimated numerous models to see if terror events were predicted by other elements of violence within societies. We found strong associations between the general level of violence within a society and that society’s later experiences of terror events. In fact, the strongest finding from our analyses was the existence of a factor score representing a culture of violence within a society and that factor score’s strong association with terror events.

As earlier studies of the association between experiences of warfare and interpersonal violence showed, when a society in general experiences high levels of legitimate violence, this creates a cultural space wherein individuals are more likely to resolve interpersonal disputes with violence (Ember & Ember, 1994; Gartner, 1990; Williams & Flewelling, 1988). Some scholars have rightly questioned the similarity between terrorist violence and more “routine” street violence, as well as criminology’s ability to study the former (LaFree & Dugan, 2004; Rosenfeld, 2002). Our findings here suggest a strong association among a number of different types of violence within a given society. In and of itself, this is an important finding. Our data establish a degree of co-occurrence between a number of qualitatively distinct forms of violence: interpersonal violence, warfare, and governmental terror. Within the parameters of our data, we think that a legitimation–habituation interpretation is the best available explanation of this association. The visible and frequent sanctioning of violence establishes the acceptability of violence within social scripts of individual social actors. Individuals
are then more likely to use violence within a variety of social interactions, including political dissent.

Our first hypothesis, drawing from the work of Ember and Ember (1994), Gartner (1990), and Landau and Pfeffermann (1988), suggested that societies that had recently experienced warfare would have higher rates of terror. In all the models estimated, this association was statistically significant and in the expected direction. Societies that experience warfare undergo periods of intense direct and indirect modeling of legitimate violence. The state itself frames such uses of mass violence as necessary and legitimate. Direct and vicarious experiences of combat will further reinforce these messages in the framing of cognitive scripts. In some cases, terror events occurring after a war may be a direct response to the outcome of that conflict—be it remnants of a defeated domestic or international dissent group having changed tactics (see discussion of reciprocality below). Given the strength and consistency of the finding, this relationship is bound to be more than redirected combat violence. In light of prior work, and the association of war experience with other violence in the data set, we suggest that a legitimation–habituation effect is not only occurring in general but is influencing a dissident group’s decision to use terror.

Our second prediction involving a relationship between homicide and terror events was significant in several of our models, again providing some support for a general linkage between types of violence within a society. As discussed above though, the connection was weaker than the others and failed to meet expected levels of significance in a couple of models we estimated. In part, this could be a result of the data itself, especially missing data from the WHO. These data have the largest number of missing values in our data set.

Our findings mirror other work in establishing a link between the use of terror and development (see Lake, 2002). After correcting for missing data, we find that societies with higher gross domestic products are more likely to experience terror, even when other measures such as population and a culture of violence are controlled for. In general, these societies tend to have more stable economies and stronger, more centralized governments. Such sociopolitical factors strongly curtail the ability of certain types of political resistance to succeed (i.e., civil wars, secessionist militia movements, etc.). Thus, resistant political actors have fewer modalities available to them and will be more likely to adopt terror over widespread resistance as they face a stronger government. Furthermore, development is negatively related to the forms of violence we use as predictors (and that form the core of the factor score representing a culture of violence). With this in mind, the robustness of our findings highlights the overall strength of the relationship between a society’s culture of violence and its experience of terror events.
One of our major predictors that did not have the expected association was capital punishment. Following prior work, we predicted that societies that engaged in legal execution would experience high levels of terrorist violence as an extension of the brutalization effect. Although there was a significant association between capital punishment use and terror experiences, it is in the opposite direction of our hypothesis. Additionally, this factor was not highly correlated with measures of Cultures of Violence. The correlations ran from .079 (State Terror) to −.359 (War). This leads us to question the social impact of capital punishment on individual social scripts vis-à-vis violence adoption. It could be that the relative infrequency and localized nature of execution publicity limits the effect that this form of state-sponsored violence has on citizen attitudes and views.

