ABSTRACT

Title of Dissertation: STATE INSTABILITY AND TERRORISM

Susan Fahey, Doctor of Philosophy, 2010

Dissertation directed by: Professor Gary LaFree
Department of Criminology and Criminal Justice

I explore the relationship between political instability and terrorism in this dissertation, using the Global Terrorism Database (GTD), which contains both domestic and transnational terrorism. I use the Political Instability Task Force data to measure political instability.

Breakdown theory suggests that the occurrence of political instability should increase levels of terrorism within a state, because when a rapid social change, such as political instability, occurs, there is a severing of social bonds that tie individuals to society. The effects of the disruption in controls should be to increase levels of non-routine collective action, of which terrorism is a form (Durkheim, 1930 [1951]; Useem, 1998). In addition, different types of instability ought to invite different levels of terrorism based on the degree of disruption to the societal controls. There are four types of political instability: ethnic war, revolutionary war, genocide and adverse regime change. Further, I extrapolate two theoretical extensions from the breakdown model. The first extension is that more instability episodes should produce more terrorism within a state. The second extension is that when two or more instability episodes occur within a

year, this increased temporal density should produce more terrorism than when one instability episode occurs within a year.

I test the theoretical framework using the negative binomial regression model with country and time fixed effects. The first model contains control variables that measure country demographics, governance and contiguity to an unstable nation with 147 states from 1970-2005. The second model examines the effects of control variables that measure the population age structure and social and economic development in a smaller sample of 116 states and years from 1981-2005. The third model adds ethnic minority group characteristics from the Minorities at Risk (MAR) dataset and contains 82 countries from 1990-2005. This three-sample strategy allows me to speak to the omitted variable and sample selection biases that may impact the results.

Empirical results demonstrate that political instability is an important predictor of terrorism incidents. The breakdown model itself is supported, but the extensions are not supported. Further research is needed to delineate the boundaries of the instability-terrorism relationship.

STATE INSTABILITY AND TERRORISM

by

Susan Fahey

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2010

Advisory Committee:

Professor Gary LaFree, Chair
Professor Laura Dugan
Professor Joseph Hewitt
Professor Alex Piquero
Professor Jonathan Wilkenfeld

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the generous support of Dr. Gary LaFree, Dr. Kathleen Smarick and the National Consortium for the Study of Terrorism and Responses to Terrorism (START) and the START Center staff. The START Center itself is funded by a generous Center of Excellence grant from the Department of Homeland Security, grant number N00140510629.

I would like to thank Dr. Gary LaFree, Dr. Laura Dugan, Dr. Alex Piquero, Dr. Jon Wilkenfeld and Dr. J. Joseph Hewitt for their time, intellect and support of my dissertation. You each contributed in your own way and for that, I am grateful. I would like to thank Dr. Amy Pate for her generous data assistance regarding the MAR database. I would also like to thank Dr. Laura Dugan for talking me off the ledge about control variables (of all things!) and for the brilliant three-sample strategy.

I would like to thank Dr. Gary LaFree, my advisor and boss for all of his help, time, discussion and most of all, his confidence in me. I would not have completed this program without it. I would like to thank Erin Miller, GTD data manager and officemate extraordinaire (for five years!). I do not know what will come of me when I Voldemort, and we can no longer have our hours of discussion over things big and small or brain borrowing time. I would like to thank Dr. Kathleen Smarick, for her cheerleading, Snoopy dancing, confidence in me, that visit to the ER, and all-around wonderful personness and for being the best political scientist I know. You are a true role-model for me. I would like to thank Dr. Katherine Izsak for her listening, her sage advice and her

anxiety soothing when I was bouncing off of the walls. I would like to thank Bianca Bersani, my study partner, dissertation partner and friend. We have shared a lot during this process and now we get to share our first year as professors! Finally, I would like to thank Summer Acevedo; it's been a joy to be your friend and share our dinners out and long discussions!

On a personal note, I thank my parents for respecting my independence and encouraging my nerdy, school-loving book-worm side. I doubt that there is a child in the world who is more assured of her parents' love and pride in her. I thank my sister, Kristin, and her husband, Paul. You always let me just float in on my free weekends and take over your social lives so I can spend time with you. You're the best sister (and brother-in-law) in the world! Thank you to Kailey and Cole for reminding me to persevere and to ROCK THE COMP[S and the] DISSERTATION!

I would like to thank my best friend Curt, for always letting me moan endlessly on the phone about school and for being my eating out partner. 2009 and 2010 were the years we got things done! To Helena, my friend for life, it's always an adventure, and you've always been with me on this one; thank you for all of your listening. You have been more patient with me than I ever had any right to ask. To Tiffany, my partner in all things test-related and life changes, your support and understanding has meant more to me than I will ever be able to express to you in words. Plus, you send a mean test-survival kit!

Finally, to my husband, Randy, you have been my everything. Without you, your support, encouragement and pride in me, I would never have passed the comps nor

written this opus. You have given more to me than I ever had any right to expect. Thank you. Lub you, with my face! Bonaventure, to the next step!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Introduction and Theoretical Conceptualization

Introduction

The purpose of this dissertation is to provide an in-depth examination of the relationship between state instability and terrorism. I use the Global Terrorism Database (GTD), the most comprehensive open-source database on terrorism in the world with approximately 82,000 incidents, to measure domestic and transnational terrorism. I use the Political Instability Task Force data (PITF) to measure the occurrence of four types of political instability around the world: ethnic war, revolutionary war, genocide and adverse regime change. I examine GTD data for the years from 1970-2005 for most nations around the world with more than 500,000 population.

I examine the distribution of terrorism and state instability at the country-level using a modified breakdown theoretical framework. This framework is based especially upon the work of Emile Durkheim and was later modified by criminologist Bert Useem (Durkheim, 1930 [1951]; Useem, 1998). In brief, at the macro-level, when rapid social change occurs, like state instability, some societies cannot absorb the disruptive effects to the social order. When the rapid social change occurs, the social ties that bond individuals to conventional society may disintegrate; individuals may also decline to engage in new conventional commitments to society. This freeing of individuals from the constraints of conventional society allows them to take on non-routine collective action, such as collective violence, rioting and terrorism. On average, according to the modified breakdown theory, states experiencing instability should have more terrorism (and other forms of non-routine collective action) than states that are politically stable. I turn now to a review of my analytic and methodological strategy.

The main independent variable of interest is the occurrence of any of four types of state instability, as measured by the Political Instability Task Force data. The four types are ethnic war, revolutionary war, genocide and adverse regime change. If more than one episode of instability co-occurred or occurred within five years, the instability was termed "complex" by PITF and treated as analytically inseparable. The dependent variable is the frequency of terrorism incidents worldwide as measured by the Global Terrorism Database. For control variables, I draw mainly from the World Bank's *World Development Indicators* (WDI) and the Minorities at Risk (MAR) dataset.

I conduct a multi-pronged set of analyses. First, I conduct the Model 1 analysis with a small set of control variables that measure country demographics, governance and contiguity characteristics on Sample 1 which is composed of 147 of the 164 possible states from 1970 - 2005. [1] Second, I run Model 2 which contains the population age structure and social and economic development variables on Sample 2, which contains a smaller sample of 116 states and years from 1981-2005 for which more complete data exist. Third, I conduct the Model 3 analysis with the Minorities at Risk (MAR) data control variables on ethnic minority group characteristics for Sample 3, which contains an even smaller collection of 82 states and years from 1990-2005. Fourth, to ensure that statistical inferences are appropriately made between the different models, I replicate the Model 1 analysis on the smaller samples analyzed in Models 2 and 3. This multi-pronged analysis gives me the flexibility to test important control variables whose data coverage

1. The 1993 data were lost years ago in an office move by the original data collectors.

are restricted to very small samples of the data as well as to conduct a basic analysis that includes many of the states most likely to experience state instability. It also informs the Model 1 analysis on the role that omitted variable bias plays in those results upon comparison to the subset analyses. By comparing the Model 1 results using Samples 1, 2, and 3, I can also examine the effects of sample selection bias.

Because the dependent variable is a count of the number of terrorism incidents per state-year, I use the appropriate statistical analyses for such a variable. These include the Poisson, the pooled negative binomial, the zero-inflated Poisson, the zero-inflated negative binomial models, the random effects negative binomial and the fixed effects negative binomial. I do the relevant model-fit testing and diagnostics to choose the best model for the data, including how to best deal with the lack of independence between state-year observations. To address the dependency across countries, I use fixed-effects negative binomial regression, which only utilizes the within-country variation to estimate the models. I also include time fixed effects in these models. Finally, the results are presented and conclusions and policy recommendations drawn.

Theoretical Conceptualization

Introduction

In this chapter, I will review how terrorism and political instability are defined in this study. I will also review the reasons that have been given in the policy literature for expecting a relationship between state instability and terrorism as well as the criticisms of this relationship that have been discussed in the literature. Further, I will discuss the macro-level theoretical framework. This is a modified breakdown theory model. I turn now to the definition of terrorism.

Definition of Terrorism

In the current research I define terrorism as "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious or social goal through fear, coercion or intimidation" (LaFree and Dugan, 2007: 184). The data set that I use here is the Global Terrorism Database (GTD), the largest open-source database of terrorism incidents in the world. It includes both domestic and transnational terrorism incidents from around the world from 1970 to 2007. The GTD is an incident-level database, meaning that the unit of analysis and collection is the individual terrorism incident. Information collected about each terrorism incident includes the basic who, what, where, and when, such as the date, city, and country of the incident, type of attack, target detail, weapon detail and information about the perpetrators, if any is available. I turn now to the definition of state instability.

Definition of State Instability

One of the earliest discussions of instability in the foreign policy sphere is Helman and Ratner (1992) in *Foreign Policy*. They defined a failed nation-state as one which is "utterly incapable of sustaining itself as a member of the international community" (Helman and Ratner, 1992: 3). This includes the breakdown of civil order, government functioning and economic deprivation which themselves can each lead to violence and anarchy. Once the state is seized by widespread violence, the outflow of refugees and outbreaks of random warfare and human rights violations can threaten to spread the violence to other nations in the region. In practice, this picture of state instability, also called coercive incapacity, is often divided into two conceptual dimensions (Piazza, 2008). The first dimension is that the state has lost control over the entirety of its territory, called loss of territorial integrity. The second dimension is the loss of the monopoly over the legitimate use of force. This second dimension means that the government of the state must be the only executors of legal force in the state, with no sub-state groups laying claim to such a right (Piazza, 2008). Helman and Ratner (1992) closed their famous article by arguing that failed and failing states constituted such a threat to international security that the United Nations ought to intervene to save or fix these failed and failing states.

The idea of fixing or even preventing states from failing proved to be interesting enough to the foreign policy world that in the mid-1990s, Vice President Al Gore commissioned a task force to study the problem and to attempt to predict the phenomenon. The State Failure Task Force was convened in 1994 and involved academic, policy and methodology experts. Over time, they broadened their focus to include not only "extreme state failure" but to include bouts of political instability and the term "state failure" was abandoned in favor of state instability or fragility (Marshall, 2009a: PITF data page). The Task Force changed its name to the Political Instability Task Force after it broadened its focus.

The Political Instability Task Force defines political instability as "civil conflicts, political crises, and massive human rights violations that are typically associated with state breakdown" (Esty et al., 1995: 1). This broad definition of state instability is operationalized as the presence or absence of any of four conflict events: (1) ethnic war, (2) revolutionary war, (3) adverse regime change or (4) genocide as well as (5) a combination of any of those discrete events termed "complex". The Political Instability Task Force data used here includes all instability episodes that occurred in states with greater than 500,000 population between 1970 and 2007. They were collected both retrospectively and prospectively by a consortium of academic experts and Central Intelligence Agency intelligence experts. In the next section, I will discuss how state instability and terrorism may be related to one another.

Connecting State Instability and Terrorism

The general interest in a connection between state instability and terrorism among those in the public policy world is intimately tied to the terrorist attacks of September 11, 2001 (Hehir, 2007). In fact, state failure had been regarded as a marginalized topic of study prior to September 11. After those terrorist attacks, however, failed states quickly came to be regarded as “more threatening” than stable states (Hehir, 2007). This was due to the seemingly free operation of training camps in the Sudan and Afghanistan by al Qaida and leader Osama bin Laden (Newman, 2007). More generally, failed states have been accused of incubating terror by transnational terrorist organizations by offering them safe havens or operational bases. These states have also been accused of allowing transnational crime syndicates to operate within their borders, which may fund and provide recruits for the terror groups (Piazza, 2008). Further, because these states are often actively at war with sub-state groups, there may be increased access to arms trafficking and illicit funding for terror activities. Finally, failed states may be sites where weapons of mass destruction can be acquired locally or from smuggling abroad (Newman, 2007). This long list of serious dangers in the current policy literature applies mostly to the threat of transnational terrorist events, particularly against the United States.

However, the connection between domestic terrorist events is also quite important and perhaps more theoretically relevant. In other words, when a state experiences breakdown in its ability to govern and function, it should stimulate attacks against it that occurs within its own borders. Instability could also stimulate transnational attacks against other states that are planned and equipped domestically. Further, this could take the form of attacks that occur on domestic soil but are conducted against targets that represent another nation on domestic soil, such as attacks on McDonalds or foreign embassies. This is what I expect given the modified breakdown theoretical perspective adopted here (Durkheim, 1930 [1951]; Useem, 1998). Piazza (2007) also expected this when he suggested that state instability at home could make conditions that are conducive to "creating" a terrorist as well as providing a wealth of opportunity for terrorist organizations to flourish. In addition, he argued that in failed and failing states, there is little to no provision of basic human needs (administrative incapacity) nor are there effective or legitimate government institutions. This power and legitimacy vacuum, combined with little human security or economic and occupational opportunity, can provide sufficient motivation for potential terrorist action against governments. Further, the lack of security can allow terrorist groups to move, recruit and attack with impunity (Piazza, 2007). In the next section, I will review the major alternative hypotheses regarding the relationship between state instability and terrorism.

Challenges to State Instability and Terrorism

The state instability and terrorism nexus has not gone unchallenged in the policy and scholarly literature. The first set of critiques primarily comes from those who are most concerned with the link between state instability in a foreign state and transnational terrorism against another state, typically the United States. For example, both Menkhaus (2003) and von Hippel (2002) remained skeptical of the nexus between state failure and transnational terrorism. This is because transnational terrorist groups, as foreigners, may be more conspicuous in such a state than in a more stable state. It also could overexpose the group to international counter-terrorism efforts, because the state government is too weak to repel such international advances. Instead, Menkhaus (2003) suggested that transnational terrorism is more likely to flourish in quasi-states – those with neither a fully functioning nor non-functioning government (see also Hehir, 2007). These are states in which the government itself is weak, but not floundering, and corrupt but able to provide some coercive and territorial control. In addition, failed and failing states may be best used as transit stations for smuggling men, money and arms into nearby states.

Alternately, Schneckener (2004) suggested that modern transnational terrorism is planned and coordinated across many states, both failed or failing and stable states. Newman (2007) suggested that the governments of failed states may actually welcome such groups because they are sympathetic to their ideological causes, rather than being unwilling, exploited victims, such as in Afghanistan and Sudan. He further suggested that the lack of operating governments and social institutions may be incidental or that it may be an enabling factor rather than a necessary cause. Most of the objections discussed above specifically refer to transnational terrorism networks. In the next section, I discuss the critiques of the state instability connection with terrorism more broadly.

The following critiques apply to both domestic and transnational terrorism. Menkhaus (2003) and von Hippel (2002) both suggested that terrorism may be less likely to occur in weak states because the weakness of the state could lower the inhibition against third-party states' intervention or the policing of transnational terrorist organizations. In addition, both of those authors asserted that it is likely unpleasant to operate in the chaos of everyday life that exists in such a state. In addition, the assumption that terrorists naturally want to operate in an environment of chaos and anarchy is probably questionable (Menkhaus, 2003). Though such an environment could lessen the probability of detection and capture by authorities, it also could increase the chances that group members are caught up in the violence and chaos there. Finally, Hehir (2007) noted that since state failure has multiple causes and contributing factors, it is unlikely that there would be a single path between state failure and terrorism.

The final challenge to the state instability – terrorism nexus is discussed below. Simply put, there is little conceptual clarity to the term "failed / unstable / failing state". It could mean coercive capacity – the loss of territorial integrity within a state and the loss of the state monopoly on the legitimate use of force. On the other hand, administrative incapacity is also defensible– the inability to make collective decisions, to carry out the social contract and to deliver service goods to the public. Still further, the concept could include legitimacy so that the citizens of the state know that their government is the only one who can act with force and legitimate power against individuals and groups within their state. Finally, it is still unclear the degree to which these incapacities may be related to one another (Hehir, 2007). Overall, the critiques to the instability – terrorism relationship are not without merit. Yet, the reality of terrorism that either occurs in an unstable state or is launched from an unstable state, such as the attacks of September 11, 2001, demonstrates that this is a topic that deserves further study, which I do here.

Conceptualization of State Instability

As discussed above, the operationalization of state instability used in this dissertation is that of the Political Instability Task Force – namely, the presence of revolutionary war, ethnic war, genocide, or adverse regime change. In this study, I adopt the legitimacy conceptualization of state instability. This conceptualization views state instability as one in which the government is not able to compel conformity in its citizens actions due to its inability to operate in an effective or legal manner. Ethnic and revolutionary wars against the state clearly demonstrate that the state has lost its ability to prevent its citizens from illegally taking up arms against it and any other groups within its borders. Genocides demonstrate that the government has improperly used force against its own citizens by slaughtering them. Adverse regime change operationalizes a lack of legitimacy, because it involves situations in which the state has experienced dramatic changes in its governmental system that would not likely occur in a functioning and effective government. These four operationalizations represent a broad, but relevant interpretation of a loss of legitimacy. In the next section, I review and discuss the theoretical framework used in this study – the modern breakdown model. I choose this particular model as it provides the best explanations for how and why I expect state instability to increase terrorism.

Breakdown Model

Classical Breakdown Model

The classic conception of the breakdown model is that individuals are more likely to engage in collective action when their ties to society have diminished (Durkheim, 1930 [1951]). The disintegration of social ties occurs when rapid social change takes place (such as war, economic crisis or disaster) and the society is not able to successfully absorb the effects of these changes. Instead, these social changes cause ruptures in the basic social order. The ruptures themselves cause tension and strain. The strains motivate people towards collective action. In the classic conception, collective action includes both positive and negative forms – that is, it includes social movements, such as participation in non-violent protests for civil rights, and destructive collective action, such as rioting and civil disorder. There are structural and individual-level consequences to these disruptions; the individual feels strain, which is interpreted as alienation or deprivation, and the society loses its binding power over its citizens through its formal and informal institutions. This loosening of ties makes individuals more likely to participate in movements because of the weakened ties and because of the new lack of community commitments (Durkheim, 1930 [1951]; Snow et al., 1998). In the next section, I review the more modern conception of the breakdown model.

Modern Breakdown Model

The first main difference between the classical and the modern breakdown model is that strain and breakdown are now conceptualized as separate but at times, overlapping results of rapid social change. Strain is a broad term that encompasses many frustrations and occurs as a result of rapid social change. Breakdown is narrower and is specifically, the disintegration of social ties between the individual and society (Snow et al., 1998). The second main difference was demonstrated in a seminal work by Useem (1998) which proffered that the "heart" of breakdown theory is that there is a difference between "routine" and "non-routine" collective action. Routine collective actions are positive forms of collective action, like social movements, non-violent protests, strikes and rallies. Non-routine collective actions are those that more seriously contravene social norms, such as collective violence, revolution, or riots. The true difference is in the mechanisms

– for routine collective action, individuals do not need to free themselves from the constraints of society to act. For non-routine collective action, they do. In fact, non-routine collective action is the result of this breakdown of social norms, but routine collective action does not emerge from the severing of social bonds. On the contrary, routine collective action comes from the strengthening and reinforcement of solidarity in these social bonds. For routine collective action, it is likely that some pre-existing formal and informal organization will help to bring about collective action. There is no obvious need for pre-existing organization (which may even be inhibiting) in non-routine collective action.

Formally, the Useem (1998) interpretation of the breakdown model is that non-routine collective action may occur when individuals are no longer controlled by the formal and informal social controls that bind them to society. The ties to society can be and often are severed in times of rapid social change, such as in times of social disorganization or mass unemployment like the Great Depression (Useem, 1980). Once the controls are disrupted, it is more likely, but not certain that individuals will engage in non-routine collective action such as rent and food riots and disturbances at relief centers (and possibly crime as well; Piven and Cloward, 1977). Overall, the modified breakdown theory gives us reason to expect that terrorism, a non-routine collective action, should be more likely to occur during times of instability, which is when a nation is experiencing breakdown in formal and informal controls.

State Instability and Terrorism

State instability is measured by the presence or absence of the following four conditions, revolutionary war, ethnic war, genocide, and adverse regime change – or combinations of them, termed complex. It is reasonable to argue that these types of events certainly meet the criteria to be considered rapid social change of the kind that can cause breakdown, the severing of social ties from the individual to the community. Thus, the modern variant of the breakdown model would predict that individuals living in an unstable state should be more likely to engage in non-routine collective action than those living in a stable state. Terrorism is clearly a form of non-routine collective action. As shown in figure 1, the causal path from these models constitutes the following: rapid social change measured as instability leads to the severing of social ties and the absence of formation of new conventional social ties which frees an individual to non-routine collective action, which is measured here as terrorism.

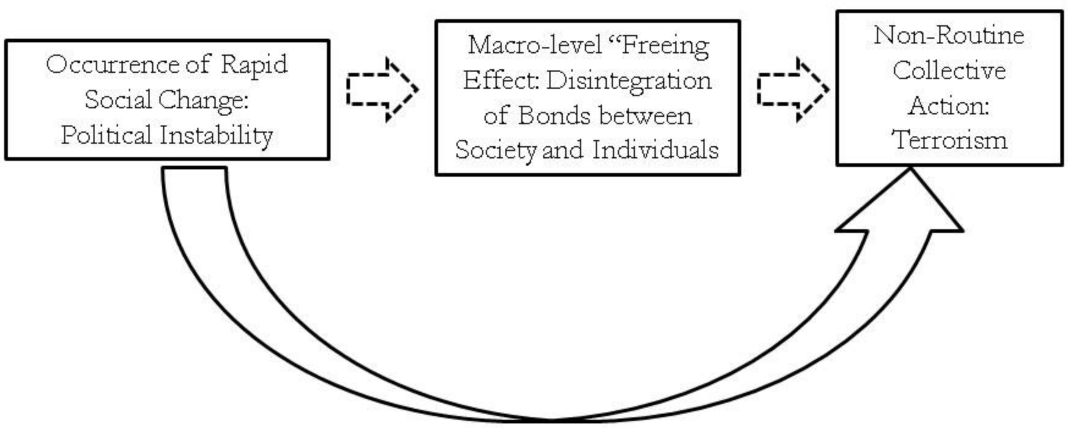

Figure 1. Modified breakdown theory relating state instability and terrorism.

The solid arrow represents causal pathways that I will test in this study by relating state instability to terrorism. The dashed arrows represent the mechanisms that the modified breakdown theory predicts are responsible for the macro-level relationship between political instability and terrorism. Although I cannot test these mechanisms, I find it important and instructive to discuss how the breakdown model works at the individual level.

Extensions to the Breakdown Model

In addition to the existing breakdown framework, I sketch out two logical extensions of the breakdown model and test them in this dissertation. Breakdown suggests that rapid social change should increase non-routine collective action, because the rapid social change loosens the controls on the behavior of individuals. I extrapolate from this two more theoretical expectations. First, more terrorism should result from two or more instabilities in a relatively short timeframe than that which results from just one instability episode during that time. This is because as the state experiences more breakdown, the constraints that bind individuals to society should be further degraded. As the controls to conventional society are ground down, non-routine collective actions, like terrorism should increase.

Second, the shorter the time frame in which multiple instabilities occur, the more terrorism incidents should be expected; that is, the temporal density of the multiple instabilities should have an effect on terrorism. In this study, temporal density refers to the number of instability episodes that occur within the same year. If a state experiences multiple instabilities in a year, it should be sent into a downward spiral of negative consequences like non-routine collective action as the controls in society are destroyed. In this case, more temporally dense instabilities should result in even more terrorism. These theoretical extrapolations are derived as logical extensions of breakdown theory and will be tested in this dissertation. In the next chapter, I will review the empirical evidence on the breakdown model.

Chapter 2

Review of Empirical Literature

Introduction

In chapter 1, I described the theoretical conceptualization supporting the proposed research. Key concepts include terrorism, state instability, and breakdown theory. In the next section, I review the empirical research that addresses the relationship, if any, between state instability and terrorism. I first examine the relatively sparse literature on state instability and terrorism, which will be followed by a brief review of the predictors of state instability, and a review of the tests of breakdown theory.

Empirical Tests of State Instability and Terrorism

There is a small but growing empirical literature on state instability and terrorism. However, there is no worldwide, historical and modern test of the relationship that includes both domestic and transnational terrorism. Yet, there is a small literature that addresses the relationship in the Middle Eastern context, that predicts terrorist group formation, and that predicts transnational terrorism worldwide. I begin with several studies that directly related state instability and terrorism.

Piazza (2007) evaluated whether democracy promotion in failed states in the Middle East had its post-9/11 anticipated effect of decreasing the levels of terrorism experienced in those states. He defined failed states primarily as having administrative incapacity, the inability to deliver the basic political goods a state is expected to provide, such as personal security. He proffered two pathways between terrorism and state instability. First, state instability could help to generate the conditions that create terrorists. Second, state instability could provide crucial opportunities for existing terrorist groups and networks if they were to move there. Once the terrorists are established in the state, the state would be unable to oust them.

Further, Piazza (2007) suggested that as the public witnessed the inability to remove the terrorist element from the failed state, the government of that state would lose legitimacy, the power to compel conformity in its citizens and may unintentionally spur some citizens toward terrorism. Once the state’s authority had been so undermined, they would be unable to maintain control over many forms of civil strife or to prevent further strife through the power of deterrence or the power of adequate law enforcement. Terrorists could also exploit the outer façade of sovereignty of the ostensibly failed state to obtain legal documents that would make their operations easier.

Piazza (2007) used the Political Instability Task Force Data (also used in this study) as his measure of state instability. He formed an additive index to create an intensity scale, which was scored from 0-4 for each type of instability (adverse regime change, ethnic war, genocide, and revolutionary war). However, he only used the data from Middle Eastern nations. For his terrorism data, he used the RAND-MIPT data. He hypothesized that state instabilities from 1972-2003 in the 19 countries analyzed would be positively related to the domestic and transnational terrorism incidents. It is important to note that from 1972 to 1997, the RAND-MIPT data did not systematically include domestic terrorism in their data collection. Thus, the analysis included only transnational terrorism from 1972 to 1997, and from 1998 to 2003, the analysis included both domestic and transnational terrorism incidents in the 19 Middle Eastern nations examined in the article.

Using a pooled time series negative binomial regression analysis, Piazza (2007) found a positive relationship between terrorism and instability, except when he included lagged prior levels of terrorism. Further, state instability was the most consistent predictor of levels of terrorism in the models. He also examined the effects of instability on the existence of terrorist groups that the RAND-MIPT analysts considered as having the home base in that country. He found that those Middle Eastern countries that were experiencing state instability were more likely to host groups that committed terror attacks domestically and transnationally. In addition, the unstable Middle Eastern states were also more likely to be attacked by groups from other states.

This study suffers from several drawbacks. First, it is not clear why he only utilized data from the Middle East, because both the terrorism and state instability databases have data for the vast majority of all states in the world. Further, it is important to note that though his transnational terrorism incident data covered the period from 1972-2003, the RAND-MIPT domestic terrorism data only covered the period from 1998-2003. Due to the limitations of the RAND-MIPT data, Piazza (2007) is unable to truly examine the domestic nature of the relationship between state instability and terrorism. Though this empirical study was limited both geographically and conceptually, the relationship between state instability and terrorism passed a crucial first test.

Piazza (2008) further explored this relationship in a subsequent article. In this second article, he conceptualized the relationship between terrorism and state instability as one of coercive incapacity rather than administrative incapacity. That is, he conceptualized the relationship as one initiated by the fragile state’s inability to maintain a monopoly on the legitimate use of force and control over the entirety of its territory.

In this analysis, Piazza (2008) utilized the Fragile State Index (FSI) for the year 2006. The FSI provides a four tier ordinal scale of the level of instability based on 12 social, economic and political / military indicators. The categories in order of seriousness include Alert, Warning, Monitoring and Sustainable. For his terrorism incidents database, Piazza used the RAND-MIPT transnational terrorism incidents from 2000-2006. First, he included transnational terrorist incidents that occurred in the state in question. Second, he included incidents launched by groups whose home base was evaluated by the RAND-MIPT as having been in the state in question but whose incidents had taken place in other nations.

Piazza (2008) hypothesized that fragile states would be more likely to be the location of transnational terrorist attacks and more likely to be the source of transnational terrorist attacks on other nations. This hypothesis was supported. On average, Alert countries were more than 3 times as likely to be the site of transnational terrorist attacks and more than twice as likely to be the host to a group which committed transnational terrorist attacks than states in the Monitoring or Warning category. In addition, the top 5 most fragile states in the FSI were the *most* likely to be targeted as the location and to be the source of transnational terrorism.

In a secondary analysis, Piazza (2008) also re-examined the Political Instability Task Force data and created an additive scale to form categories of states based on the intensity of their instability. Using the ITERATE transnational terrorism database and a host of controls, he found that states with more intense state instabilities were more likely to have transnational terrorism incidents originate in their borders. They were also more likely to have nationals of their states initiate transnational terrorism incidents in other places. Further, quasi or weak states did not experience markedly more terrorism incidents. Piazza (2008) concluded that state instability is an important dimension of transnational terrorism.

However, this study has several drawbacks. First, in the primary analysis, the causal ordering of state instability measured only in 2006 and terrorism measured from 2000-2006 is at best, contemporaneous and at worst, reversed. Second, by creating an additive scale of the intensity ratings of four very different types of instability in the PITF data, he equated them as if they were similar or equally likely. In fact, each type of instability is not equally likely to occur in any given state. He also seemed to examine more states (195) than are available in the PITF data from 1991-2003 (162). Finally, this analysis necessarily excluded incidents where the perpetrating group and therefore, the nationality of the group were not known. This is a very serious under-counting of potentially informative incidents. In the end, however, these are drawbacks in what is nevertheless an interesting and informative analysis.

Marshall (2002) briefly examined the connection between state instability and terrorism using the Political Instability Task Force Data in a larger analysis of the predictors of global terrorism. For his terrorism data, he compiled his own domestic and transnational data set using the Keesing's World Archives from 1991 to 2000. He defined the terrorism concept to exclude incidents in which the victims were not civilian or non-combatant populations.

Overall, Marshall (2002) found that the predictors of state instability and terrorism were quite similar. Specifically regarding terrorism, he found that armed conflict in bordering nations (the ethnic or revolutionary war categories from the PITF data) was positively and significantly related to the incidence of terrorism in the state. He also found that a history of ethnic and revolutionary war or adverse regime change within the state itself increased the probability that terrorism would occur there later.

Finally, Marshall (2002) attempted to differentiate between Collective Political Violence that included violence against civilians by state or non-state actors, like rebel groups, and terrorism proper. Very little was able to differentiate between them. States that experience terrorism relative to the lower level collective political violence with some violence against civilians were more likely to have advanced or post-industrial economies, but these incidents were less likely to draw fatalities. These states were also more likely to be democracies with lower quality of life, youth unemployment, systematic ethnic discrimination in the political and economic sphere, to have a larger agricultural sector, to be more likely to be involved in international violence and wars, and to have a relatively higher proportion of autocracies in their immediate region. Though this was not a direct test of the instability – terrorism nexus, it did demonstrate the importance of diffusion of armed conflict over borders and of the history of armed conflict or regime changes in predicting later terrorism incidents.

Newman (2007) conducted a simple test of the state instability - terrorism nexus. Conceptually, Newman viewed the state instability issue as one of safe-haven. Without the justice apparatus to prevent and deter the settlement of transnational terrorists within the borders of the state, transnational terrorists could train and even settle there. However, he did point out that, even in Afghanistan and the Sudan, the government may have allowed al Qaeda to operate there or even welcomed their operations there. Further, since most terrorism occurs domestically against the domestic government and businesses, he questioned the analytical usefulness of the instability – terrorism nexus.

For his simple test, Newman (2007) examined groups in the RAND-MIPT Terrorist Organization Profiles and 84 other groups that were listed on the American, United Kingdom and European Union's terrorism watch lists. Using a subsample of 54 terrorist organizations that had conducted incidents which claimed fatalities, he looked at the data and found that the more dangerous groups were more likely to have originated from states with weakened state capacity as judged by the Failed States Index's Conflict Assessment Tool. Further, if the European nationalist and ideological groups from the developed world were excluded from the subsample, weak states were more likely to host the base of operations for one of these groups. However, Newman concluded that although terrorist groups do sometimes operate in these types of states, at best, instability is only an enabling condition and did not approach necessity or sufficiency. Further, terrorist organizations certainly operated in stable and functioning states. He concluded that there were clearly important intervening variables in the relationship between state instability and terrorism.

However, this study does not represent a strong test of the instability – terrorism relationship. In fact, it is unclear whether the author undertook an actual data analysis or test; from the description, it seemed as if he simply visually inspected the data. Further, his sample of groups included those that do not perform acts of terrorism but who utilized terrorist-type rhetoric. This is due to the inclusion of the United Kingdom's watch list, which includes groups that incite terrorism. In the end, however, despite the serious drawbacks of the study, Newman (2007) contributed to the debate by problematizing the importance of these types of states.

Tikusis (2009) reevaluated the skepticism with which Newman (2007) approached the state instability - terrorism link. Tikusis saw the instability and terrorism relationship as one of the conditions that enable existing terrorist groups to function, particularly due to population displacement, group grievances, inconsistent economic development and lack of public services and security. However, he took issue with the Newman (2007) contention that if a state did not host a major terrorist group (the foundation of the Newman analysis) that it negated any relationship between instability and terrorism incidents themselves.

Tikusis (2009) tested the instability – terrorism incident link with 2 years of data. He utilized the Fragile States Index rankings for 2006 and 2007 – looking at states ranked over 90 on that scale. He then compared the data for these weak and failing states to the RAND-MIPT terrorism incident data (both domestic and transnational) for 2005 and 2006 using a cluster-analysis. Tikusis found that weaker states were significantly more likely to have experienced fatal terrorism incidents than relatively stronger states. In fact, none of the "most stable" states experienced any fatal terrorism incidents while only one of the fifteen "stable" states experienced fatal terrorism for those years. However, weak states did not differ significantly from stronger states in the actual number of fatalities experienced for those fatal incidents. Weak states were only slightly more likely to have experienced terrorism incidents regardless of whether they drew fatalities.

Finally, Tikusis (2009) examined whether there were any differences between weak states that hosted major terrorist group operations (based on the RAND-MIPT

Terrorist Organization Profiles) and weak states that did not host a major terrorist group on the 12 sub-indicators that make up the Fragile States Index ranking tool. He found that terrorist group-hosting weak states were slightly less likely to have experienced a sharp and / or severe economic decline on the FSI. They were also more likely to have experienced political instability and violence. Overall, though, there were few differences between weak states that hosted major terrorist groups and those that did not. Tikusis concluded by "unequivocally" asserting a relationship between weakness of states and the occurrence of fatal terrorism incidents.

In a final simple assessment of the strength of the relationship, LaFree, Dugan and Fahey (2008) used the Political Instability Task Force data to examine the relationship between state instability and terrorism via the Global Terrorism Database from 1970-1997. The terrorism data were first categorized into two groups: those states that ever experienced an episode of instability from 1970 to 1997, even if only for a year (ever failing) and those that never experienced an episode of instability from 1970 to 1997 (never failing). The number of incidents (or fatalities) was then averaged over the number of states in each category. From 1970 to 1978, never failing states experienced more terrorism incidents and more fatalities than ever failing states, though levels of terrorism and fatalities were low in both categories. However, from approximately 1978 onwards, the levels of both terrorism incidents and fatalities in ever failing states grew to surpass those in never failing states.

In a second analysis, the researchers re-classified states as "in failure" only for the years in which they experienced the episode of instability. States were classified as "out of failure" when the instability episode ended. Again, the number of incidents (or fatalities) was then averaged over the number of states in each category. Of the top 25 countries with the most terrorism incidents, 15 of those countries had experienced at least one year of instability and 12 states had experienced at least one decade of instability. The instability – terrorism incidents and fatalities relationships were even clearer when a state was "switched out of failure" when the instability episode ended. For incidents and fatalities, in-failure states far surpassed out of failure states in incidents and fatalities for nearly the entire post-1978 series. No explanation was offered, however, for why the relationship between instability and terrorism took root only in the post-1978 period. LaFree, Dugan and Fahey's (2008) simple test suggested that state instability and terrorism are linked for at least some states and some times.

In a related study, Fahey, LaFree and Dugan (2007) examined whether there were differences by type of instability in the time-trend relationship between state instability and terrorism. Overwhelmingly, they found that the meat of the relationship between instability and terrorism was in the complex category of instability. The states that experienced the most terrorism were those which had ever experienced a complex instability. Recall that the complex instability is made up of states which experienced two or more instabilities in the same year or within five years of one another. They also examined whether the timing of the instability mattered; they tested both lagged and "early" timing formulations of instability. That is, they examined time trends when the currently in fragility status was turned on a year before the instability started and turned off a year before it ended as well as models in which the instability start year was lagged one year and ended one year late. None of the timing measures seemed to matter, however, as the strength of the in-fragility – terrorism relationship remained substantively the same despite the timing of the instability indicator. This small study further endorsed the value of examining the state fragility and terrorism relationship, particularly research which disaggregated the complex category by type and state-year.

Though the empirical literature on state instability and terrorism is modest, it has shed light on the utility of further examination of this connection. There does appear to be some support from the current literature for a significant relationship between state instability and terrorism, but further and deeper analysis is needed to flesh out the parameters of this relationship. In the next section, I will briefly review the predictors of state instability.

Empirical Predictors of State Instability

Predicting state instability is certainly not the main focus here. Yet, in order to guard against omitted variable bias, it is important to include variables in my models that measure each of the domains that are related to both state instability and terrorism. I now turn to a brief review of the predictors of state instability.

The original purpose of the Political Instability Task Force was to find the predictors that signaled the onset of state failure. It was believed at the time that there was likely some combination of factors that would warn policy makers that failure was imminent (Marshall, 2009a). These policy makers would then presumably send in the appropriate resources to forestall the failure. However, this process would not end up being as simple as it first seemed. The Task Force spent years working on and refining both technically simple and complicated models for simple post-diction within-sample. Within-sample post-diction consists of splitting the sample between earlier data, for example 1955 – 2000, and using the earlier data to come up with a set of social, political and economic demographics that are able to predict the onset of instability in the later data from 2001 to 2003. However, a full early warning system for detecting an imminent instability and sounding the alarm has not been put into place. However, the Task Force members have been able to come up with a set of variables that are able to post-dict reasonably well within-sample. I present the recent results of those efforts below.

Goldstone et al. (2005) examined the onset of instability from 1955-2003 using a case control method. They sought to identify the risk factors for instability two years prior to the event occurrence. Over that time period, the PITF data includes 111 adverse regime changes, 74 ethnic wars, 62 revolutionary wars and 40 genocides. Because these events can and do overlap within-country and within-year, there were a total of 141 instability episodes. Their two-year post-diction models achieved 80% accuracy. Instability was fairly evenly distributed over time, save for a peak in the early 1990s. This peak was then followed by a declining trajectory. Regionally, sub-Saharan Africa led with 35% of the instability episodes.

Goldstone et al. (2005) used case control matching with logistic regression to analyze their data. They matched country-years with instability to stable country-years (no instability for two years prior and four years hence). They determined that further breaking down of instability into its four categories (ethnic and revolutionary war, adverse regime change and genocide) was extraneous, because the models did not differ across type of instability. Out of the many variables they tested in their models, there were only four important factors.

The most important predictor of state instability was the nature of the regime type. Full autocracies and democracies were the safest from instability (Goldstone et al., 2005).

Yet, full democracies were 3-5 times more likely to experience instability in the next two years than full autocracies. However, partial democracies were at even higher risk of instability. Partial democracies were those regimes in which there were elections with unobstructed political participation, but they fell short of full democracy otherwise. Similarly, partial democracies beset by factionalism had the highest odds of experiencing instability. Partial democracies with factionalism are those nations where ethnic or other groups control the political system such that the special interests of the group in power are promoted and in-group members are held in higher esteem than out-group members. Partial autocracies (those which allow competitive elections or substantial political openness but not both) were also at increased risk of instability.

Infant mortality was also an important predictor. Nations at the seventy-fifth percentile of infant mortality (compared to the twenty-fifth) had 4-7 times higher odds of experiencing instability two years hence (Goldstone et al., 2005). Though this factor could be proxying for many concepts, they believed that it referenced the level of economic development in the nation. Countries with four or more neighboring countries experiencing instability were far more likely to experience instability themselves. Finally, nations that have discriminated against ethnic minorities living within their borders were twice as likely to experience instability in the next two years.

Marshall and Cole (2008) examined state instability and conflict around the world between 1995 and 2007 and its relationship with income. Though Marshall works regularly with the PITF data, he utilized a different measure of state instability for this paper. The authors made use of the State Instability Matrix which rates states both on their effectiveness and legitimacy on four domains: security, governance, economic development, and social development. This is a broad but classic view of the concept. They found that states with higher GDP per capita were much less likely to experience instability. However, there was very wide variation on instability scores for all income levels. That is, income is certainly a factor, but it cannot be the only good predictor. Some states with high income per capita had less than ideal-instability scores whilst some states with low income per capita were more stable than expected. Marshall and Cole also examined the instability scores for oil-producing nations (in which their annual net production was at 10 or more barrels per capita) and found that only three had the instability scores that their income level would have predicted; the rest were far more prone to instability. Those three nations were Denmark, Russia and Kazakhstan. Overall, the relationship between income and state instability is complicated, and it is far from a perfect predictor.

Finally, Marshall (2008) issued a report on the systemic risk of instability using the PITF data. He reviewed the extant literature on the subject and concluded that periods of instability most often followed a prior period of less severe political instability, rather than stability. He suggested that instability tended to break out most often in relatively newer autocratic states or states with factionalism problems (when a state's political system is dominated by an ethnic or other specialized group and the government is used to pursue the specialized interests of that group). This is because instability tended to happen in states which either moved further towards autocracy to consolidate their disorder (adverse regime change) or ethnic or revolutionary war broke out when the factionalism in the system proved untenable. The results he reviewed demonstrated how inadvisable it is to ignore factionalism or to crack down on groups seeking political voice. These actions can polarize the citizenry and the political society until a spark sets the tension aflame into ethnic or revolutionary war. Once the instability begins to set in, it tends to persist over time. He concluded that it is important to address the predisposing factors so that the process could be cut off before it could cascade into more and new problems.