Some scholars may see this as support for the deterrent effect of capital punishment. Although this may be the case, it could also be an artifact of the data. Over recent decades, there has been an increase in the number of nations abolishing capital punishment for both ordinary crimes and for all crimes. Most of these nation-states are newly formed in the wake of the collapse of the Soviet Union or products of civil and political disorder in the developing world. Because of abolitionist trends in international law and politics, these states have put in place legal and constitutional changes abolishing execution. For those states in Europe, this is clearly a part of their preparation for joining the European Union, which holds abolition of capital punishment as a prerequisite for admission. In developing nations, capital punishment abolition is often a response to experiences of abusive regimes that drew heavily on judicial and extrajudicial executions to maintain political and social control. Many of these countries have thus recently experienced higher levels of violence and social disorder, heightening their levels of interpersonal and political violence (including terror). Furthermore, executions in the modern world are rarely of the highly visible and widespread nature of the other types of violence that form our culture of violence factor score. Compared with homicide, war-based violence and government terror, executions are less frequent and less visible in nature (done within prisons and other nonpublic locales). Such a use of sanctioned violence may not have as strong of an effect as those types of violence that are more immediate to a society’s (or an individual’s) perceptual consciousness. In sum, these results suggest further exploration of the relationship between the death penalty and terrorism. We encourage probing the robustness of link between capital punishment and terror as well as examining individual countries to trace the mechanisms at work.

As with all studies, there are limitations to ours. First, as is typical of international data, missing data was a concern. To address this, we engaged in a variety of types of imputation, all of which produced similar results. Where differences occurred, we attempted to explain these differences. Although many studies of
violence avoid these problems and simply use listwise deletion techniques, we attempted to avoid selection problems with this approach by using various forms of imputation. Although the need for better data still exists, using a variety of ways to deal with the missingness problem provides greater confidence in our results. More complete data are always desirable in cross-national studies, and we drew on the best available sources. Second, because of the nature of the GTD, we could not separate terror incidents by group ideologies. It is possible that different groups are more or less influenced by the broader cultural attitudes toward violence, both legitimate and illegitimate. Future work will hopefully disaggregate data along these lines. Third, there is a clear possibility that there exists a degree of reciprocality between our measures of state use of terror and violence against its own citizens and the amount of nonstate enacted terror events a society experiences. Simply stated, some of the terror in these states may be retaliatory in nature and not legitimated via our habituation model. Groups may be more likely to resort to terror against a state that uses terror against them. Although we cannot completely discount this possibility, the fact that our other measures of societal violence and the factor score representing a culture of violence in later models estimated are robustly related to terror indicates that there are other factors in play than simply retaliatory motivations.

Explanatory studies of terrorism are rare within the field of criminology. As better data become available, we are sure that the number of studies will increase. This study acts as an early step in the explanation of terrorism. There are other variables of importance that may warrant consideration, especially data drawn from both the meso and micro levels of analysis. Yet our findings are clear. Societies that experience higher levels of violence overall, be it interpersonal or political, experience higher levels of terrorism. This suggests that there are some common underpinnings to violence in general. It also establishes that, to some degree, terrorist violence is similar to other forms of violence studied by criminologists. Both these findings strongly suggest that criminologists should focus more attention on terrorism to further delineate the similarities and differences between it and more typical forms of aggressive and violent behavior.

Appendix

We also estimated a series of negative binomial regression models (NBRM) including a population-averaged model, a fixed effects model, and a random effects model. Models 1 to 3 are estimated with the individual predictors of the culture of violence. Models 4 to 6 use the factor scores. These models are estimated using the nonimputed data. The number of observations is between 1,020 and 1,039 for all six models. The difference in number is because of the fact that
the fixed effects models drop some observations for panels with all zeroes. Because the NBRM does not assume that there are two different zeroes present in the data, this is not a two-step estimation procedure. Instead, all the covariates are used to estimate the expected counts for the number of terror events. The results are largely consistent with the above models. Government Terror’s impact is smaller and varies in terms of significance across the models. When the factor score is used the effect is closer to the above models, but the effect is also muted somewhat. When we estimated models with the imputed data, the results are even closer to the results from the ZINB. The Fixed Effects NBRMs should be interpreted with care as well because panels with all zeroes are dropped from the analyses because of multicollinearity with the fixed effects.