The Marshall (2008) review of the literature hints at the possibly distinct causal factors that may be behind the different types of instability. If there are distinct causes, it is important for me to disaggregate the instability independent variable into its component types (adverse regime change, ethnic or revolutionary war, and genocide) to assess any *differential effects* on the prediction of terrorism incidents worldwide. I will briefly examine the literature on each different type of instability from the PITF data.

Empirical Predictors of the Types of State Instability

Civil Wars: Ethnic and Revolutionary War

I will first review the recent report on the predictors of ethnic civil wars as defined by PITF. To review, ethnic war is defined as an"[episode] of violent conflict between governments and national, ethnic, religious or other communal minorities (ethnic challengers) in which the challengers seek major changes in their status" (Marshall, Gurr and Harff, 2009: 6). Ethnic wars are a subset of the more general "civil war". An example of an ethnic war included in this analysis is the one fought by the Serbs in eastern Croatia and Krajina against the newly independent Croat government from 1991 to 1995. I will also briefly review the literature on the more general "civil war" as defined by each of the studies' authors that I review below. First, I turn to the PITF report on ethnic war.

Gurr et al. (2005) used case-control methods combined with logistic regression to post-dict the onset of ethnic war from 1995-2003 for all nations over 500,000 population. Over that time, there were 74 ethnic wars. This is about three times as many wars as the other type of war PITF includes, which is revolutionary war. Ethnic wars were fairly evenly distributed over the time period, except for a steady increase of ethnic war onsets in the 1980s, which peaked in 1991. This peak constituted 21% of the 157 included nations. Ethnic wars tend to be a precipitating event in setting off more instability events (putting the nation into the complex category), particularly another ethnic war and genocide. This demonstrates the importance of separating out ethnic war from revolutionary war, as the same cannot be said for revolutionary war.

Gurr et al. (2005) achieved roughly 80% correct post-dictive classification in their ethnic war models. There were 50 onsets of ethnic war during the period. They matched three "healthy" country-years for each ethnic war onset country-year. Their most impactful predictor was the presence of active, systematic state led discrimination against minorities within the nation. This factor best signaled the onset of ethnic war. In addition, higher levels of ethnic diversity greatly increased the odds of experiencing an ethnic war.

Regime type also had important and strong effects on the odds of ethnic war. Specifically, partial democracies with factionalism were the most likely to later experience ethnic war (Gurr et al., 2005). Interestingly, partial democracies without factionalism and partial autocracies did not have increased odds of experiencing ethnic war. Abutting states with current civil or ethnic war and the state's own prior ethnic war or genocide in the last 15 years significantly increased the odds of ethnic war onset later. Finally, a larger than expected youth population increased the odds of ethnic war onset by three to four times. Overall, this model supported the conceptual importance of prior grievances (prior conflict, state-led discrimination, partial democracy with factionalism) and greater opportunity to go to war (youth bulge, ethnic diversity, conflict in neighboring states).

Sambanis (2001) published an interesting bridge between the specialized civil war literature, like Gurr's and Marshall's work on ethnic wars, and the aggregate civil war literature (presented below). He tested whether there were differences in the predictors of onset of ethnic war versus non-ethnic civil war. Non-ethnic civil wars were defined as revolutionary or other wars while ethnic wars were operationalized using the PITF definition of ethnic war. He predicted the onset of ethnic and non-ethnic wars using a random effects probit analysis for 161 countries over the period between 1960 and 1999. This period covers 77 ethnic war onsets and 32 revolutionary war onsets.

First, ethnic wars were unlikely to break out in democracies; in addition, the more democracies in the state's region, the lower the risk for the onset of ethnic war in a state (Sambanis, 2001). Ethnic heterogeneity significantly increased the probability of later ethnic war onset. Further, conflict in neighboring states increased the probability of the state experiencing an ethnic war. Per capita real income had a moderate negative influence on the likelihood of subsequent ethnic war onset. Overall, politics had an important influence on the onset of ethnic civil war.

With regards to differences between onsets of different civil war types, Sambanis (2001) found that there were important differences between ethnic and revolutionary war onsets. For example, per capita real income was a far stronger negative predictor of the onset of revolutionary civil wars. In addition, regime type itself did not significantly affect the likelihood of revolutionary war onset nor did ethnic heterogeneity. However, *changes* in regime type, towards democracy, significantly increased the probability of the onset of revolutionary war. Years of prior peace and conflicts in neighboring states also failed to predict the onset of revolutionary war. Sambanis (2001) concluded that there were important differences between the predictors of ethnic wars, which are wars of identity, and revolutionary wars. Wars of identity seemed to be fought primarily over political grievances rather than economics while revolutionary wars did not seem to be fought over political grievances, as defined here. The work of Sambanis (2001) supported the separate examination of ethnic and revolutionary war.

Civil Wars Not Separated by Type

Despite the evidence presented by Sambanis (2001) on the dissimilar causation of ethnic and non-ethnic wars, I will briefly review the literature on the aggregate civil war category. This literature mainly draws from the Correlates of War data, as well as the Sambanis updated version of that data. An example of a civil war in this data includes a war in 1993 between the government of Congo-Kinshasa and the rebel group there (Sarkees, 2000). The majority of this literature does not differentiate between the type of civil war fought based on the underlying disagreement. Marshall and Cole (2008) reported that at the same time that the onset of international war clearly declined, civil war increased in prevalence since the end of World War II and peaked in the late 1980s, with an average of four civil war onsets per year. In fact, 20 of the 21 wars ongoing in 2008 were civil or communal wars. I briefly review the literature on predicting civil wars below.

In a series of papers, Paul Collier and Anke Hoeffler set out an economic theory of civil war causation. This economic model stands in stark contrast to the models of political grievance characterized by Gurr et al. (2005). Over time, Collier and Hoeffler refined and elaborated their economic rational choice perspective on the costs and benefits of civil war. In sum, their rational choice framework suggests that civil rebellion will occur when the incentives for rebellion are larger than the costs of rebellion. Rebellion occurs for the purposes of replacing the regime or to force state secession. The benefits of rebellion include victory over the government (tempered by the probability of obtaining it) and the spoils of either being in charge of the state now (and its tax revenue or looting during the chaos) or having seceded and won their independence. The costs of the rebellion are disproportionate for the rebels compared to the government which has far more resources upon which to draw. These costs include the monetary costs of conducting civil war, like the costs of outfitting a rebel army and their labor (Collier and Hoeffler, 1998, 2002). However, once the rebellion is underway, the rebellion will pay for itself monetarily such that the "start-up" costs are far more prohibitive than the costs of continuation (Collier and Hoeffler, 2004). If the state is high in lootable natural resources, such as oil or diamonds, then these will be regarded as a benefit of rebellion and they will function to help finance the continuation of the rebellion (Collier and Hoeffler, 2002). Rebellions will occur when the costs are outweighed by the benefits. This is independent of the level of political grievance among the rebels which may include state discrimination against the rebels if they are ethnic or religious minorities. Collier and Hoeffler's (1998, 2002, 2004) economic model of civil war causation stands in general contrast to the political grievance model of ethnic civil war. I present their most recent test of the model below.

Collier and Hoeffler (2004) tested the political grievance model against their own economic framework of civil war. Over time, they adjusted their model to shift away from the economic costs of rebellion and have begun to look more at opportunities for rebellion. They tested this for 98 countries for each five-year period from 1960 to 1999. Their civil war data set followed the classic Correlates of War definition: a conflict between a state and a non-state challenger that claimed 1000 battle-deaths over the course of the conflict, with each side inflicting at least 5% of those casualties (Small and Singer, 1982). Thus, these civil wars do not focus on the type of war, either ethnic or revolutionary; their dataset simply includes all intra-state civil wars that meet the inclusion criteria.

The economic / opportunity factors generally performed as expected. First, they found that the proportion of the GDP accounted for by natural resource exports (such as diamonds, oil and lumber) was highly significant and non-linear in its effects on the onset of civil war (Collier and Hoeffler, 2004). The risk of civil war onset was at its peak when approximately 1/3 of the economy was accounted for by natural resource exports, which the authors labeled as a highly dependent economy. Further, GDP per capita and growth in per capita GDP were both significantly negatively related to the onset of civil war. Their proxies for the high costs of starting a civil war included male secondary school enrollment (if it is low, it is easier to recruit men to the rebel army), the length of peace prior to the conflict (need to lay out more costs initially to equip and outfit a rebel army after a long time at peace), heavily mountainous terrain (in which the rebels can hide from government forces), geographic dispersion of the population (if they are highly concentrated, it makes it harder for the rebels to hide amongst them), and the social fractionalization of the people (which makes it more difficult for the rebels to communicate amongst themselves). The proxies for the high costs of starting a civil war were all at least marginally statistically significant at the .10 level in the expected direction.

On the other hand, Collier and Hoeffler's (2004) political grievance measures did not predict civil war well. If political grievances against the state or regime in charge were relevant predictors of civil war, then high levels of ethnic and religious fractionalization and polarization along these lines should be supported. In addition, it would be expected that the unequal distribution of income and land would be positively related to the onset of civil war. Ethnic fractionalization was only marginally statistically significant at the .10 level, and religious fractionalization was not able to achieve statistical significance. Further, ethnic and religious fractionalization was not statistically significant and was even negative rather than positive. Ethnic dominance, wherein the largest ethnic group constituted 45-90% of the population, was also statistically insignificant as were both measures of income and land inequality. The only political variable that performed as expected was regime type: democracy was negatively related to the onset of civil war. Overall, the political grievance underperformed.

Collier and Hoeffler (2004) also tested a combined model of the onset of civil wars. They found that all the included economic / opportunity variables performed as expected: natural resource exports, especially oil, school enrollment, population dispersion and social fractionalization. The only political grievance factor that was even significant in the combined model was ethnic dominance; when one ethnic group constitutes the plurality or majority of the population, there was a high risk of civil war onset. They concluded that the economic / opportunity model was the best supported. However, Collier and Hoeffler (2004) can likely be reasonably be criticized for their loose interpretation of political grievance or control variables as support for the economic / opportunity model (such as social fractionalization or male school enrollment). In addition, it is reasonable to assume that their model would suffer from multi-collinearity issues given the amount of ethnic and religious dominance / fractionalization / polarization included in the models. Yet, the clearest criticism is of their dependent variable. The results offered by Sambanis (2001) and others clearly demonstrate the importance of separating civil war into its components of ethnic and revolutionary war, which I do here. I turn now to an additional model for an aggregate civil war measure.

Gurr and Marshall (2000) also examined a combined measure of civil warfare from the Minorities at Risk database. Their measure of war was limited to any type of war that was conducted by an ethnic minority at risk. However, their war measure was actually included in a larger "rebellion" variable, which included terrorism, declarations of independence, guerrilla violence and full-scale civil war. They measured this is as a scale with political "banditry" and non-systematic terrorism at one end and full-blown civil war at the other. Thus, they partially predicted the onset of terrorism, as well as lesser and greater forms of political violence, like war. Their model of the onset of civil war conducted by ethnic minorities at risk covered 1997 and 1998; the predictors were measured in the years prior.

Gurr and Marshall (2000) found that the following factors increased the likelihood of rebellion, which ranged from non-systematic terrorism up to and including protracted civil war: five or more years of persistent protest activity (including strikes, demonstrations and riots) by the ethnic minority, organization by the ethnic minority into political groups, support for the ethnic minority by foreign governments, high concentration of the ethnic minority in geographic space, government repression in the prior year, and regime instability over the prior three years. These were consistent and strong predictors of rebellion; there were also some less consistent predictors of rebellion. Minority-specific factors that increased the likelihood of rebellion included previously losing their political autonomy, ethnonationalist ideology in the minority, whether the group is a communal contender, support from related groups elsewhere in the world, and ample armed conflicts in nearby states and in the overall region. Other factors that decreased the likelihood of rebellion were increased ethnic group support for conformist organizations, support from regional and international organizations, and whether the group is an indigenous ethnic minority. These models predicted political rebellion, including protracted civil war as well as less contentious actions, amongst a population of ethnic minorities. This model is related to the others presented above but also pulls in characteristics of the group itself to predict the occurrences of violence. Where the data are available for the period from 1990 to 2005, I include many of these predictors in my Model 3, which contains control variables that measure ethnic minorities at risk characteristics. I turn now to the literature on adverse regime change, another type of state instability collected by the Political Instability Task Force and used in this study as an independent variable.

Adverse Regime Change

The Political Instability Task Force's Ulfelder and Lustik (2005) presented the results of their examination of the predictors of adverse regime change. Adverse regime change was defined by PITF as "major, adverse shifts in patterns of governance, including major and abrupt shifts away from more open, electoral systems to closed, authoritarian systems; revolutionary changes in political elites and the mode of governance; contested dissolution of federated states or secession of a substantial area of a state by extrajudicial means; and or near-total collapse of central state authority and the ability to govern" (Marshall, Gurr and Harff, 2009: 10). Operationally, this shift involved a six or more point swing in the POLITY score as well as the interregnum code for complete collapse of the central government from Polity (-77). POLITY scores rate regime types and range from -10 for full autocracies to +10 for a full democracy (Marshall and Jaggers, 2007).

In this paper, Ulfelder and Lustik (2005) specifically modeled the transition towards autocracy, a form of government they defined as a government that institutionally lacks accountability to its citizens. These transitions towards autocracies were labeled as "backslides" and specifically involved situations when unelected officials replaced elected officials. An example of a backslide occurred in 1980 in Burkina Faso. The democratic election of the president of that country was greeted by labor and economic unrest and was subsequently overthrown by a military coup, after which the constitution was suspended. Sixty backslides occurred from 1955-2003 for the 162 nations examined. They achieved 85% correct classification in their post-dictive models.

First, the age of the democracy was an important predictor of backslides; the risk rose steadily after two years and stayed high until the democracy had endured for 15 years, after which the risk of backsliding declined (Ulfelder and Lustik, 2005). They hypothesized that either this timing indicated that the danger usually coincided with the timing of the second election or that there were two qualitatively different types of democracies, one of which was destined to fail early and one of which was destined to last long-term. Economic development was also important; they specifically tested infant mortality, but overall, the rest of the indicators also demonstrated that the higher the development level of the democracy, the less likely it was to backslide towards autocracy. Factionalism, or democracies in which specialized interests to the party in power are favored, also significantly increased the odds of backsliding. The growth in the per capita GDP over the prior two years was only weakly significant, though negative. They suggested that due to the importance of economic development and the weakness of two-year changes in GDP, the long-term economic well-being of the democracy mattered more than short-term changes for predicting backslides. Interestingly, they were unable to find any important effects for trade openness, region effects or prevalence of democracy in nearby states. Backslides, or transitions towards autocracy, were well predicted by a small set of variables, including the regime characteristics, long-term economic health, and factionalism. I turn now to the predictors of genocide.

Genocide

Harff (2003) presented a model that examined the antecedents of genocide from 1955 to 1997 using the same case control method and logistic regression method utilized by other PITF research. Genocide was measured using the PITF definition: events which "involve the promotion, execution and / or implied consent of sustained policies by governing elites or their agents – or in the case of civil war, either of the contending authorities – that result in the deaths of a substantial portion of a communal group or politicized non-communal group" (Marshall, Gurr and Harff, 2009: 14). An example of this is from 1956 to 1972, the Sudanese government slaughtered civilians living in the southern portion of that country because it was thought that these civilians may support secession. Unlike the other forms of state instability, genocide only occurred once on its own in a state-year. The rest of the genocides occurred nested in a complex instability that included other ethnic and revolutionary wars and adverse regime changes; there were 126 such instances that included 35 genocides. Because these occur almost exclusively in a nested way, the purpose of Harff's (2003) model was to ask what can distinguish between instabilities that included genocide and those that did not. The predictors were measured for the prior year.

Harff's (2003) post-dictive model of state instabilities with genocide events achieved 74% accurate classification. Recall that this model predicts the likelihood of experiencing a state instability that includes a genocide versus a state instability episode that does not also include genocide. This model does not predict genocide relative to no instability.

Prior state instability over the preceding 15 years was a positive and statistically significant predictor (Harff 2003). States that had experienced a prior genocide were about three and a half times more likely to experience another. States in which the ruling party espoused an ideology that singled out certain groups of people for discriminatory, persecutory or genocidal treatment were marginally significantly more likely (at the .10 level) to experience an instability with an episode of genocide than those without such an ideology. States in which the ruling party was part of an ethnic minority (relative to the people they are ruling) were two and a half times more likely to experience an instability with a genocide than those in which the ruling party is part of the majority. States governed by autocracy rather than full or partial democracies were about three and half times more likely to have an instability episode that included a genocide. Finally, states that were less economically connected to the world (lower trade openness) were more likely to have an instability that included a genocide.

Autocratic states with previous instability, a previous episode of genocide, a political elite that is both an ethnic minority (relative to the population of the state) and espouses an exclusionary ideology, and a state with few international trading partners had a predicted probability of .90 for instability with genocide. However, a state in instability that had no risk factors had only a .028 predicted probability of genocide occurring in that instability. Harff (2003) tested many different models, including models without repeat genocides in the dependent variable, and the model stayed substantively the same. However, in none of the alternate models were ethnic diversity or ethnic discrimination able to achieve statistical significance, which is an interesting null finding; perhaps discrimination is less important once instability has already set in. Overall, a relatively simple model was able to distinguish between instabilities that experienced genocide and those that did not.

After examining the predictors of the types of state instability that will be included as an independent variable in this analysis, it is reasonable to conclude that they are at least a partially unitary phenomenon. That is, they are predicted by many of the same variables and are similarly “caused”. However, though they may be similarly caused, it does not follow that they exert similar effects on the probability of a state also experiencing terrorism incidents, the dependent variable in this analysis. The question of whether each type is equally likely to result in terrorism incidents is an open, empirical question, one which I intend to test here. The different types will be disaggregated and tested to see if their effects on terrorism are the same. Having reviewed the literature on the similar predictors of the different forms of state instability, the main theoretical, independent variable in this analysis, it should be noted that although it is not possible to include every single variable from prior studies due to lack of annual data from 1970 to 2005, I am able to include variables that tap all of the domains shown as important in prior work. If these domains are also related to terrorism, then the model is less likely to suffer from serious omitted variable bias. I turn now to the empirical results of tests of breakdown theory, the main theoretical framework in this analysis.

Empirical Tests of Breakdown Theory

Over the years, different forms of the breakdown model have been developed across disciplines and dependent variables. I will review the empirical evidence on the form closest to what I adopt here as the most applicable breakdown model for the state instability – terrorism question. That is, social ties bind and restrain the actions of individuals and provide formal and informal social controls on their actions. Rapid social change can sever these ties. These loosened and severed ties can then leave those individuals free to engage in non-routine collective action, such as rioting, rebellion and civil violence, including terrorism. I turn now to the relevant research.

Attitudinal Studies of African Americans after the Race Riots

Caplan and Paige (1968) utilized samples of Newark, NJ and Detroit, MI residents to study riot participation in those cities, sites of two of the more serious race riots of the period. Specifically, they surveyed representative samples of households living in census tracts that had seen violence and property damage during those riots. They achieved approximately 2/3 response rates in both cities and assessed riot participation by asking whether the respondents were “active” or had committed physical destruction during the riots. In Detroit, the survey of all members of the household over age 25 netted 11% of the sample self-identifying as rioters. For Newark, which was a sample of only-black males between 15 and 35, 45% of the sample self-reported riot participation. There were differences across samples in the demographics of participants but overall, the rioters were neither the poorest of the poor nor the least educated. They did differ, however, in their beliefs regarding the positions of blacks in society. For example, the rioters were more likely to perceive themselves as falling behind other blacks, to report racial discrimination and to disagree that the US was "worth fighting for". Overall, the data supported the importance of the exclusion of blacks from economic and social betterment and the resulting discontent caused by this exclusion. This resulting discontent is largely supportive of the breakdown perspective.

In another examination of the race riots of the period, Miller et al. (1976) reanalyzed survey data from 2800 African Americans in 15 cities. Unfortunately, riot participation in the sample was too rare to enable conclusions about actual rioters, but they were able to extract two other groups from the data by analyzing responses to questions about protesting, the riots themselves and attitudinal measures. They termed the first extracted group nonviolent protesters and the second riot-prone protestors. These two groups were clearly different on social integration. The nonviolent protestors were more likely than the violence-prone protestors to have higher levels of education, income, to be in a more skilled job, to be from an unbroken home, to be married and to be older. This study clearly supported the breakdown hypothesis that individuals who engage in non-routine collective action (protesting with the potential to turn to violence) are likely to be low on social integration compared to individuals who engage in routine collective action (non-violent protesting). These survey studies of individuals clearly showed a negative relationship between social integration and potential to riot. I turn now to two studies of an aggregated unit of analysis: cities.

City-level Analyses

Lieske (1978) analyzed cities themselves for their proneness to be the site of riots. He found that more socially disorganized cities were more likely to have experienced a race riot than cities with lower levels of social disorganization. He measured social disorganization with a composite of measures, such as divorce, separation and birth illegitimacy rates, non-white population changes and moving, and levels of crime. This study supported the breakdown model's contention that high social disorganization makes non-routine collective action more likely. Further, Gurr (1976) similarly found that times of high civil strife and high crime covaried in his study of London, Stockholm, New South Wales and Calcutta. Analyses at the city-level also demonstrated a correlation between social disintegration and non-routine collective action. I turn now to specific case studies of the breakdown model.

Case Studies

Piven and Cloward (1977) evaluated the breakdown model in their qualitative case study of poor people's movements. First, they determined that the idea of political protest is not a commodity that is available to all classes of society; in fact, it only becomes available to the poor during certain times, namely during times of massive social dislocation. This is because people are usually acquiescent regarding their lot in life, and they will continue living their daily routine unless forced to action by massive social changes. This shift to protest first requires a change in consciousness: a change in beliefs about whether the system is unjust and wrong, about whether their demands for change will be heard and a belief that they have control over their destinies. Then, it requires a change in behavior, which involves widespread law violation, performed en masse. Piven and Cloward found that the Great Depression involved so many spontaneous protests in the streets, rent and food riots and disturbances at relief centers, because it involved both massive unemployment and (forced) migration.

Piven and Cloward (1977) also found that the release from the daily rhythms and controls of the work day and the loss of home and community destroyed the structure and routine of everyday life for those individuals affected. The loss of structure and the de-routinization of everyday life allowed the collective actions to occur. Economic change, such as massive loss of employment, in particular, affects the structure and institutional control of everyday life. This is because work is such an integral part of the routine of everyday life on the one hand and on the other, work provides sustenance. After the loss of work, the "comforting banalities" of everyday life disappear; if sustained, crime will rise, families will be destroyed, and non-routine collective action will result as individuals attempt to struggle through life. Unfortunately, during the Great Depression, forced migration in search of work further broke down communities, social relationships and thus, formal institutional control over the actions of men.

Piven and Cloward (1977) also discussed how individuals chose one collective action relative to another. They concluded that the poor are less likely to use violence, because the risks of such action may involve brutal repression by the government and exact too high a price. Generally, though, individuals use collective action that involves institutions to which they have access; workers strike and the unemployed riot. Overall, Piven and Cloward endorsed the breakdown model in their qualitative case study of poor people's movements.

Useem (1980) examined survey data from the anti-busing movement that resulted from school desegregation in Boston in 1974. The movement itself involved both routine (school boycotts, formation of neighborhood information centers, mass demonstration, and a formal opposition organization) and non-routine (violent mass demonstrations) collective action to prevent busing for the purposes of school desegregation. Useem examined in-person interview data of 468 white Bostonians. These individuals resided in mostly white neighborhoods that were disproportionately affected by the desegregation order and were the site of activities in the anti-busing movement. He strove to answer whether social disorganization increased discontent, whether discontent made collective action in the anti-busing movement more likely, and whether social solidarity helped or hindered the movement. Social solidarity is an important conceptual counterpart to breakdown (which will be discussed further later). Basically, it is the opposite of social disorganization: integration of the individual into society via informal social bonds, such as work, school, church and other voluntary activities. Useem measured participation in the movement as: participation in school boycotts, the establishment of private schools for students who refused the busing, protest marches and the organization of anti-busing organizations. Social solidarity was measured as: involvement in group activities, community attachment, attachment to primary groups and attachment to secondary group organizations.

First, Useem (1980) found that community and secondary group attachment made anti-busing movement participation more likely. Primary group attachment had a negative or null relationship with participation depending on whether social class was included in the model. Yet, discontent did stimulate movement participation. However, it seemed that solidarity, as manifested by community attachment and secondary group participation, *not disorganization* made this discontent stronger and stimulated participation in the movement. Thus, less connected individuals were less likely to join the movement. In the end, both solidarity (not disorganization) and discontent stimulated both types of collective action. These findings both supported (the discontent finding) and contradicted (the disorganization finding) the breakdown model.

Useem (1985) examined the New Mexico prison riot of 1980 using a breakdown framework. In normal times, he emphasized, the larger societal structure keeps men's appetites in check. However, when disorganization strikes at this societal structure, it frees individuals from the normally inherent regulatory structure that keeps people engaged in conformity. This disorganization increases the discontent within society. Individuals who live in that society are freed to act in antisocial ways by this loss of regulatory control and because of this discontent, want to act in unusual and law-violating ways.

Useem (1985) viewed prison riots as collective action; the prison was treated as society at the micro-level. Prisons are a society of already extreme deprivation; their very purpose is to control the behaviors of individuals through deprivation of liberty, personal autonomy and security, heterosexual relationships and goods and services. Although prisons constitute a very controlled social structure to begin with, it is certainly possible for disorganization to break out and stimulate the freedom to act in illegal ways. Useem examined interviews of a random sample of 49 inmates and 28 guards by the New Mexico Attorney General's Office as well as conducting 36 additional interviews of his own. He found that these very brutal riots were set off after a period of perceived worsening of conditions in the prison. The breakdown in the prison conditions started when a progressive warden was transferred out of the prison; this progressive warden had allowed prisoner organizations, high school and college classes and civic and charitable activities. In the five years after the transfer, subsequent wardens revoked all of the liberties and privileges that the prisoners had grown accustomed to under the prior warden. The loss of programming coincided with overcrowding, prisoner boredom and poor administration and combined to clearly increase the discontent felt by inmates. When the riot subsequently broke out, it was vicious and took the lives of 33 prisoners and involved extensive torture of many of the guards. Useem (1985) concluded that the breakdown model provided a fitting explanation of the events that led up to the brutal riot – loss of organization in prison life stimulated discontent and ultimately, riots.

Useem (1997) continued his breakdown research agenda by examining the Los Angeles riots and the governmental response to the riot's breakdown in social order and collective violence. He set up a theory test between breakdown and resource mobilization. The main point of contention was whether the state has a role in shaping the course of the collective action; in resource mobilization, it has little to no role but in breakdown, the state has a clear role.

In general terms, the first role of the state is to choose how to react to the destruction of law and order – either by diplomacy or by force (Useem, 1997). In the Los Angeles case, the riot itself came about as a reaction to a government action – the acquittal of the four police officers accused in the Rodney King beating. According to Useem, the police department had planned to keep on-duty all officers coming off-duty around the time of the verdict announcement (5 pm). However, due to a miscommunication, this was not done. The riot broke out at the intersection of Florence and Normandie streets when police officers used force and arrested a stone-throwing youth in front of approximately 100 disorganized residents who had taken to the streets after the verdict. Further force was used to control the now-inflamed crowd. By early evening, the riot was spreading to the rest of the city. This early mistaken choice of force over diplomacy was compounded by further mistakes, such as placing a command post in the field with too few resources, improper delegation of too much responsibility to lower level officers, and uneven riot preparations during the trial.

Further, there was a mistaken choice of diplomacy over force in the rest of the city as the riots spread, and the police chose to patrol normally and to avoid making arrests (Useem, 1997). The height of the riot occurred at 7pm, a time at which there was only one riot-ready police squad in the entire city. This squad was quickly overwhelmed and recalled for their safety. Finally, the police were not able to regain order until the riot had virtually ended, businesses had been burned and the rioters had left the streets, which occurred at approximately 8:30 pm. Useem concluded that the breakdown perspective was supported by the inadequate tactical preparations before the verdict announcement. In addition, the generally incompetent state of the city government at the time of the riot prevented it from deterring such collective violence. Overall, it was clear from this qualitative case study of the Los Angeles riots that the breakdown perspective was correct in its hypothesis that agents of social control had a role to play in the prevention of collective violence.

LaFree and Drass (1997) provided an interesting comparative test of the routine and non-routine dimension of collective action. Traditional breakdown theory would predict that all forms of social pathology should covary, such as antisocial behavior, suicide, divorce, crime and protest (Useem 1985). LaFree and Drass explicitly tested this notion in post-World War II America. To get at collective action, they examined reports from an index of the *New York Times* from 1955-1991. Collective action included civil rights-related riots, marches, sit-ins, rallies, boycotts, protests, and demonstrations. For social pathology, they examined arrest rates for homicide, robbery and burglary. To truly get at the notion of covariation between the forms of collective action, they examined African American arrest rates and civil rights-related collective action separately from arrest rates for whites, which should have been less explicitly and directly connected to civil rights-related collective action. Traditional breakdown would predict that arrest rates (crime) and all forms of collective action should not only be related, but that they should be symmetrically related – as one rises or falls, so should the other.

LaFree and Drass (1997) demonstrated a clear relationship between both black and white arrest rates and civil rights collective action – to a point. They covaried symmetrically from 1955 until the early 1970s. At this point, collective action fell off dramatically while arrest rates stayed high. LaFree and Drass tested the significance of these relationships and found that arrest rates were significantly related to collective actions for the most part until the 1970s and then generally were unrelated for the rest of the series. It is not clear whether these relationships would have been different had they only examined non-routine collective actions (such as riots) and its relationship with crime, as the newer Useem (1998) formulation of the breakdown model would predict. In the end, though, there are certainly other predictors of arrest rates. Yet once the political grievance of civil rights was at least partially resolved, the movement ended its collective actions independently of the state of crime. It is also alternately possible that crime should not be considered a collective action. LaFree and Drass generated at least partial support for the breakdown perspective.

Useem (1998) used secondary data to test whether riots (non-routine collective action) represent a clear breakdown in the social order to citizens, as measured by handgun purchasing. He examined homicide rates, handgun production for domestic sale and riot activity from 1964-1994 and found that homicide rates and handgun production rates were closely related except for the years during which there were increases in riots. These years, the handgun production rates increased more than expected from the correlation with the homicide rate alone. These were statistically significant relationships. Clearly, at some level, riot activity is feared by citizens enough that the option of self-protection with handguns (which is not often used as a hunting weapon) seems attractive to the American citizenry. This supported the breakdown perspective that non-routine collective action represents a "felt" breakdown in the social order and social controls.

In the preceding section, I demonstrated that there is ample support for the breakdown model in the literature. This evidence demonstrated that it is a useful perspective for the current study. However, it is worthwhile to examine the work of the breakdown model's greatest detractor: the resource mobilization model, which is most actively promoted by Charles Tilly. In the next section, I do this.

Resource Mobilization Model

The vast majority of the evidence marshaled against the breakdown model comes from the resource mobilization area. The primary researcher in this area is Charles Tilly. The resource mobilization movement fundamentally disagrees with the breakdown perspective that collective action comes about due to a breakdown in social order. In fact, since discontent and political grievances have existed at all times, in all societies, discontent and grievance cannot be the most important explanatory factors for collective action according to the resource mobilization movement. If breakdown theory is unable to explain the relationship between terrorism and state instability, resource mobilization can provide an alternate explanation.

Organization is at the root of collective action; collective action of nearly all types requires some sort of social organization and resources. Thus, the most important explanatory factor of collective action is social organization and the resources that come along with that organization. Isolated people are less likely to engage in collective action, and their collective action is not driven by discontent, because isolated individuals lack nearly any type of organization. Individuals need to be plugged into the social structure and social networks to be recruited into a movement. Finally, because collective action is an organized, social activity of the socially connected, crime and other social pathologies do not covary with collective action nor do they spring from the same causes (Lodhi and Tilly, 1972; Useem, 1980; 1985). Further, the resource mobilization model does not recognize a difference between routine and non-routine collective action; in other words, there is organization inherent in even a spontaneous street riot such that the model explains all types of collective action (but not social pathologies like crime). I turn now to a short review of the literature as it is relevant to the breakdown model.

Lodhi and Tilly (1972) examined crime and collective violence (riots, strikes, demonstrations) between 1830 and 1931 in France. They hypothesized that if the breakdown model was valuable, then crime and collective violence ought to be related to urbanization (which is the rate of change in the proportion of persons living in 10,000 person communities) rather than urbanity (the proportion of the population living in 10,000 person communities relative to the total population). This is because it should be the tension-producing change and not the experience of living in a city itself that is "causing" the collective violence and crime. They found that property crimes declined during France's major urbanization period. Person crimes fluctuated without any clear trend. Meanwhile, collective violence varied quite a bit over the years. Thus, urbanization, which was steadily (and at times, dramatically) increasing could not explain a trendless or declining trajectory in a manner that is consistent with breakdown. Yet, urbanity was a strong predictor of property crime and some forms of collective violence. Thus, crime and collective violence constituted two separate social phenomena. Further, urbanity – that is, the experience of living in a city – better explained crime and some types of collective violence than urbanization – which represents a changing society. This study did not provide any clear support for breakdown.

Snyder and Tilly (1972) also challenged another breakdown hypothesis; does strife and hardship bring about discontent, which in turn leads individuals to collective action? Snyder and Tilly disagreed that hardships can create the discontent necessary to motivate collective action. They hypothesized that collective violence occurs when there is a shift in the locus of coercive power, manifested as repressive actions and policing by the government. They felt that people who engaged in collective disturbances were actually contending for power in an organized and mobilized way.

Snyder and Tilly (1972) examined the manifestations of collective disturbances in France from 1830 to 1960. Their breakdown variables specifically measured hardships, such as changes in the price of manufactured goods and in the food index, with the thinking that if these prices went up, it would create hardship for the majority of the populace. Their resource mobilization variables were intended to measure the social organization of the disturbance participants and included deviations from the five-year average of arrests, the size of the national budget and the number of persons in jail during that year. They found that both of the breakdown variables were not correlated with collective violence. However, the resource mobilization variables were correlated over time with collective violence.

Tilly et al. (1975) analyzed data from France, Italy and Germany to examine the breakdown notion that collective violence concentrates itself during periods of high social change. In this study, periods of high social change were proxied using growth in urbanization. However, they found no correlations between large changes in urbanization and collective violence. Further, episodes of collective violence actually tended to occur during ordinary non-violent gatherings of people, like festivals and meetings. Thus, neither the gathering nor the violence that may have resulted was actually related to major social changes. Rather, it was the normal social organization of people who were interconnected in society, both at the primary (family group) and secondary (voluntary associations) levels that led to the collective violence. Organization and political action, not isolation and anomie, were endorsed and support was not found for breakdown. However, even though the Tillys concluded that the participants in the collective violence were well-connected to the society, their conclusion does not negate the breakdown notion that the society itself may have been experiencing losses in social organization that were simply not measured in the study.

In the end, the proponents of the resource mobilization model concluded that resource mobilization was the supported model, not the breakdown model. The simplest critique they leveled at breakdown bears repeating: social change, conflict, and social disorganization exist at all times and in all societies; thus, how can a constant explain a change (Tilly et al., 1975; Lodhi and Tilly, 1972, Snyder and Tilly, 1972; McCarthy and Zald, 1977)? However, that is an open empirical question, one that I intend to test in one form. My test asks whether the occurrence of state instability, as a form of social disorganization or rapid social change, is associated with changes in the level of terrorism experienced during the instability. I turn now to review the current focus of this study before moving to the next chapter.

Current Focus

The focus of the current study is to examine whether the distribution of terrorism is related to the distribution of state instability. That is, I test whether changes in instability are associated with changes in terrorism incidents. This is expected given the theoretical orientation of this study.

Theoretically, I adopt a modified breakdown theory to explain the distribution of terrorism incidents around the world. Specifically, in times of rapid social change which rupture the institutional and informal controls that govern society under normal circumstances, non-routine and often violent collective action is more likely to occur. State instability constitutes one form of rapid social change and is expected to cause ruptures in the institutions of formal and informal social control. Terrorism is one type of non-routine collective action due to the violence done to person and / or property.

When state instability occurs, it is observed here as the outbreak of ethnic or revolutionary war, genocide, or an abrupt change in governance. If the society is unable to absorb the shock these events present to the social order, the social ties that bind the individual to society may be cut off. In addition, individuals may avoid making new conventional commitments to society. The demise of the prior attachments to society and the lack of new commitments will free individuals from the societal restraints on their behavior. This freeing will allow individuals to take part in non-routine collective action, including terrorism. These are the general nation-level mechanisms I expect are at work. I expect that on average, a state will experience increases in terrorism when it experiences increases in instability. I turn now to the Methodology chapter, in which I lay out the data and methods used to test the relationship between terrorism and state instability.

Chapter 3

Data and Methodology

Introduction

This chapter discusses the methodology used to test the relationship between state instability and terrorism. I will describe the unit of analysis as well as the dependent variable, terrorism incidents. The data for the dependent variable are from the Global Terrorism Database (GTD), which was the most comprehensive open-source terrorism database in the world when this dissertation was written. The GTD is actually comprised of two separately collected and recently reconciled datasets, the GTD1 and the GTD2. The GTD1 contains data from 1970 to 1997 and was collected by the Pinkerton Global Intelligence Service (PGIS). The GTD2 was collected by the Center for Terrorism and Intelligence Studies (CETIS) and spans 1998-2007. The independent variable measures state instability, such as ethnic or revolutionary war, adverse regime change, and genocide. It is from the Political Instability Task Force (PITF). The control variables I use here come primarily from the World Bank's *World Development Indicators* (WDI) and the Minorities at Risk (MAR) dataset. I conduct multiple analyses to maximize the number of state-years that can be included in the statistical models while balancing the need for control variables to guard against omitted variable bias. I use statistical analysis that is appropriate for count data. I turn now to the unit of analysis.

Unit of Analysis

The unit of analysis for this project is the state-year. I use cross-sectional time-series data. For 147 nations and 35 possible years between 1970 and 2005, there are 4541 country-years without the lost year 1993.[2] When I add the country-level marginal distribution of incidents to describe terrorism incidents for 1993, then there are 4687 state-year observations.[3] It is important to note that using the marginal country-level distributions is not without its downsides. These will be discussed in more detail later in the chapter.

It is important to note that not all states were in existence for the entire observation period. Some states became extinct, and their parts became new states. Examples of this include the Soviet Union and its division into the separate states of Russia, Ukraine, Azerbaijan and others as well as Czechoslovakia and its division into the Czech Republic and Slovakia. In addition, some new states were born of independence struggles from previously sovereign states. An example of this is Eritrea, which formed from territory that had previously been part of Ethiopia. There are also states that gained independence from either a colonial territorial status or United Nations trusteeships, such as East Timor, under Indonesian rule, and Papua New Guinea, which was ruled under an international trusteeship before gaining independence in 1975. Since the GTD is an incident-level dataset, I am able to observe independence and deaths of states when they occur, provided that terrorism incidents occur in that state near the time of independence or death. In other words, I code any incidents that occur in a sovereign state down to the month, day or year of independence or death of the state.

---

2. The 1993 data were lost in an office move by the original data collectors, the Pinkerton Global Intelligence Service (PGIS).

3. The original data collectors, PGIS, issued yearly reports on acts of terrorism around the world. Although the actual data for 1993 are lost, copies of the report for this year do exist. From these reports, I have reconstructed the total numbers of incidents by country, adjusted downward for the cases lost due to excluding incidents against military targets and for cases that were deleted during the GTD1/GTD2 synthesis process, which is discussed in greater detail below.

For the analysis, since the unit of analysis is at the state-year, birth of a state is observed at the year of occurrence. Death of a state is observed the year before. For example, Czechoslovakia is coded as having died in 1992 while the Czech Republic and Slovakia are observed as having been born in 1993. In addition, because the PITF data only include sovereign states over 500,000 population, I include terrorism in a territory of a state as terrorism against that state if that territory is evaluated as a part of the state by the PITF. For example, I include the incidents that occur in Corsica as a part of French terrorism, but I exclude the terrorism incidents that occurred in Puerto Rico as part of American terrorism.[4] These decisions were made in consultation with Dr. Monty Marshall, the lead data collector on the PITF (Marshall, 2009b, email communication). All efforts have been made to ensure that states included as the part of the dependent, independent and control variables are the same across these datasets. I turn now to an in-depth explanation of the data I analyze.

Data

Dependent Variable

The Global Terrorism Database (GTD) is the source for my dependent variable of interest, terrorist incidents. The GTD1 was collected relatively contemporaneously (close to real-time) from 1970 to 1997 by the Pinkerton Global Intelligence Services (PGIS). The GTD2 was collected for the period 1998 to 2007 by the Center for Terrorism and Intelligence Studies (CETIS). CETIS began collection of terrorism incidents in the open-

4. I am able to do this for the PGIS report of 1993 data, because PGIS reported incidents down to the location of the incident, rather than the sovereign country. For example, PGIS reported the number of incidents that occurred in Northern Ireland and Corsica, rather than just including them in the totals for the United Kingdom and France, respectively. This is a major strength of the PGIS reports.

source media for the period 1998-2007 upon receipt of funding in 2005. The divergent methods of collection are accounted using an indicator for the data collection agency. [5]

Collecting the GTD1

The collection of the GTD1 involved newspapers from around the world and the US, news wires, US State Department reports, PGIS reports from satellite offices and reports from PGIS clients around the world, among other sources. Two data managers were in charge of the data collection process for the entire 28-year period. In addition, the information collected about each incident remained roughly equivalent although the actual hand-written sheet on which the information was recorded had three versions (LaFree and Dugan, 2007). The data collection for GTD1 remained remarkably consistent over the 28-year period although it should be made clear that the data likely suffer from reporting bias and incomplete data to differing degrees over time. These issues will be further discussed in the section that addresses the weaknesses of the GTD.

PGIS defined terrorism as “the threatened or actual use of illegal force and violence to attain a political, economic, religious or social goal through fear, coercion or intimidation” (LaFree and Dugan, 2007: 184). This excludes acts undertaken by a state (state terrorism), criminal acts that lacked a political, social, economic or religious goal, and acts of open combat between state or guerrilla armies. Yet, it is important to note the GTD1 is a particularly broad database in which there was a clear effort to err on the side of inclusion for questionable incidents. In addition, the GTD includes both domestic and

5. In sensitivity analyses, I also ran a negative binomial regression that calculated robust standard errors and clustered by country-group. In these analyses, an indicator for the GTD2 data was a negative and significant predictor of terrorism. However, when separate models were run for GTD1 and GTD2 data, no substantive differences were seen in my theoretical variables of interest.

international acts of terrorism which is a major advantage over all of the other terrorism databases currently in use.