| Effects of Cultures of Violence Indicators and Factor Score on Terrorism Events Using Various Negative Binomial Models, 1970-1997 |
|---|---|---|---|---|---|
| | Model 1, Pop Averaged | Model 2, Rand Effects | Model 3, Fixed NBRM | Model 4, Pop Averaged NBRM | Model 5, Rand Effects NBRM | Model 6, Fixed NBRM |
| Government terror | 0.008 | 0.221*** | 0.185*** | — | — | — |
| Homicide | 0.024*** | 0.014*** | 0.014*** | — | — | — |
| War | 1.383*** | 0.734*** | 0.664*** | — | — | — |
| Culture of violence | — | — | — | 0.534** | 0.491*** | 0.432*** |
| Death penalty | −0.318 | −0.354*** | −0.266* | −0.368 | −0.392*** | −0.311** |
| Democracy | −0.063 | 1.482*** | 1.527*** | 0.544 | 1.612*** | 1.647*** |
| Population | 0.683*** | 0.086* | −0.010 | 0.621*** | 0.090* | 0.001 |
| Development | −0.076 | 0.020 | 0.030*** | −0.065 | 0.017 | 0.024 |

NOTE: NBRM = negative binomial regression model. Significance levels: ***p<0.01; **p<0.05; *p<0.10.

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Notes

1. This definition is consistent with Young and Dugan (2008).
2. They used the following as potential theoretical models to explain homicide rates after armed conflicts: artifact of the data, increased social solidarity caused by experiencing an external war, decreasing homicides, increased disorganization because of war increasing homicides, an economic model suggesting scarcities and employment issues increase crime, a catharsis model suggesting innate drives for violence are expended during war and thus postwar crime rates should be lower, a violent veteran model attributing increasing violence to veterans habituated to violent acts, and a legitimation model as explored here.
3. These data were acquired from START researchers in the fall of 2008.
4. The GTD, however, shows increases in terror starting in 2003. This is likely because of attacks in Iraq. Although these data are not yet publically available, further research can investigate this issue.
5. Although it is not possible to perfectly distinguish in the GTD transnational from domestic terror events, we use a measure that is mostly composed of domestic events. We also tried models using mostly transnational events and a combination of the two. The results across various coding rules are similar. One exception is that the ZINB models on nonimputed data using listwise deletion struggle to converge when using the total domestic and international data.
6. We coded these data using information from Amnesty International’s database on capital punishment. Where this information was silent, we made individualized searches in media and governmental databases (i.e., to find last date of execution, etc.).
7. This approach stands in contrast to confirmatory factor analysis where, for example, “the researcher may anticipate or hypothesize that there are two different underlying dimensions and that certain variables belong to one dimension and not the other” (Kim & Mueller, 1978, p. 9).
8. We use eigenvalue criteria to evaluate how many factors are present. In both the imputed and nonimputed data, only this factor has an eigenvalue greater than 1. We also tried maximum likelihood estimation and least-squares methods to find a solution. Either method produces nearly identical results. Additionally, we tried
different rotations (oblique and orthogonal) and the results were again consistent. When we added the Death Penalty measure, we found that it loaded on a different dimension and was not highly correlated with the other measures.

9. Others such as Fearon and Laitin (2003) use this measure to proxy for the capacity of the state. Because Lake (2002) asserts that strong states are usually the targets of terrorist violence, the implication is the same.

10. The third alternative is that the data are missing because of some nonobservable factor. Although imputation may not completely reduce bias in this case, it still is at least as good as listwise deletion and likely better at reducing bias (King, Honaker, Joseph, & Scheve, 2001).

11. Beyond the covariates from our model we did a series of robustness checks using measures of whether the state is an oil exporter, the level of ethnic and religious fractionalization, several measures of democracy, and the percent of society between the ages of 15 and 24. Results were generally consistent with the models presented. When using measures of religious or ethnic fractionalization, development stays positive in the count equation and is significant.

12. In this stage, the signs are opposite from the first stage. Positive signs indicate increasing expected counts whereas negative signs indicate reducing expected counts.

References


**Bios**

**Christopher W. Mullins** is an assistant professor of criminology and criminal justice at Southern Illinois University in Carbondale. His research focuses on structural and cultural aspects of violence, especially the intersections of gender, street life subculture, and violence. He is the author of 3 books and more than 20 articles and book
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