Collecting the GTD2

The GTD team recognized that it was important to update the data beyond 1997. As a result, the GTD2 was born. The data collection responsibilities were led by Gary Ackerman and the data were managed by Charles Blair of CETIS in association with the National Consortium for the Study of Terrorism and Responses to Terrorism (START). CETIS sought to preserve the character of the GTD1 and the actual GTD1 variables but also, to extend the breadth of variable collection in the new GTD2, which covers the period from 1998-2007. The GTD2 was collected by the CETIS team for 1998-2007 upon receipt of funding in 2005. I turn now a discussion of this type of data collection.

To be clear, relatively contemporaneous data collection such as the PGIS collection of GTD1, even before the age of extensive internet resources, is a task that would be expected to net a larger number of terrorism incidents than the data collection conducted by CETIS which did not begin until 2005, seven years past the start of the period they were charged with collecting, 1998-2007. Thus, GTD1 would be expected to have collected many more terrorism incidents simply by virtue of collecting the data closer in time to when the incidents occurred. For the GTD2 data collectors, who searched for incidents up to seven years after their occurrence, fewer incidents would be expected to be netted simply based on the size of the lag in time between occurrence and collection. The size of the lag in data collection was a difficulty for the GTD2 collection team. The main difficulties are the lack of access to resources that would have been available if the data had been collected contemporaneously with or closer in time to the occurrence of the incident. This lack of access occurs because of the lack of electronic archiving and / or inaccessibility of media resources, government reports, and other sources. The most troubling evidence of the effects of the change from relatively contemporaneous data collection to collection begun seven years later is evidenced by the gap between the levels of terrorism observed in GTD1 in 1997, 3192 incidents and 901 incidents in GTD2 for 1998. To be fair, GTD1 had been trending downward from its peak of 5115 incidents in 1992, but such a large decline between 1997 and 1998 suggests that something more than declining terrorism levels is responsible for these differences in level. Further, this difficulty is perhaps also reflected in lower numbers of terrorism incidents over the entire course of GTD2 than would be expected given the large volume of incidents in the GTD1. However, as already noted, the PGIS data were already trending downward from the 1992 peak by 1997. I turn now to the definition of terrorism used by the GTD2 team.

Because there is much academic controversy over the best definition of terrorism (Schmid and Jongman, 1988), the GTD Criteria Committee declined to develop a specific definition. Instead, they chose to structure a set of criteria that included the original PGIS definition but also set out additional parameters that the Committee felt were important. *All three* of the first-level criteria must be met for the incident to be included in the GTD2. These include:

1. "The incident must be intentional – the result of a conscious calculation on the part of a perpetrator." [this is assumed *prima facie* to be correct in cases in which it is difficult to assess the intentionality of the incident (LaFree and Dugan, 2007: 200, note 23)]

2. "The incident must entail some level of violence (including violence against property) or the threat of violence."

3. "[T]here must be sub-national perpetrators. That is, at the time of the incident, the perpetrator group must not be exercising sovereignty (unequivocal, stable control of

demarcated territory; functioning government structures).” (LaFree and Dugan, 2007: 188)

The Criteria Committee further refined the cases to be included in the data by requiring that *at least two of three* of the following criteria be met.

1. “The act must be aimed at attaining a political, economic, religious or social goal. In terms of economic goals, the exclusive pursuit of profit does not satisfy this criterion.”

2. “There must be evidence of an intention to coerce, intimidate or convey some other message to a larger audience (or audiences) than the immediate victims.”

3. “[T]he action must be outside of the context of legitimate warfare activities; that is, the act must be outside the parameters set by international humanitarian law (particularly the admonition against deliberately targeting civilians or non-combatants).” (LaFree and Dugan, 2009: 188)

Note that these criteria are actually quite similar to the definition of terrorism in the GTD1. I turn now to the explanation of how these two different databases were merged into one Global Terrorism Database.

Reconciling the GTD1 and the GTD2

The GTD1 and the GTD2 were combined into one synthesized database by the GTD data team at University of Maryland and CETIS using a combination of automated coding and person coding from May 2008 until March 2009. The new, synthesized data were released to the START research community in April 2009. There were two basic problems to be addressed during the synthesis process, which is explained below.

The first problem was reconciling the GTD1 collection definition and the GTD2 definition-less criteria. The GTD1 was collected broadly using the PGIS definition while GTD2 was collected using the 6 criteria described above (3 of which were always mandatory with a rotating 2 more required). The criteria are remarkably similar to the GTD1 definition, but data collectors may have construed the criteria in a more or less restrictive manner than the GTD1 definition. For this reason, the purpose of the synthesis process was to examine the existing GTD1 data with the rotating GTD2 criteria in mind. A systematic review process was employed to evaluate all GTD1 cases from 1970 to 1997 to ensure that they met at least two of the three rotating GTD2 criteria.

The following guidelines were set for evaluating each GTD2 criterion for the GTD dataset. For Criterion 1 (a political, social, economic or religious goal), a rebuttable presumption was employed, such that the data coders assumed that it was met unless there was specific evidence to the contrary of no political, social, economic or religious goal for the incident. The reasons for employing the rebuttable presumption were two-fold. First, particularly in the early days of the GTD1, there was far less information regarding the goals of the perpetrators available in the open-source media or in the data captured by PGIS than would ideally satisfy this criterion. Second, the trained data collectors and coders at PGIS had already evaluated the data; it was assumed that the coders only collected incidents that fit their own definition. I turn now to the second criterion.

Criterion 2 addresses whether there is evidence of "an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims" (START, 2008: 10). Again, the rebuttable presumption was employed here for the same reasons as in Criterion 1; since PGIS's own definition included a similar clause it was assumed that these incidents had already been evaluated for this requirement and that there were some cases with too little information to properly assess it at the time of the synthesis. I turn now to Criterion 3.

Criterion 3 dictates that the attack must be in violation of the provisions regarding non-combatants in International Humanitarian Law (IHL). Briefly, IHL defines non-combatants as persons who do not engage in or who have stopped engaging in hostilities, including captured combatants, civilians, civilian “objects”, and medical personnel and places, including military medics. It is important to note that there is no rebuttable presumption for Criterion 3; it was either fulfilled or not based on the data. Cases with large amounts of unknown information were flagged for later review.

Automated coding was used to convert the majority of the rest of the variables in the GTD1 into the structure and formats of the GTD2. Few problems were encountered in converting existing GTD1 variables into their GTD2 counterparts because the GTD2 data were collected with the GTD1 variables in mind. However, the new variables collected for GTD2 are missing for GTD1. Though the synthesis process was far from perfect, we believe that it managed to impose consistency on two differently collected databases. I turn now to a brief review of the strengths and weaknesses of the synthesized Global Terrorism Database, 1970 to 2007.

Strengths of GTD

The Global Terrorism Database has four main strengths. First, starting with the original data collectors, GTD has included domestic terrorism incidents. This is probably the most important strength of the data, because the large majority of terrorism incidents occur within the state from which they were launched (LaFree and Dugan, 2007). Because the number of domestic terrorism incidents is much larger than the number of transnational terrorism incidents, any analysis which relies only on transnational terrorism incidents or domestic coverage for only certain years or regions of the world would severely undercount the true total of terrorism incidents.

Second, the GTD has been collected over nearly four decades. This coverage is unparalleled in the world of unclassified terrorism event databases. In fact, this coverage is much better than the any of the cross-national homicide databases despite the fact that homicide is the best-measured crime in any nation. The old adage that it is hard to hide a body for very long explains why homicide is the best-measured crime in any state. However, as LaFree (1999) notes, the World Health Organization, which is the most valid source for cross-national homicide statistics, contains usable homicide statistics for only highly industrialized, mostly western nations. The coverage of the GTD data across the globe for thirty-seven years stands in sharper contrast when compared to homicide statistics, which are only available for a handful of countries over time.

Third, over the course of the last 37 years, there have only been 4 data managers and two data collection agencies responsible for collecting the GTD. This helps to ensure that the data have been collected and coded in a consistent manner.

And finally, due to the very broad nature of the definition and collection criteria used, the GTD can be customized to fit many different definitions of terrorism. For example, in this analysis, I exclude all terrorism incidents that target the military of a state in order to avoid confounding the revolutionary war and ethnic war categories in my independent variable with a terrorism incident against a military in my dependent variable. This decision is discussed in more depth in the Data Appendix. There are many other such customized datasets that can be made simply by filtering on GTD variables.

The GTD is far from perfect, but at the moment it is the most comprehensive unclassified terrorism event database in the world. I turn now to the weaknesses of the GTD.

Weaknesses of GTD

It is important to note that the weaknesses of the GTD discussed below are serious but not insurmountable. After I discuss the weaknesses of the database, I lay out a plan to address these as best as possible. I turn now to the first and likely most serious, of the four major weaknesses discussed in this dissertation.

First, any terrorism incident event database will suffer from undercounting of terrorism. On the one hand, most terrorists want publicity, because one of the main purposes of terrorism is to convey a message, to coerce, or to intimidate a larger audience into doing something the perpetrators find desirable as well as to inflict personal or property violence. On the other hand, these are illegal actions that are carried out covertly, and the open-source media may never learn of incidents or report them. This is likely to vary by country, because the distribution of open-source media outlets around the world is not random. It is likely that there are more media outlets in the developed world and thus, more opportunity for terrorism incidents to be reported in that media. In addition, this means that the data are also biased not only towards more media-saturated nations and parts of nations (capital and major cities versus the rural countryside of a nation), but that media reports are biased towards more newsworthy terrorism (LaFree and Dugan, 2007).

Second, there are often missing details in GTD incidents, save for the most famous incidents or perpetrators. For example, the GTD collects the basic who, when, what, and where regarding the incident, but this information is not uniformly available for all incidents, in particular, the name of the perpetrator group. There can also be false claims of responsibility for events. Further, because the GTD is an incident-level database, it excludes other potentially interesting information, such as group-level information about terrorist groups or specific governmental responses to terrorism incidents though efforts are in process to incorporate this supplemental information (LaFree and Dugan, 2007).

On the other hand, as discussed above, cross-national homicide data are far worse. Even in the United States, homicide data, though the best there is, often has little or no detail, including perpetrator identity information. This is despite the Supplemental Homicide Reports, which is supposed to contain the who, what, when, and where of each homicide and despite the expansive new crime reporting system, the National Incident Based Reporting System (NIBRS). NIBRS has been vastly underutilized by police agencies across the country because of the expense involved in hiring and training individuals to complete the NIBRS reports properly (Mosher, Miethe and Philips, 2002). The situation is far worse in other nations (LaFree, 1999).

Third, although efforts were made to maintain the consistency and to keep control of the level of bias in the Global Terrorism Database, it is impossible to ignore that data collection has changed from 1970 to 2007. The much wider availability of small, foreign news sources with the advent of the internet most likely has increased the news coverage of terrorism around the world, particularly from the developing world.

In addition, the change in collection entities between GTD1 and GTD2 with its associated move from a standardized definition of terrorism to a definition-like set of criteria created its own set of problems which were at least partially ameliorated when the data were reconciled during the synthesis process discussed above. In addition, although efforts were made to preserve the continuity of sources between PGIS and CETIS, there were sources that PGIS used to collect data that are either no longer in existence (such as

Patterns of Global Terrorism / *Country Reports on Terrorism* by the US State Department) or that were specifically internal PGIS sources (like reports from satellite PGIS offices around that world). Without these sources, it is impossible to say that their coverage is identical. However, the UMD GTD team has undertaken extensive data cross-validation procedures to supplement the data with outside terrorism databases.

As a result of the very extensive cross-validation of the GTD against other available terrorism datasets, the GTD has been non-systematically updated with data from Northern Ireland, the US, Turkey and South Africa. These changes were a part of efforts to update and increase the inclusiveness of the data. I will control for these non-systematic inclusions in an effort to decrease the bias of the data by using fixed effects, in which only within-country variation is utilized to estimate the model and each country essentially serves as its own control. In this way, the non-systematic updates are irrelevant since between-country variation is not used to estimate the models.

Finally, the data for 1993 were lost in an office move by PGIS many years before the team at University of Maryland acquired the data. PGIS reported country totals for this year in their annual risk assessment report. Efforts by CETIS and the UMD team were made to recover the data through recollection, but these efforts were only ever able to recollect 15% of the total data for the year. I use the country-level marginal totals for 1993 in analyses, which is discussed in depth below.

Addressing the 1993 Data

The PGIS country-level distribution of incidents for 1993 is simply a table, which lists all of the countries and the number of incidents that PGIS observed in those countries. I use this distribution to proxy for the 1993 data in my analysis. Using this table of incident totals by country to substitute for actual data in my analysis is not without its downsides. I discuss these below.

First, there is always the possibility that the listed countries were not in fact, the places where the incidents occurred. This could happen due to the creation and break-up of countries in 1992 and 1993 as well as errors in coding and reporting. If there were actual incidents attached to the incident totals by country, the details of the incidents, particularly the free-text city field, could be checked to determine whether they were correctly coded. This was done extensively to the existing incidents in the GTD. However, it is not possible to do this with the PGIS 1993 totals and this builds error into my model when I use this data. Second, the country-level totals were never reconciled with the GTD2 definition-less criteria by the GTD team as discussed above. The synthesis process to reconcile GTD1 incidents with the GTD2 definition-less criteria likely would have excluded some of these incidents and this adds another layer of error into my model. In addition, I have undertaken to remove all incidents from the GTD that included any military targets so as to provide as clean an association as possible between state instability and terrorism. (For more information on this, please see the Data Appendix.) I simply cannot do that with the PGIS 1993 totals given the lack of incident details to examine, such as target type.

Finally, the GTD team discovered that the PGIS yearly reports of the total number of incidents never completely matched the incident totals in the original GTD before the synthesis. The reports generally overestimated the amount of terrorism by an average of several hundred incidents per year. The possible sources for this mismatch are outlined below. The GTD team believes that the most prominent source of the data undercount in the GTD relative to the over-count in the PGIS reports is that when the data were computerized, duplicate incidents were deleted. In addition, PGIS often recorded updates to existing cases much like they recorded new incidents, with a separate index card. PGIS may have accidentally counted these update cards as new incidents. Whatever the source of the mismatch in counts, the fact that there is a mismatch between data in the GTD and the PGIS report totals indicates that there is another source of error introduced into my analysis with the use of the PGIS 1993 totals, which may overestimate the level of terrorism in that year. However, the introduction of these sources of error into my model is outweighed by the bias created by the loss of an entire year of data. In order to include the country totals for 1993 in my analysis, I undertook a cleaning process to make the PGIS totals as comparable as possible to what the data totals would look like. I describe this process below.

First, I compared the PGIS 1992 and the GTD 1992 total counts by country. Due to the loss of duplicates in the computerized GTD and the synthesis process, the PGIS 1992 and the GTD 1992 differed by 288 incidents, or 5.3% of the PGIS total for 1992. In addition, I must adjust the PGIS total to account for my decision to delete terrorism incidents that involved military targets from the GTD. When the deleted military incidents are accounted for, this brings the differential between PGIS 1992 and GTD 1992 total difference to 783 incidents or 14.5% of the PGIS 1992 total. This was done for each country separately. I did the same for the 1994 in PGIS and 1994 GTD, which differed by 380 incidents or 9.9% of the total PGIS 1994 incidents. The deleted military incidents brought the differential up to 797 incidents, or 26.3% of the 1994 PGIS total. I then averaged the 1992 and 1994 proportions to create an estimated metric by which to adjust the 1993 PGIS totals downward to account for the mismatch between GTD and PGIS, the cases lost due to the synthesis and the deletion of military incidents.[6] I multiplied the averaged proportion and the 1993 totals in PGIS by country to estimate 1993 total incidents by country. I used this estimated 1993 in the analyses. Although there is certainly bias introduced by the use of the estimated 1993, it is outweighed by the bias created by the loss of the entire year of data. [7]

Dealing with the GTD Weaknesses

The first issue to be dealt with is the variation in media reporting across countries due to freedom of press. Unfortunately, there is no simple solution to this problem. There are no data on the degree of media penetration nor on the freedom of the press across the world for the period from 1970 to 2005. Van Belle (1997) undertook collection of a dataset on press freedom that examines the period from 1970 to 1995 for 2/3 of the nations in my dataset, however. I am not willing to truncate my data at 1995 nor am I willing to lose one-third of the nations in my sample since the bias created by this data loss outweigh the omitted variable bias of not controlling for press freedom. Yet, I did examine the correlation between this data and a related concept. Press freedom is much more controlled in autocratic regimes so that it is reasonable to assume that controlling for autocracy would begin to control for press freedom. In fact, the concepts are quite related with a correlation of -.5037. This indicates a moderate, negative relationship

6. If the state was no longer in existence or had 0 incidents for 1992, I used the 1994 proportional difference between the GTD and the PGIS report and vice versa. Thus, I used both years of data to estimate the 1993 totals by country when both years had data. When only one year, either 1992 or 1994, had reported incidents, I only used that one year of data.

7. I ran the models both with the adjusted 1993 PGIS totals as well as without 1993. They were substantively the same. Since there were no substantive differences across the models, I ran all subsequent models with the adjusted 1993 totals.

between autocracy and press freedom with more autocratic states experiencing less press freedom. In addition, since I utilize the fixed effects modeling technique, which controls for time-stable unobserved differences between countries, the omitted variables bias threat only arises from changes in press freedom within-country. Although neither the use of the autocracy measure to proxy for press freedom nor the use of fixed effects to control out time-stable differences between countries on press freedom (among other time-stable differences between countries) are perfect solutions, they do begin to deal with the variation in reporting by the freedom of the press in a way that does not truncate my sample of countries and years.

The second issue is the problem of missing information in reported incidents. Fortunately, I rely mainly on the country/location and year fields, which were quite complete. In fact, all incidents that were missing on either of these fields were tracked down and corrected by the GTD team. Thus, this is less of a concern in my analyses.

The third and fourth issues are the change in data collection agencies and the methodologies of collection as well as the non-systematic updating of data for countries such as the United States and South Africa. I addressed the third problem by including an indicator for the data collection agency in all models.[8] I address the fourth problem using statistical controls. I use a fixed effects negative binomial regression model to analyze the relationship between terrorism and state instability. This method basically allows for each country to serve as its own control over the years of inclusion in the sample. It only

8. The model results I present here do include an indicator for the data collection agency. The results for this indicator will be presented in Chapter 4. I also ran a negative binomial regression that calculated robust standard errors and clustered by country-group using this indicator. In these analyses, an indicator for the GTD2 data was a negative and statistically significant predictor of terrorism, but no changes were observed in the theoretical variables of interest. In addition, I ran separate models for GTD1 and GTD2 data and no substantive differences were seen in my theoretical variables of interest.

models the variation within the country to estimate the coefficients. It does not utilize the between-country variation when estimating the effects of state instability on terrorism. In this way, I am able to essentially ignore these issues since my model does not rely on the problematic variation between countries that these weaknesses raise. [9]

In the end, the GTD, though an imperfect database is by far the best open-source dataset available to study domestic and international terrorism from 1970 to 2007. In fact, it is surprising how the cross-national homicide statistics are unable to attain the same level of coverage of states across the world through official data collection channels. Yet, the GTD has managed to amass data on far-flung and developing nations through the open-source media. I turn now to the independent variable of interest, state instability.

Independent Variable of Interest

The Political Instability Task Force (PITF) data are my source for the main independent variable of interest, state instability. At the behest of Vice President Albert Gore's office and the Central Intelligence Agency's Directorate of Intelligence, a task force was convened in 1994 to determine the predictors of what was then-termed state failure. The task force was composed of academic experts from around the country and partnered with the Consortium for International Earth Science Information Network and Science Applications International Corporation. They began by examining profound failures, such as that which occurred in Somalia, but they broadened their focus to include political instability and state fragility over time. They examined all state

9. In sensitivity analyses, I also ran a negative binomial regression that calculated robust standard errors and clustered by country-group. In these analyses, an indicator for the GTD2 data was a negative and significant predictor of terrorism. However, when separate models were run for GTD1 and GTD2 data, no substantive differences were seen in my theoretical variables of interest. I also included controls for the United States, South Africa and Northern Ireland in these models, all of which were significant predictors of terrorism.

instability episodes in states over 500,000 population from 1955-2007 (though here, I only utilize the data from 1970 to 2005 onwards to ensure the same number of state-years of terrorism and instability and the control variables).

State failure is defined by the PITF as “a label that encompasses a range of severe political conflicts and regime crises exemplified by macro-societal events such as those that occurred in Somalia, Bosnia, Liberia and Democratic Republic of Congo (Zaire) in the 1990s” (Marshall, 2009a: PITF data page). Political instability is described as partial state failure (Marshall, 2009a: PITF data page). Political instability is operationalized as the presence or absence of four discrete events or a combination of them termed “complex”. The four events are: revolutionary war, ethnic war, adverse regime change, and genocide.

Revolutionary war consists of “episodes of violent conflict between governments and politically organized groups (political challengers) that seek to overthrow the central government, to replace its leaders or to seize power in one region. Conflicts must include substantial use of violence by one or both parties to qualify as ‘wars’” (Marshall, Gurr and Harff, 2009: 5). These politically organized groups can include revolutionary groups, political parties, student organizations or state agents such as the military or regime members. The majority, however, have been guerrilla armies. There are two minimum thresholds for an event to qualify as a revolutionary war: mobilization and conflict intensity. The mobilization threshold dictates that both sides must have at least 1000 or more people involved in the cause; this can include demonstrators or troops. The conflict intensity threshold directs that at least 1000 conflict deaths must occur over the full conflict, with at least one year of the conflict claiming 100 or more fatalities and with no period more than three years in a row without at least 100 fatalities. Conflict-related fatalities are defined rather broadly; they can result from “armed conflict, terrorism, rioting or government repression” (Marshall, Gurr and Harff, 2009: 5).[10]

Ethnic wars are defined as “episodes of violent conflict between governments and national, ethnic, religious or other communal minorities (ethnic challengers) in which the challengers seek major changes in their status” (Marshall, Gurr and Harff, 2009: 6). It does not include warfare between different ethnic groups unless political power or government policy is part of the conflict. The same two minimum thresholds apply to ethnic wars as revolutionary wars: the mobilization and conflict intensity thresholds. The majority of these types of wars have involved guerilla or civil wars where the challengers have sought some type of independence or self-determination.[11]

Adverse regime changes are “major, adverse shifts in patterns of governance, including major and abrupt shifts away from more open, electoral systems to closed, authoritarian systems; revolutionary changes in political elites and the mode of governance; contested dissolution of federated states or secession of a substantial area of a state by extrajudicial means; and or near-total collapse of central state authority and the ability to govern” (Marshall, Gurr and Harff, 2009: 10).

---

10. An example of a revolutionary war occurred in Guinea from September 2000 to March 2001 (Marshall, Gurr and Harff, 2009). Rebel groups attack Guinean forces in the Parrot's Beak region from bordering areas of Sierra Leone and Liberia. Rebellion is crushed in March 2001 (Revolutionary war: 9/00-3/01).

11. An example of an ethnic war occurred in Chad from October 2005 to January 2007 (Marshall, Gurr and Harff, 2009). Dominance of the central government by President Déby's clan and ethnic-Zaghawa supporters led to a mutiny by elements of the army in October 2005, a coup attempt in March 2006, and an attack on the capital in April 2006 (Ethnic war: 10/05[-1/07]). Failing to unseat the government, FUC rebel forces took refuge in border regions with Sudan and Central African Republic. A peace agreement with the rebels was reached in December 2006 and fighting largely ended in January 2007. The FUC leader, Capt. Nour Abdelkerim, was appointed Minister of Homeland Defense in March 2007.

Adverse regime change is operationalized first as a six point or more drop in the nation's POLITY score. This is a change towards the -10 end of the POLITY scale (fully institutionalized autocracy) and away from the +10 end of the scale (fully institutionalized democracy) from the Polity IV dataset (Marshall and Jaggers, 2007). Though a six-point drop may seem arbitrary, the POLITY coders assert that it is a meaningful metric by which to capture the associated qualitative changes in the openness of the executive politics or political competitiveness. They defined borderline countries (approximately 15% of the total number of cases) as those experiencing a four-point drop and reviewed them individually to assess whether they should be included.

To assess the collapse or near-collapse of central authority, they first defined this collapse or near-collapse to include revolutionary changes in the central authority, contested state dissolutions, and a general collapse of central state authority which may have been due to internal war, corruption, poverty, failure of leadership, etc. Generally, this involves the inability to control at least half of the state's territory or population by failing to provide basic human services (administrative incapacity) and security and the authority to enforce it (coercive incapacity). They used the Interregnum code in the POLITY IV data to identify periods during which there was a "complete collapse of central political authority" (Marshall and Jaggers, 2007: 17). Adverse regime change involves either a rapid and distinct move towards autocracy and away from democracy or a collapse or near-collapse of central state authority.[12]

---

12. It is important to note that adverse regime changes are often short, usually lasting for no more than one month. Because these are so short in duration, my hypotheses will query whether their effects differ significantly from longer duration instability events, such as revolutionary war or ethnic war. Sometimes, these adverse regime change events occurred on their own, without stimulating another instability event. An example of this type of adverse regime change occurred in Bangladesh in January 2007 (Marshall, Gurr and Harff, 2009). Increasing tensions between the ruling Bangladesh Nationalist Party (BNP) and the main opposition Awami League (AL) over the conduct of new parliamentary elections

Genocide is the fourth included category. These events "involve the promotion, execution and / or implied consent of sustained policies by governing elites or their agents – or in the case of civil war, either of the contending authorities – that result in the deaths of a substantial portion of a communal group or politicized non-communal group" (Marshall, Gurr and Harff, 2009: 14). The genocide instability category includes both genocides and politicides, which are genocides of a people for their political beliefs. Victims of genocide are defined "primarily in terms of their communal (ethnolinguistic, religious) characteristics" while the victims of politicide are "defined primarily in terms of their political opposition to the regime and dominant groups" (Marshall, Gurr and Harff, 2009: 14). The purpose of genocide is to kill enough members of the reviled group such that they no longer pose a threat to the state's grip on power or their interests.[13]

Several criteria were used to fully get at the notion of genocide as opposed to just mass murder. First, there must be demonstrated a "persistent, coherent pattern of action"

---

leads to a paralysis of the caretaker government and imposition of a military-backed State of Emergency on January 11, 2007. New elections are delayed while military government conducts "anti-corruption" campaign to diminish patronage structures built by party leaders Hasina and Zia (Adverse regime change: 1/07 – 1/07).

Other times, an adverse regime change stimulated a second instability, such as in Chile. There was an adverse regime change there in September 1973, which stimulated the onset of a genocide of people for their political beliefs from September 1973 until December 1976 (Marshall, Gurr and Harff, 2009). President Allende's democratically elected socialist government is overthrown in military coup. General Pinochet consolidates power, dissolves Congress, and suppresses left and center opposition (Adverse regime change: 9/73-9/73). Supporters of former regime and other leftists are arrested, tortured, disappeared, exiled, and summarily executed (Genocide: 9/73-12/76).

Still other times, an adverse regime change was of long duration without stimulating any other instabilities. This occurred in Armenia from July 1995 until September 1996 (Marshall, Gurr and Harff, 2009). President Ter Petrossian suspends country's most influential opposition party. Electoral malpractice and government intimidation tarnish subsequent legislative and presidential elections. Generally, adverse regime changes are of short duration, however. That this short duration could have an influence on the terrorism expected when they occur is precisely why the effects of adverse regime change will be explicitly examined in the second set of hypotheses.

13. An example of a genocide (of a political group) occurred in Uganda from February 1971 to April 1979 (Marshall, Gurr and Harff, 2009). Gen. Idi Amin seizes power in 1971 and systematically exterminates political opponents and personal enemies. Tribes closely associated with his predecessor also are targeted (Genocide: 2/71-4/79).

(Marshall, Gurr and Harff, 2009: 15) by the government, a dominant social group or one of the parties to an internal war to intentionally end the existence of a set of people living in that state. It must be a sustained pattern of action covering six months or more. Third, the victims must be unarmed civilians. Fourth, they chose not to specify a threshold of casualties in order to allow for the inclusion of genocides of groups that were quite small. It simply needed to be a substantial portion of the existing group.

The last instability type is the complex category. This includes any combination of the instabilities occurring at the same time or within a five-year period of one another. This catch-all was created and used in the coding scheme partially because it was determined that instabilities which occurred so close in time to one another could not be analytically separated from one another when searching for causation.

I also created several new concepts, which ought to be defined in this study. I use a country-year dataset, which contains one row in the data for each year for every state in the sample. The unit of analysis is the state-year. *Stability* refers to a state-year in which instability did not occur. *Instability* describes a state-year in which instability did occur. A *non-complex singular instability* is just one episode of the four types of instability within a five-year period (ethnic war, revolutionary war, adverse regime change, and genocide). In contrast, a *complex singular instability* describes a state-year in which an instability occurred in that year and then, another within five years. These episodes did not occur in the same year, however. Finally, a *same-year complex instability* is composed of a state-year in which multiple instabilities occurred in that year, such as when a state experiences an ethnic war in the same year as an adverse regime change.

Strengths of the PITF Data

There are four main strengths of the PITF data. First, regional and subject matter experts collected the PITF data. These experts were overseen in the collection process by a widely respected panel of academic scholars who consulted on matters of definition and specific case collection and coding. This depth of expertise makes these data extraordinarily valuable. Second, the PITF, like the GTD, has global coverage, over a long period of time. The data used in this analysis span 1955 to 2007, and annual updates are offered approximately one to two years behind real time. The coverage with regards to states is also quite wide. Though there is a population minimum of 500,000 persons, when a state passes this minimum threshold, it is added to the sample of states and data are collected for the time frame.

Third, the PITF data were collected and coded by type of instability. This is unlike the POLITY state failure code, which is a single unitary code that does not allow for disaggregation by type of instability nor does the POLITY data clearly lay out what types of events would count as a complete collapse of the central government (Marshall and Jaggers, 2008). Because the PITF data separate the events by type, such as ethnic war, revolutionary war, adverse regime change and genocide, it is possible to run analyses by type of instability. This is important, because there are likely different causes and different effects of each type of instability. Most important here are the different effects; it is reasonable to expect that ethnic war will have a much different effect on levels of terrorism as an outcome than adverse regime change due to the differing levels of control exerted by the state over the actions of individuals in those situations. I take advantage of this disaggregation and will run the analysis accounting for type of instability so as to observe any differential effects on terrorism incidents.

And finally, the PITF provides clear information on the definitional and operational criteria used to collect and code the data and the data narratives. The narratives provide a small paragraph with the basic details of the instability for each state. The narratives even break down the complex category into the component types that make up that instability period. There is a separate paragraph for each period of instability. The clear operational criteria and the narrative paragraphs make the data customizable to the user. For example, to avoid confounding the independent variable of state instability with the dependent variable, terrorism, I have excluded all terrorism campaigns from the data as a period of instability. I have also excluded all government reactions that are a direct result of the terrorism campaign from being counted as a period of instability. These are discussed in depth in the Data Appendix. This would not be possible without the final strength of this data, the clear operational criteria and data narratives. I turn now to the weaknesses of the PITF data.

Weaknesses of the PITF Data

It is important to note that the weaknesses of the PITF data discussed below are serious but not insurmountable. After I discuss the weaknesses of the data for each type of instability, I lay out a plan to address these as best as possible. I turn now to a criticism of the overall PITF data before criticizing the data for each type of instability.

The first and most obvious weakness of the PITF data is the broadness of its definition and operationalization. The definition and operationalization is extremely broad and covers two types of war, change in governance type and complete collapse of the central government and indiscriminate slaughter of civilians based on ethnic or political affiliations. It is reasonable to question whether this broad definition and operationalization encapsulates only one definition of state instability or if it contains a mixture of several of them.

Second, the data were collected by subject matter and regional experts whose methodology and source material have not always been clear, though the definitions and operational criteria have been. To guard against the effects of lack of clarity in methodology, I use the discrete event data rather than relying on the more subjective ratings of the intensity and magnitude of the instability. Further, only those states which have achieved and maintained a 500,000 person population are eligible for inclusion in the dataset. This biases the data and does not allow it to speak to the workings of smaller states. In addition, there are individual weaknesses for the ways in which each *type* of instability were operationalized and collected. I review these below.

Ethnic and Revolutionary War

The PITF uses a minimum conflict deaths threshold to regulate the inclusion of conflicts into the ethnic war and revolutionary war categories. To review, the threshold is 1000 or more conflict deaths over the full conflict, with at least 100 fatalities in a year and no period longer than three years without 100 fatalities. In addition, there must be at least 1000 persons mobilized in the conflict. This high bar means that the data are biased against smaller conflicts and those conflicts that occurred in states with poorer data collection procedures for recording conflict deaths. Although there are datasets which use a lower threshold for inclusion (such as the Uppsala data discussed in Gleditsch et al., 2002), they were compiled by different individuals. Relying upon those data would introduce a bias in the independent variable by virtue of the different collectors. This is undesirable. As Gleditch et al. (2002) discuss, the issue is primarily a methodological one rather than a conceptual problem. With fewer conflicts counted as war, “there are simply ‘not enough wars’ for statistical analyses over shorter periods of time” (Gleditsch et al., 2002: 617).

Further, the accuracy of the counts of mobilized individuals and conflict-related deaths may be questioned. As LaFree and Tseloni (2006), among many others, note, cross-national homicide statistics in stable countries are often poor. Yet, the counts relied upon to form the basis of inclusion as an ethnic or revolutionary war are collected and reported in conflict-ridden states. This likely means that conflicts that ought to have been included may have been inaccurately excluded from the independent variable’s ethnic and revolutionary war category, and vice versa. Thus, clearly, this category includes biased data.

To guard against this problem in the analysis, I have disaggregated the independent variable by instability type and will be able to observe the independent effects of ethnic war and revolutionary war. I choose to use the PITF data although I recognize that it is biased against smaller wars as well as those that occurred in nations with poorer data collecting capabilities. I turn now to the weaknesses of the genocide data.

Genocide

The genocide dataset, originally compiled by expert Barbara Harff, is basically the only one in existence due to its coverage over time and space. The major weakness of the genocide data is the highly subjective nature of the collection criteria. Unfortunately, demonstrating a “persistent, coherent pattern of action” (Marshall, Gurr and Harff, 2009: 15) for six or more months by the government, a social group or combatants in a civil war may prove difficult to execute consistently over the entire sample. In addition, the lack of a minimum fatality threshold is a two-edged sword; on the one hand, it does allow the mass murder of tiny social groups to be included in the sample as genocide. On the other hand, it also means the data are not uniform across social groups. In addition, it is not clear what proportion of the group needs to be killed in order for it to meet the "substantial portion" of the group threshold. These subjective collection criteria will likely lead to data inconsistency across nations and regions. I use it knowing that the data are likely inconsistent but also that it is unparalleled in the field. I turn now to adverse regime change.

Adverse Regime Change

Adverse regime change draws upon a well-established political dataset on the regime characteristics of states and their place on the continuum of governance. POLITY, currently in its fourth incarnation, is a well-established expert review dataset which scores regimes from -10 for a full autocracy to +10 for a full democracy (Marshall and Jaggers, 2007). A weakness of the PITF data is that it uses an admittedly arbitrary cutoff on this scale to identify an adverse regime change. Although Marshall, Gurr and Harff (2009) assert that a six-point drop in a POLITY score (always towards autocracy) is meaningful, they offer no evidence to support its substantive meaning. However, the PITF staff review all borderline cases, which are defined as four-point drops, for potential inclusion in the adverse regime change category; these borderline cases constitute 15% of the total. The second criterion for inclusion in the adverse regime change category is also decided by expert review. This second criterion is the interregnum code in POLITY (-77) and is called upon when the central government suffers a complete collapse (Marshall and Jaggers, 2007). This criterion may suffer from inconsistent coding across nations and years. However, since the POLITY data are well-regarded in the field, my concerns about the weakness of the adverse regime change category stem primarily from the arbitrariness of the cut-off.

Overall, the largest concern over the PITF data stems from the use of expert review without significant information regarding the methods used to build the dataset. Since the portion of the PITF that I use here simply categorizes the fairly public discrete events that have occurred, I have less concern over the lack of publicity regarding their methods. Over the course of the analyses to follow, I will conduct sensitivity analyses and robustness checks to ensure the robustness of my results.

The Dependent and Independent Variables

For the dependent variable, I use the total number of terrorism incidents per state-year for the states and years included in this analysis (see table 12 in the Data Appendix). In order to avoid confounding the independent and dependent variables, I exclude all terrorism incidents in which any target type identified is a nation's military. I exclude the military targets, because two of the state instability categories involve war. This is a conservative way to avoid double-counting an incident against a military as part of a war instability event. The exclusion of military-targeted incidents is necessary, because if I did not, I could be running the risk of using events to code times of instability to predict terrorism incidents that are composed of those same events. This strategy is discussed in more depth in the Data Appendix.

For Hypothesis 1, I use a state-year indicator of instability as my main instability variable, which is a 1 for the state-years in which there is an ongoing instability event in that nation, and 0 for all other years. To test Hypotheses 2, 2a and 2b, I use dichotomous variables for each type of instability, which are coded as a 1 for each year that type of instability occurs and a 0 otherwise. To test the third and fourth sets of hypotheses, I use dichotomous variables to indicate complex singular instability, non-complex singular instability, same-year complex instability and stability when each occurs. I turn now to a description of the control variables.

The Control Variables

Attaining adequate control variables for the period from 1970 to 2007 for all states over 500,000 population is a difficult task. Unfortunately, the states of greatest interest here, the ones suffering a state instability and / or terrorism, are perhaps the *least* likely to have reliable and valid data collected about their political, social and economic characteristics. For this reason, I have decided to take a multi-pronged approach to maximize the number of state-years that can be included in the analysis while balancing the need to include control variables to guard against omitted variable analysis.

The first model, Model 1, includes basic control variables that have the most states and years with complete data on the country's demographics, governance and information on whether states that are contiguous via a land border or a river border are contemporaneously suffering state instability. There are 147 countries and 35 years of data, from 1970-2005, in the sample for Model 1, which I call Sample 1. The next model, Model 2, includes population age structure and social and economic development variables from the World Bank's *World Development Indicators* database for 116 nations from 1981-2005. I call this sample of countries and years Sample 2. The final model, Model 3, includes data on the characteristics of ethnic minorities at risk from the Minorities at Risk (MAR) dataset for 82 nations from 1990-2005. This final sample of countries and years is called Sample 3. In order to justify statistical inferences across the three models, I will replicate the Model 1 analysis on Samples 2 and 3. The comparison between the results of the Model 1 analysis on Samples 1, 2 and 3 allows me to examine the effects of sample selection bias in Models 2 and 3 results as well as the effects of omitted variable bias on Models 1 and 2. I describe all three sets of control variables below, and I mark which variables are included in each model. I describe the summary statistics for each sample in the first section of Chapter Four, where I describe the results, and in tables 4-7, which contain these summary statistics.

It is important to note that the country-year coverage is also contained in table 12 in the Data Appendix. The first column is a listing of all of the states included in Sample 1. The second column includes all of the years each state has data on the country's demographics, governance and contiguity characteristics. In essence, this column either includes the entire observation period (1970–2005) or the first year of data collection after the birth of the state and the final year of the observation period as the end year or the first year of the observation period and the final year of data collection upon the death of the country. The next two tables in the Data Appendix contain the countries and years for which there are available data for Sample 2 and Sample 3.

It is important to include control variables in my analyses to guard against omitted variable bias, because if these variables are excluded from the model and are related to both terrorism and other independent variables that are included in the model, the coefficients for the included variables will be biased. The domains that I test with the control variables I use in my models have all been demonstrated to have important effects on terrorism and / or terrorism. These domains include country-level demographics (Piazza, 2008), governance characteristics (Eyerman, 1998; Li, 2005), instability in a neighboring state (Iqbal and Starr, 2008), population age demographics (LaFree and Ackerman, 2009), social and economic development (Marshall, 2002; Piazza, 2008), and ethnic minority group characteristics (Marshall, 2002; Gurr and Marshall, 2000). I turn now to the description of the control variables. I expand on these prior works by including some new innovative measures of economic development, such as the Food Price Index, and the level of carbon dioxide emissions in the state, which to my knowledge have not been used in the instability and terrorism literature. Further, I examine the effects of many controls on domestic and transnational terrorism back to 1970, which to my knowledge has not been done before while testing the instability – terrorism relationship. A listing of the variables and the domains they measure is found in table 1.

Table 1. Variables and their domains

Variables	Domain
Terrorism incidents	Dependent variable of interest
Instability	Main theoretical variable of interest; tests breakdown theory
Hypothesis 1	Instability
Hypothesis 2	Instability by type
	Complex instability (complex singular and same-year)
	Ethnic war
	Genocide
	Adverse regime change
	Revolutionary war
Hypotheses 3 & 4	Multiple instabilities & temporal density
	Stability
	Complex singular instability
	Non-complex singular instability
	Same-year complex instability
Model 1: Governance, contiguity and country demographics	
Governance	Type of governance on terrorism
Full autocracy	An autocratic government (-6 through -10 on polity2)
Full democracy	A democratic government (+6 through +10 on polity2)
Transitional	Neither fully democratic nor autocratic (-5 through +5, -66, -77)
Contiguous state instability	Possible diffusion of violence across contiguous state borders
Country demographics	Population demographics on terrorism

Variables	Domain
Total population	Total size of the population
Population change	Percent change in population size
Population density	The dispersion of the population per square kilometer
Urbanity	The percentage of citizens living in cities
Land area	Total land area
Data collection agency	Divergent methods of collection for GTD1 & GTD2
Model 2: Population age structure and social and economic development.	
Population age structure	Bulges in certain age groups ought to effect terrorism differently
% Population aged 0-14	Percent of the population from 0-14
% Population aged 15-65	Percent of the population from 15-65
% Population aged 65+	Percent of the population from 65+
Social and economic development	
Telephone lines	Proxies for social development of the society
GDP per capita	Size of the current economy
Change in GDP per capita	Change in the size of the current economy
Food production index	Represents a more agriculturally based economy
CO_2 emissions	Proxies for an industrial or industrializing society
Model 3: Ethnic minority group characteristics	
Religious restrictions	Religious discrimination may generate the motive for terrorism
None	None
Informal	Informal restriction on the group's practice of their religion
Some	Some restriction on the group's practice of their religion
Sharp	Sharp restriction on the group's practice of their religion
Political discrimination	Political discrimination may generate the motive for terrorism
None	None
Neglect with help	Historical neglect of the group's political participation but policies to right this
Neglect	Historical neglect of the group's political participation but no policies to right this
Social exclusion	Social exclusion of the group from political participation
Formal exclusion	Formal exclusion of the group from political participation or repression
Economic discrimination	Economic discrimination may generate the motive for terrorism
None	None
Neglect with help	Historical neglect of the group's participation in the economic sphere but policies to right this
Neglect	Historical neglect of the group's participation in the economic sphere but no policies to right this
Social exclusion	Social exclusion of the group from participation in the economic sphere

Variables	Domain
Formal exclusion	Formal exclusion of the group from participation in the economic sphere
Protest	Political protest activity of the group may lead to or replace terrorism
None	None
Verbal	Verbal or written forms of political protest, such as letter writing or petitions
Symbolic	Sabotage, symbolic destruction of property or political activity like sit-ins
Small	Participation in demonstrations, etc. with 10,000 or less people
Medium	Participation in demonstrations, etc. with 10,000 - 100,000 people
Large	Participation in demonstrations, etc. with 100,000+ people
Group spatial distribution	Distribution of ethnic minority groups may influence the amount of terrorism
Dispersed	Group is widely dispersed
Urban	Group is primarily urban or the minority in one region
Regional	Majority of the group is in one region
Concentrated	Group is concentrated in one region

Model 1 Control Variables: Country Demographics, Governance and Contiguity Characteristics

First, I control for regime type. Regime type has been demonstrated in much of the previous literature as an important predictor of terrorism (Eyerman, 1998; Li, 2005). I use the POLITY data to control for regime type. Specifically, I include dichotomous indicators of *Full Autocracy* and *Full Democracy.* Full autocracy is constructed from values of -10 through -6 on the polity2 scale and is a binary variable, with a 1 indicating that it is scored as a full autocracy and 0 otherwise. Full democracy is coded as +6 through +10 on the same scale and is a binary variable, with a 1 indicating that it is scored as a full democracy. The reference category is the transitional government, -5 through +5 on the same scale as well as the foreign interruption and interregnum codes. [14]

14. It is important to note that the adverse regime change category of the state instability data was coded primarily from the POLITY data. As noted in the data section, it was primarily coded as a six-point drop in the state's polity score on the autocratic end or a complete collapse of central government termed

Next, I control for *instability in a contiguous state*. I utilize the Correlates of War Project's *Direct Contiguity Data, 1816-2006* to determine which countries share a land or river boundary (Correlates of War Project, 2009). I then use the contiguous nation's own instability data (PITF) to code a dichotomous variable, 1 if *any* of the contiguous nations (those with a land or river shared border) were unstable in that year, and 0 if none of the contiguous nations were unstable in that year.

I also control for the effects of some basic country demographic characteristics. First, I control for the *total size of the population*. I use the World Bank *World Development Indicators* (WDI) population data here. I also examine *annual percent change in population* using WDI data to capture the effects of changing population levels on terrorism levels. I also look at the effects of *population density* (per square kilometer) on terrorism levels using WDI data (World Bank, 2009). All three variables are continuous variables. I adjust the scale of the total population variable by dividing each observation by 100,000 so the standard errors and coefficients in my models are more easily estimated and are on-par with the rest of the variables in the model.

I control for population size due to prior findings that a larger population size, a growing population and more densely packed population ought to increase levels of terrorism simply by increasing the number of potentially motivated offenders circulating

an interregnum. Naturally, this shared coding brings up concerns about collinearity between the instability variables and the governance variables. The correlation between the full autocracy variable and the adverse regime change categories is -.0591, indicating only a very small, negative relationship between them, and a correlation between the adverse regime change categories and full democracy of -.1491, indicating only a small, negative relationship between them. The correlation of .2442 between the adverse regime change categories and transitional governance variable that is the reference category in the analyses indicates a small to moderate positive relationship. These small to moderate correlations indicate that including them in the same model is certainly possible without plaguing the model with multicollinearity issues. It is more important to include them and risk a small amount of multicollinearity than risk the larger omitted variable bias inherent in leaving out governance, which is a well-validated predictor of terrorism.

in the population as well as by increasing the probability that such motivated offenders will converge in time and space with unguarded targets in the absence of capable guardianship (Cohen and Felson, 1979). I also control for these population demographics based on prior literature on both state instability and war, two types of which are included as state instability types.

I use World Bank data to control for the well-established relationship between urban dwelling and non-routine collective action (Snyder and Tilly, 1972). I control for the effects of *urbanity,* which is measured as the percentage of the total population which reside in cities. I also control for the *size of the land area* of the state (World Bank, 2009). Both of these demographics are continuous variables. I divide the land area observations by 1,000,000 so that the standard error and the coefficient for this variable are on a similar scale as the rest of the variables in the model.

I control for the degree of urbanity and the size of the land area of the state because of the extant literature. Crime rates and rates of non-routine collective action are higher in cities than in rural areas so all else equal, terrorism rates should be higher in highly urbanized societies (Snyder and Tilly, 1972). I control for the size of the land area of the state, because a larger land area may allow perpetrators of terrorist incidents or rebel groups to have more room to hide in the state (Collier and Hoeffler, 2004). It may also indicate that the government may have a harder time maintaining its state integrity and may predispose the state to instability (Menkhaus, 2003).

I also control for the *data collection agency* (GTD2) since I expect differences in the results based on the different ways in which the data were collected. This variable is coded as a 1 for the 1998-2005 time period and zero for the 1970-1997 period.

Please refer to table 12 at the end of the text for a list of the states and years included in Sample 1. I turn now to the variables included in Model 2.

Model 2: Population Age Structure and Social and Economic Development

I describe the control variables I use in Model 2 below. I control for the age structure of the population – specifically, *percent of the population aged 0-14*, *percent of population aged 15-64*, and / or *percent population aged 65 and over* (World Bank, 2009). These are continuous variables. The reference category is the over-65 age group.

The idea behind controlling for the age-structure of the society is that crime and is disproportionately committed by younger people. There are indications that the younger age groups disproportionately engage in terrorism as well (LaFree and Ackerman, 2009). If a society has an unusually large young-adult population, all else equal, the society should have higher levels of terrorism.

Unfortunately, the World Bank data are not structured such that the violent crime-prone years (18-25) can be isolated, but it does begin to control for societies with a good deal of very young people, very old people and all of those in-between. An additional reason why it is important to control for the age structure of the state is that the typical recruitment pool for those committing both terrorism and the ethnic and revolutionary war types of state instability are younger people, certainly those under 65. A society with a surplus of these younger people in society should have a larger volume of both terrorism and instability, all else equal (Collier and Hoeffler, 2004). However, it is important to note that these variables do not actually tap the ages of individuals committing terrorism. It is only an indicator of the distribution of the population in the state by age. I turn now to controls for the state's social and economic development.

Social and economic development is often discussed as an important predictor of terrorism and as such ought to be controlled (Abadie, 2006; Piazza, 2008; Marshall, 2002). Regarding social development, I examine *telephone lines* per 100 people, which is a continuous variable (World Bank, 2009). More landline telephones is used as a proxy to indicate that a society is more technologically and socially advanced. Such social development ought to affect terrorism levels and thus should be controlled.

To get at the idea of economic development, I use several proxy indicators of the concept. I examine indicators of *gross domestic product (GDP) per capita* and the *GDP change rate* (World Bank, 2009) since more economically developed states may be less likely to experience terrorism. I also use the *food production index,* which measures the agricultural production of edible food, excluding coffee and tea (World Bank, 2009); this measure may indicate a more agriculturally based economy. I also use *carbon dioxide emissions* in kilotons to proxy for newly industrializing nations or fully industrialized economies versus primarily agrarian economies. These are all continuous variables. I adjust the scale of both the GDP per capita variable and the carbon dioxide emissions variable by dividing by 10,000.

It is generally acknowledged that economic development and strength ought to play some role in determining where terrorism occurs. However, GDP has never truly been shown as a consistent predictor of terrorism, with some studies reporting positive significant relationships (Piazza, 2008) and others reporting no relationship (Abadie, 2006). To delve into this relationship, I have included a whole host of economic variables. With GDP per capita, I intend to tap the effects that the current size of the economy has on the probability of terrorism. With change in the GDP per capita, I intend to capture the effects of changes in the size of the economy, both positive and negative. Both a rapidly growing or shrinking economy can create the motive for more terrorism. With the food production index, I try to capture the effects of a more agrarian economy. All else equal, I would expect less terrorism in a more agrarian society. Finally, the carbon dioxide emissions are intended to capture a rapidly changing industrial sector or a well-developed industrial sector in comparison to a low-industry society. All else equal, I would expect more terrorism in a rapidly industrializing or an industrialized nation than in a non-industrial society. These economic variables are intended to capture the effects of the economy on the occurrence of terrorism.

Table 12 at the end of the text lists the states and years available for the population age structure and social and economic development variables. I turn now to the control variables that will address the ethnic minority group characteristics included in Model 3.

Model 3: Ethnic Minority Group Characteristics

I utilize the Minorities at Risk data (Minorities at Risk, 2008) to control for ethnic majority – ethnic minority relations within a state that may play a role in the outbreak of ethnic war and genocide on the one side and terrorism on the other. The Minorities at Risk dataset examines ethnic groups they term minorities at risk. A minority at risk is a group with definable hereditary cultural characteristics, such as custom, language or religion, whose membership in the group is recognized by others in the society, with a membership of at least 100,000 members (or 1% of a state's population), and who is targeted by either malevolent or benevolent systematic differential treatment. Finally, the group also must be able to organize in its own interests (CIDCM, 2008). As of 2008, the

MAR data team has identified 282 ethnic minorities at risk from 1945-2006.[15] Table 12 at the end of the text contains the list of states and years in this analysis.

Using the MAR data, I control for *group spatial distribution* because a more concentrated group may be better able to mobilize for terrorism than a more widely dispersed group. [16] Conversely, a dispersed group may be able to coordinate attacks in many more regions of the country. This is a scale variable in the original MAR data. I operationalize it for my analysis as a series of binary variables as follows. The reference category is a dispersed population, with no concentration. The next binary variable, Urban, is coded as a 1 when the group is either primarily in an urban area or constitutes the minority in one region in a country and is 0 otherwise. The next binary variable,

---

15. The MAR data are organized with group-country-year as the unit of analysis; that is, groups can cross countries so that country-year is not unique as a unit of analysis. In addition, there can be multiple MARs per country. In order to deal with the fact that there can be multiple MARs per country at the same time that there can be multiple countries per MAR, I chose to select one MAR per state. Following common practice (Pate, 2009, personal communication), I chose the MAR within a multiple-MAR state that had the highest level of political discrimination leveled against it. In the case of ties, I broke the tie by choosing the MAR with the highest level of economic discrimination leveled against it. When even that tied, I chose the MAR with the highest number unique id as a pseudo-random selection procedure. The unique ids were assigned by me while the data were sorted to within country-year and ascending levels of political discrimination. Given a double tie, I see no way in which the data are systematically made biased by the pseudo random selection procedure.

It is important to note that this method of choosing MARs allows the MAR to vary per state-year so that the most discriminated against MAR per state-year will be chosen. By allowing the MAR chosen per state-year to vary, this introduces error into the model, but it also provides for a stricter test of the independent variable when the control variable is chosen at its highest level of political and / or economic discrimination. It also capitalizes on the state-year as the unit of analysis.

16. For 229 of the 1242 observations for the group spatial distribution scale, there was missing data. I utilized the carry-forward method of missing data imputation in which the prior year's data are utilized to fill in the missing data. I did so with the advice and consultation of the MAR Research Director on the appropriateness of this method of imputation (Pate, 2009, personal communication). It is important to note that these data are missing because the data were not collected, not because they were unavailable. For 217 of the observations, it was one year of data missing. For 9 observations, I needed to fill in two years of data with the non-missing observation coming from 2 and 3 years prior. For 3 observations, I needed to fill in three years of data with the non-missing observation coming from two, three and four years prior. The listwise deletion of these cases carried with it a higher risk of bias through sample selection than the error inherent in carrying forward the prior year's data which would only introduce error if the observation would have changed values had it been observed. Pate (2009, personal communication) assured me that this was a slow-changing variable.

Regional, is coded as a 1 when the group constitutes a majority in one region and others are dispersed and is 0 otherwise. The final category and variable is Concentrated, which is coded as 1 when the group is concentrated in one region and is 0 otherwise.

Next, I control for the degree of restrictions placed on the *group's practice of their religion*. Restrictions on the practice of the group's religion may create the motive for terrorism so it is important to include this variable in my analysis. This is a scale variable in the original MAR data.[17] I disaggregate it into a series of dichotomous variables. The reference category is no religious restrictions, which is coded as 1 when no restrictions are placed on the group's practice of religion. The next variable is Informal Restriction, which is coded as 1 when there is an informal but prevalent discrimination against the group's practice of their religion and 0 otherwise. The next variable is Some Restriction, which is coded as 1 when there are some restrictions placed on the group's practice of their religion and 0 otherwise. The final variable is Sharp Restriction, which as coded as 1 when the group's practice of their religion is sharply restricted (CIDCM, 2008).

I also control for the degree of *economic* and *political discrimination* faced by the group.[18] It is important to control for these types of discrimination, because they may

---

17. I also utilized carry-forward imputation for the same 229 missing observations for this variable. See prior footnote.

18. The economic and political discrimination variables were updated and the missing data that had not previously been collected were collected by members of the MAR team (Asal and Pate, 2005). I use this data to update the original MAR data on these variables so that there are no missing observations on economic and political discrimination. Error is introduced by using a separate source to update the missing observations. However, MAR team resources were utilized in this update collection, and it was overseen by the MAR Research Director. Thus, the error introduced by using the updated data is outweighed by the costs of listwise deletion. It is also outweighed by the costs of using carry-forward imputation with this variable as it is not a slowly-changing variable (Pate, 2009, personal communication). The tie-breaking procedure to choose the MAR group for that year was performed again. The data are available for public download on the MAR website.

manufacture the motive for terrorism incidents. These are scaled variables, and they range from no discrimination, neglect with remedial policies intended to right this neglect, neglect without such policies, social exclusion and ineffective positive or neutral policy to right the effects of this social exclusion and finally, formal exclusion (from either political or economic participation) and repression (CIDCM, 2008). I break these into a series of dichotomous variables as follows.

The reference category for economic discrimination is no discrimination, which is coded 1 when there is no economic discrimination aimed at the group and 0 otherwise. The next variable is Economic Neglect with help, which is coded as 1 when the group suffers from historical neglect, such as being underrepresented in valued occupations or significant poverty, but the government has introduced policies to make the group's economic situation better and 0 otherwise. The next variable is Economic Neglect, which is coded 1 when the group suffers from historical neglect, such as being underrepresented in valued occupations or significant poverty, but the government has not introduced policies to make the group's economic situation better and 0 otherwise. The next variable is Economic Social Exclusion, in which a 1 means that the group has been excluded from valued occupations or is in significant poverty by social practice but not by formal government practice and 0 otherwise. The final economic discrimination variable is Economic Formal Exclusion and is 1 when the government takes formal steps to exclude the group from meaningful economic participation compared to other groups and is 0 otherwise.

The reference category for political discrimination is no discrimination, which is coded 1 when there is no political discrimination aimed at the group and 0 otherwise. The next variable is Political Neglect with help, which is coded as 1 when the group suffers from historical neglect, such as being underrepresented in the public sphere, but the government has introduced policies to make this neglect better and 0 otherwise. The next variable is Political Neglect, which is coded 1 when the group suffers from historical neglect, but no government policies have been undertaken to right this wrong and 0 otherwise. The next variable is Political Social Exclusion, in which a 1 means that the group has been excluded from the political process by social practice but not by formal government practice and 0 is otherwise. The final political discrimination variable is Political Formal Exclusion and is 1 when the government takes formal steps to exclude the group from the political sphere or represses the group and 0 otherwise.

Finally, I will control for group political activity. Finally, I will control for whether the group engages in *group protest* (MAR, 2008).[19] *Protest* is a scaled variable, which ranges from verbal opposition, civil disobedience and small, medium and large physical gatherings of group members (including riots, strikes and rallies) (CIDCM, 2008). It is important to control the political protest activity of a group since it will likely affect the levels of terrorism in a state by providing a legitimate alternative to terrorism. Groups that are able to actively protest activities of the state may not need to turn to terrorism.

I operationalize protest as a series of dichotomous variables as follows. The reference category is no protest. The next category and variable is Verbal Protest, which

19. Rather than carry-forward imputation, I also updated the 229 missing observations that were not collected for this variable with an updated MAR dataset that was assembled by Steven Saideman upon the advice of the MAR Research Director (Pate, 2009, personal communication). The data are referenced here (Saideman and Lanoue, In Process). The error introduced by using a third source to update the missing observations is outweighed by the costs of listwise deletion. It is also outweighed by the costs of using carry-forward imputation with this variable as it is not a slowly-changing variable (Pate, 2009, personal communication).

is coded 1 when the group engages in verbal or written forms of political protest, such as letter writing or petitions, to gain regional independence or autonomy and 0 otherwise. The next category is Symbolic Protest which involves "[s]abotage, symbolic destruction of property OR political organizing activity on a substantial scale (e.g. sit-ins, blockage of traffic)" (CIDCM, 2008: 22) and 0 otherwise. Small Protest is coded as 1 when the participation in the protest activity does not number above 10,000 people and 0 otherwise. Medium Protest is coded 1 when the number of protest participants is between 10,000 and 100,000 and 0 otherwise. Finally, Large Protest is coded 1 when the participation is more than 100,000 persons and 0 otherwise. I turn now to the central hypotheses in this study.

Hypotheses

I have four main hypotheses in this study. The breakdown model predicts that non-routine collective action is more likely to occur after rapid social change. This is because the rapid social change may sever the social ties that bind the individual to the society and induce conformity. The rapid social change and the disruption to current social bonds also may inhibit the creation of new ties to the society. The disintegration of existing ties and the lack of creation of new ties are what suggest that terrorism, a form of non-routine collective action, may be more likely to occur during state instability, a form of rapid social change (Durkheim, 1930 [1951]; Useem, 1998). Thus, I hypothesize that changes in instability status will coincide with changes in terrorism. That is, the very same state should experience higher levels of terrorism when it changes to instability than during changes to stability. This leads me to H1, formally stated below.

H1: Changes in instability status should be associated with changes in terrorism.

Breakdown suggests that once a rapid social change occurs, non-routine collective action may occur. However, not all rapid social change is created equally (Durkheim, 1930 [1951]; Useem, 1998). Wars are likely to loosen controls on individuals' behavior more dramatically and should increase levels of non-routine collective action more than other instability types. Adverse regime changes towards autocracy are likely to increase controls over the behavior of individuals because autocracies by their very nature control their citizens more than any other form of government. This high level of control may decrease the level of terrorism observed. Further, adverse regime changes tend to be short, usually contained during one month of a year. This would also suggest that the effects of adverse regime change on terrorism would be smaller. This difference by instability type is why it is important to analyze the relationship between instability and terrorism by type of instability. I have disaggregated all types of instability out to the state-year. Therefore, I hypothesize that the effects of changes in instability status will vary by the type of instability that the state experiences. I expect that changes in adverse regime change should be associated with small increases in terrorism while changes in ethnic war or revolutionary war status should be associated with large increases in terrorism incidents. I have developed these expectations from the tenets of breakdown theory. This leads me to H2, formally stated below.

> H2: The effects of changes in instability status on changes in terrorism will vary by the type of instability experienced.
>
> H2a: Increases in adverse regime change should be associated with the smallest increases in terrorism.
>
> H2b: Increases in ethnic war or revolutionary war should be associated with larger increases in terrorism.

To review, complex singular instabilities refer to multiple instabilities that occurred within five years but not within the same year. For example, a revolutionary war followed by an adverse regime change two years later would constitute two complex singular instabilities: complex-revolutionary war and complex-adverse regime change. A non-complex singular instability is the occurrence of ethnic war, or any other type, without any other form of instability occurring in that five-year period. Same-year complex instability is when a state experiences more than one instability in the same year. For example, this is when a state experiences an ethnic war in the same year as a genocide. It is possible to experience all four types within the same year. This hypothesis is a logical extension of breakdown theory and is intended to explore the effects of multiple instabilities on terrorism. When multiple rapid social changes occur, they should disintegrate the ties that bind individuals to society more than when one rapid social change occurs within a short time. Thus, one state instability should open the door to non-routine collective action like terrorism; more than one should create more breakdown in the society and create more terrorism due to the grating down of social ties. Finally, stability ought to be associated with less terrorism, because the state has not lost control over the actions of its citizens. H3 and its sub-hypotheses are stated below.

> H3: Increases in terrorism ought to occur when a state experiences increases in complex singular instability as opposed to non-complex singular instability.
>
> H3a: Increases in terrorism ought to occur when a state experiences increases in same-year complex instabilities relative to non-complex singular instability.
>
> H3b: Decreases in terrorism ought to occur when a state experiences increases in stability relative to non-complex singular instability.

For my final hypotheses, I examine not whether multiple instabilities produce more terrorism, but whether the temporal density of the multiple instabilities has implications for how much terrorism should occur. Temporal density refers to the number of instabilities that occurred within a time period; in this case, I refer to the number of instabilities within one year. The comparison is between state-years in which more than one instability occurred and state-years in which only one instability occurred (but multiple instabilities within five years). Here, I make a second logical extension to breakdown theory to hypothesize that a state should be even more at risk of terrorism when it is experiencing more than one instability in a year than when it is experiencing more than one instability within five years but not within the same year. This is because when multiple instabilities occur within the same year, the state should be in a downward spiral of problems caused by the disintegration of existing social ties and the lack of creation of new social ties. This downward spiral ought to include plenty of terrorism so that more than one instability within the same year should be associated with more terrorism than multiple instabilities within a five-year period but not within the same year. That is, more terrorism should occur during same-year complex instabilities than complex singular instability if the temporal density of instability matters. Further, stability should be clearly associated with less terrorism than complex singular instability. I formally state my fourth hypothesis and sub-hypothesis below.

> H4: Increases in terrorism ought to occur when a state experiences increases in same-year complex instability relative to complex singular instability.

> H4a: Decreases in terrorism ought to occur when a state experiences increases in stability than when a state experiences complex singular instability.

I have hypothesized four sets of relationships here, with several sub-hypotheses. Two of these hypotheses come directly from breakdown theory while the other two hypotheses are logical extensions of the breakdown model. In the next section, I describe my analytic strategy for testing these hypotheses.

Analytic Strategy

Because the dependent variable is a count of the number of terrorism incidents within a given state-year, I use a statistical method that models count data appropriately. Linear regression is inappropriate for count data, because it can provide inefficient, inconsistent and biased estimates (Long, 1997). There are several appropriate models to consider. I review these below.

First, there is the classical Poisson model. This model treats the conditional variance as equal to the conditional mean, which is often unrealistic given the nature of most count data. In addition, Poisson often underpredicts the number of zeros (state-years with no terrorism) that should be in the sample (Long, 1997). Upon further examination of my data, I discovered that my data are in fact overdispersed and that there are many more zero country-years in my data than can be handled by the Poisson regression model (see table 3 for the frequency distribution of terrorism and table 4 for summary statistics of terrorism by sample). When I use a pooled Poisson regression with standard errors that take into account the clustering by country, the model under-predicts the volume of zeroes in the data and slightly overpredicts the counts of 1, 2, 3 and 4. Figure 2 demonstrates the model fit of the four analytical strategies tested in this section. The lines represent the difference between the observed and the specific model's prediction of that count of terrorism incidents. The solid line with the closed circle represents the Poisson model, which poorly predicts both zeros and the lower-level counts.

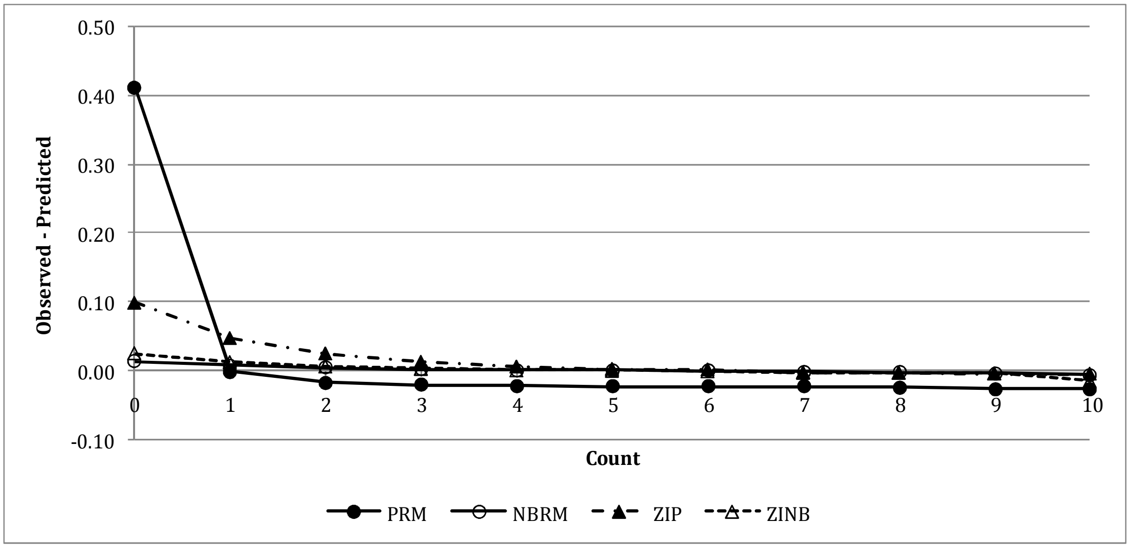

Figure 2. Model fit of observed and predicted counts for four count models.

Second, I tested a pooled negative binomial regression model (NBRM) with clustered standard errors. The negative binomial separately models the conditional variance from the conditional mean to account for overdispersion (Hilbe, 2007). In fact, in a pooled negative binomial regression model with standard errors that take into account the clustering by country, the likelihood ratio test for nested models rejects the null hypothesis of equidispersion, meaning that there is likely overdispersion ($p < .000$). In addition, it does not underpredict zeros as dramatically as the Poisson model. It achieves the best fit of all the models, as demonstrated in Figure 2. The solid line with the open circle represents the NBRM model, and it achieves the smallest differences between the observed and predicted counts 0 through 10. In addition to the good fit achieved by the pooled NBRM model, this model type is able to incorporate more rigorous controls for dependence of observations, such as fixed and random effects. Since this model was chosen, these extensions are explored later. I move next to the zero-inflated Poisson and negative binomial models. However, it is important to note that these zero-inflated models are unable to incorporate fixed or random effects.

The concept behind the zero-inflated models is simple. Statistically, they assume that two different data generation processes and thus statistical distributions underlie the observations that are zeros, states-years that have never experienced the dependent variable, and the non-zeros, those that have experienced terrorism, possibly multiple times (Long, 1997). That is, those state-years that are a zero are allowed to follow their own distribution and are estimated separately using the logit or probit while the state-years with greater than zero values follow their own distribution and are estimated separately using either Poisson or negative binomial. A downside to the zero-inflated models is their inability to incorporate fixed or random effects to control for dependencies within country-groups in the sample. They do allow for clustering by state so that I can start to control for the dependency.

The zero-inflated Poisson (ZIP) is better able to handle the volume of zeros than the PRM as evidenced in Figure 2. The dashed and dotted line with the closed triangle represents the ZIP model. This line shows that the ZIP model provides a better fit to the data than the PRM, but it does not provide the best fit overall. The Vuong test, which is a test to determine whether the zero-inflation is necessary, rejects the Poisson model in favor of the ZIP model ($p<.0000$) (Erdman, 2008; Young and Dugan, Forthcoming). I turn now to the zero-inflated negative binomial model.

The zero-inflated negative binomial model (ZINB) demonstrates adequate model fit (see Figure 2). The dashed line with the open triangle represents the ZINB model, and it follows the NBRM line closely although the NBRM model fits slightly better. The Vuong test preferred the ZINB model over the NBRM ($p<.0000$). This suggests that I ought to select the ZINB model over the NBRM from a model fit perspective. Yet, in

Figure 2, it is clear that the NBRM model provides a very adequate fit to the data as well. However, there are three other important criteria to consider. I turn to these now.

First, I must consider whether I expect a theoretical and essentially qualitative difference between the processes that drive country-years with terrorism and those without (Long, 1997). I do not. My theoretical model predicts that any country-year can experience terrorism if it experiences breakdown, such as state instability, and that breakdown does not influence how many incidents they suffer (counts) differently from whether they experience terrorism (0/1). Without a theoretical model that predicts two different data generating processes, there is little reason to move to the zero-inflated model. The second criterion to consider is parsimony and the ease of interpreting model results (Cameron & Trivedi, 2009). The zero-inflated models are computationally complex as well as conceptually difficult to interpret. The final criterion to consider is the ZINB model's inability to incorporate fixed and random effects. Fixed and random effects allow one to address the dependence between observations in addition to reducing the omitted variables bias in the most rigorous way currently available. Thus, based on the three criteria discussed above as well as the adequate model fit provided by the NBRM, I have chosen the negative binomial regression model.

Negative Binomial Regression Model

Random Effects

The random effects negative binomial regression model (RENBRM) uses both within-country variation and between-country variation to estimate the effects of the independent variables on the dependent variable. This estimation technique allows the user to preserve the data for countries in which there is no variation on the dependent variable over the panel data set in the model, because in this case, the RENBRM will use the variation between countries to produce the estimates. It assumes that the differences across countries and time are essentially random processes. The RENBRM also allows the user to examine independent variables that do not vary over time, which can be quite useful. However, the RENBRM does not allow for the independent variables to be correlated with the time-invariant portion of the error term (Dugan, 2010). In addition, the RENBRM may provide inconsistent estimators in cases in which the dependence between observations overwhelms the model (Cameron and Trivedi, 2009). I turn now to an explanation of the fixed effects negative binomial regression model before providing model fit statistics for each.

Fixed Effects

In contrast, the fixed effects negative binomial regression model (FENBRM) only uses within-country variation to estimate the effects of the independent variables on the dependent variables. This type of analysis allows the purest theoretical test in this case, because it only uses the within-country variation to estimate the coefficients; specifically, it uses the deviations from the country-specific mean to estimate the coefficients. It essentially creates a series of dichotomous variables that allow the model to control for all of the time-invariant differences without knowing what those differences actually are. The FENBRM reduces the correlations between the independent variables and the time-stable unobserved differences (fixed effects) from the error term by absorbing them into the fixed effects. This is a much more realistic assumption in the prediction of terrorism than the no correlation assumption in the RENBRM model (Cameron and Trivedi, 2009). If there is enough variation in the dependent and independent variables to successfully estimate the model and to include time fixed effects, then, it is preferred because it allows me to examine the effects of instability *within-country* only. This is the purest test of the concept, because it gets at the effects of instability itself most cleanly and most conservatively without contaminating the effect with between-country variation and by using changes in instability to predict changes in terrorism. Thus, the FENBRM fits my theoretical model the best.

There are three main downsides of using the FENBRM to control for dependence between observations. One is that since the model only uses within-country variation to produce the coefficients, it drops any observations that do not vary on the dependent variable over time. This is a serious drawback. Due to this lack of variation on the dependent variable, four countries are lost in my model (from 151 countries to 147).[20] Because the model only uses within-country variation to estimate the coefficients, the FENBRM model can produce larger standard errors. [21] The second downside is that the

---

20. The following countries were dropped from Model 1 because they did not experience any terrorism incidents over the observation period: Bhutan, Mongolia, Oman, and Turkmenistan. In addition, of these, only Oman experienced any instability which was a revolutionary war from 1970-1976. Fortunately, this is only a minor threat to my hypotheses and theoretical framework, because for three of the four countries, no instability and no terrorism over the observation period is what I would expect given my theoretical framework. However, the case of Oman is slightly more problematic. Given my theoretical framework, I would expect that during the years of revolutionary war, Oman would have experienced terrorism incidents. This is not true. Since this only occurred in one country of my original 151 country sample, I am not very concerned that it constitutes a major threat to the validity of either breakdown theory or my model. Nonetheless, it is still an important contradiction of breakdown theory.

21. I have also rerun all of my models by using an unconditional fixed effects negative binomial model by manually including time and country fixed effects with clustered robust standard errors in a standard (NB2) negative binomial model. All theoretical variables of interest behaved as expected. However, in some models, the model was clearly losing efficiency (inflated standard errors) upon the inclusion of so many parameters. (Allison, 2009). I also ran the Allison (2009) hybrid unconditional fixed and random effects models. This model manually includes the means and deviations from means that are the hallmark of the fixed effects model in a random effects negative binomial model that includes time fixed effects. The story remained substantively the same and my theoretical variables behaved as expected. Since my theoretical variables of interest behaved as expected and the story remained the same, I do not present these models.

To address potential serial correlation above and beyond that which the fixed effects negative binomial is already designed to handle (Cameron and Trivedi, 2009), I ran the standard Stata command for fixed effects negative binomial regression with bootstrapped standard errors. Bootstrapped standard errors at least theoretically control for serial correlation by sampling across clusters during the bootstrapping process when the standard errors are calculated (Angrist and Pischke, 2009). The story remains substantively the same in both significance and direction. Instability is a robust and positive predictor of

FENBRM requires many degrees of freedom to compute, and it requires a good deal of variation on the independent and dependent variables to estimate the model. The third downside is that the model cannot estimate coefficients for independent variables that do not vary over time. However, the advantages of reducing the correlation between the independent variables and the errors through the fixed effects as well as essentially controlling out across-country variation as an alternate explanation of any observed effects of the independent variables on the dependent variable outweigh the inability to use time-invariant regressors. I turn now to a discussion of model fit indices.

Model Fit Indices

I analyzed Model 1 using both the RENBRM and the FENBRM. The model fit indices indicate a clear preference for the fixed effects variant of the negative binomial regression model. I discuss these now. Hausman provides a test for this purpose. The null hypothesis is that the time-invariant part of the error term is uncorrelated with the regressors. If the null cannot be rejected, this means that the RENBRM is a consistent estimator. Since the RENBRM can be much more efficient than the FENBRM, this would provide strong support for the RENBRM (Cameron & Trivedi, 2009). However, the null hypothesis is rejected ($p<.01$). This means that the RENBRM provides inconsistent estimates of the effects of the independent variables for Model 1. This is evidence in support of the selection of the FENBRM.

Further, there are two model fit indices that are appropriate for non-nested models such as the FENBRM and the RENBRM. They are the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). Both of these tests provide

---

terrorism incidents. For simplicity's sake, I present the results using the standard Stata command for fixed effects negative binomial regression with time fixed effects but without bootstrapped standard errors.

comparative fit indices, in which the log of the likelihood function is examined for each model, and then the model that provides the smallest values on either index, BIC or AIC, provides the best fit. In both cases, the AIC and the BIC prefer the FENRBM over the RENBRM as demonstrated in table 2. Given that both sets of model indices endorse the FENBRM and that I prefer the FENBRM as discussed above, I have chosen to estimate the remaining models with the FENBRM.[22] Equation 1 describes the model I will be using for the rest of the study (StataCorp LP, 2009: 368).

$$\Pr\left(Y_i = y_{i1}, \ldots, Y_{in_i} = y_{in_i} \middle| \boldsymbol{X}_i, \Sigma_{t=1}^{n_i} Y_{it} = \Sigma_{t=1}^{n_i} y_{it}\right)$$

$$= \frac{\Gamma\left(\Sigma_{t=1}^{n_i}\lambda_{it}\right)\Gamma\left(\Sigma_{t=1}^{n_i} y_{it}+1\right)}{\Gamma\left(\Sigma_{t=1}^{n_i}\lambda_{it}+\Sigma_{t=1}^{n_i} y_{it}\right)}\Pi\frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \quad (1)$$

The conditional log likelihood is contained in Equation 2.

$$lnL = \sum_{i=1}^{n_i} w_i \left[ln\Gamma\left(\sum_{t=1}^{n_i}\lambda_{it}\right) + ln\Gamma\left(\sum_{t=1}^{n_i} y_{it}+1\right) - \ln\Gamma\left(\sum_{t=1}^{n_i}\lambda_{it} + \sum_{t=1}^{n_i} y_{it}\right)\right.$$

$$\left. + \sum_{\mathrm{t}=1}^{n_i}\{\ln\Gamma(\lambda_{it}+y_{it}) - ln\Gamma(\lambda_{it}) - ln\Gamma(y_{it}+1)\}\right] \quad (2)$$

where $\lambda_{it} = \exp(x_{it}\beta + offset\ _{it})$, w_i is the weight for the *i*th group, and $\boldsymbol{X}_i = (x_{i1}, \ldots, x_{in_i})$. In addition, I include time fixed effects in each model with 2005 excluded as the reference year. I include the time fixed effects because there are likely many changes over time between 1970-2005 that are likely to influence both instability and terrorism (Dugan, 2010).

Table 2. RENBRM and FENBRM Fit Statistics

22. I reran Models 1, 2 and 3 excluding the 10 highest and lowest residuals, and I also reran the models excluding outliers (defined as more than 400 reported incidents per country-year). All models remained substantively the same.

Criteria	FENBRM	RENBRM
BIC	18176.58	20065.22
AIC	17892.67	19767.24
Hausman Test	$\chi 2(43) = 72.83$	$p < .01$

I present my results with raw coefficients, in incidence rate ratios, and in the predicted probability, expressed as the expected counts of terrorism incidents given that the control variables are held at certain values. Incidence rate ratios report exponentiated coefficients. The predicted probabilities I present actually predict the number of expected events which is more meaningful in this context, rather than the linear prediction, while holding certain interesting dichotomous control variables at 0 or 1 and all other continuous control variables at their median.[23] I turn now to an explanation of the changes in data coverage across the control variables.

Accounting for Differences in Data Coverage across Control Variables

In a perfect data world, I would be able to include as many control variables as I felt were needed to allow for the cleanest inferences about the relationship between political instability and terrorism. Unfortunately, the coverage in data sources does not allow for this for all states included here from 1970 to 2007. For these reasons, I have divided my analysis into three models, each with their own sample of nations and years.

Model 1 uses country demographics, governance and contiguity characteristics control variables for Sample 1, which is composed of 147 nations from 1970 to 2005. Sample 1 contains a total of 4687 observations. It is important to understand that even this group of countries and years is a sample of the possible nation-states in the world. Of

23. I use the median because many of the control variables are skewed and the use of the median avoids using an inflated or deflated mean.

a possible 164 nations evaluated by PITF, only 147 are included in Model 1. I am unable to include such countries as Afghanistan and Iraq in Sample 1 due to the lack of basic country demographics from the World Bank data. This is particularly unfortunate, because these are perhaps the two countries in which state instability and terrorism are discussed the most in the policy and practitioner domain in recent years. However, due to the decade of war that each experienced, in Afghanistan the war to repel the Soviets from 1979 to 1989 and in Iraq, the Iran-Iraq war from 1980 to 1988, control variable data simply does not exist for these states. Further, the PITF data simply does not examine countries with less than 500,000 population, which they term micro-nations. These states are simply excluded from Samples 1, 2, and 3. In addition, the selection of 1970 as a starting year for countries that existed before this date is only a sample of possible years that is predicated on the beginning of the GTD data. In this way, even this large group of nations and years constitute a sample of the possible countries and years. However, to date, this is the most comprehensive examination of the relationship between domestic and transnational terrorism and state instability and represents a distinct improvement over prior efforts and a contribution to the literature.

Model 2 adds population age structure and social and economic development control variables for Sample 2, 116 states from 1981 to 2005, with a total of 2624 observations. Model 3 adds the ethnic and minority group characteristics for control variables on Sample 3, 82 nations from 1990 to 2005, with a total of 1242 observations. I also replicate the Model 1 analysis on Samples 2 and 3. The comparison between the results of Models 2 and 3 allows me to examine the effects of omitted variable bias on the Model 1 analysis. The comparison between the differences between the Model 1 analysis on Sample 1 and the Model 1 analysis on Samples 2 and 3 allow me to comment on the role that sample selection bias plays in the results. I turn now to my results chapter.

Chapter 4

Results

Descriptive Statistics

Introduction

In this chapter, I begin by reviewing the summary statistics for terrorism and instability in each of my three samples. The samples varied from 147 nations from 1970 to 2005 in Sample 1 to 116 nations from 1981 to 2005 in Sample 2 and finally, 82 nations from 1990 to 2005 in Sample 3. I also compare the samples to one another via the summary statistics for terrorism, instability and the common control variables, which are the variables that measure the country-level demographics, governance and contiguity of unstable nations. Then, I present the results for Hypothesis 1 for all three models. I also review the results of each model's control variables in the context of Hypothesis 1. I use these results as well as the results of the Model 1 replication on Samples 2 and 3 to comment on the degree of omitted variable and sample selection biases present in my models. Then, I conclude the chapter. I turn now to the summary statistics for the three samples.

Summary Statistics Review for Sample 1

In this section, I review the summary statistics for terrorism and instability for my three samples. Then, I compare across the samples to demonstrate the differences between each of them using the summary statistics on terrorism, instability and the common control variables. I turn now to Sample 1. The summary statistics for each model and sample are contained in separate tables while the distribution of terrorism incidents by sample is contained in table 3.

Table 3. Distribution of terrorism incidents for all samples (truncated at 47)

Incidents	Sample 1	%[a]	Incidents	Sample 2	%[a]	Incidents	Sample 3	%[a]
0	2,358	50.31	0	1,105	42.11	0	434	34.94
1	514	61.28	1	299	53.51	1	136	45.89
2	286	67.38	2	168	59.91	2	98	53.78
3	190	71.43	3	105	63.91	3	51	57.89
4	136	74.33	4	86	67.19	4	38	60.95
5	102	76.51	5	69	69.82	5	39	64.09
6	83	78.28	6	51	71.76	6	29	66.43
7	56	79.48	7	37	73.17	7	18	67.87
8	42	80.37	8	25	74.12	8	11	68.76
9	41	81.25	9	26	75.11	9	10	69.57
10	44	82.18	10	32	76.33	10	17	70.93
11	39	83.02	11	25	77.29	11	17	72.30
12	28	83.61	12	18	77.97	12	10	73.11
13	25	84.15	13	18	78.66	13	7	73.67
14	24	84.66	14	17	79.31	14	8	74.32
15	24	85.17	15	17	79.95	15	10	75.12
16	28	85.77	16	18	80.64	16	7	75.68
17	22	86.24	17	19	81.36	17	13	76.73
18	23	86.73	18	16	81.97	18	9	77.46
19	17	87.09	19	11	82.39	19	7	78.02
20	15	87.41	20	8	82.70	20	4	78.34
21	14	87.71	21	13	83.19	21	8	78.99
22	19	88.12	22	13	83.69	22	10	79.79
23	24	88.63	23	16	84.30	23	8	80.43
24	9	88.82	24	6	84.53	24	1	80.52
25	11	89.05	25	8	84.83	25	7	81.08
26	9	89.25	26	8	85.14	26	5	81.48
27	11	89.48	27	10	85.52	27	6	81.96
28	11	89.72	28	9	85.86	28	4	82.29
29	12	89.97	29	9	86.20	29	7	82.85
30	12	90.23	30	9	86.55	30	8	83.49
31	8	90.40	31	3	86.66	31	1	83.57
32	6	90.53	32	3	86.78	32	1	83.66
33	9	90.72	33	7	87.04	33	5	84.06
34	5	90.83	34	3	87.16	34	2	84.22
35	7	90.98	35	6	87.39	35	4	84.54
36	6	91.10	36	6	87.61	36	4	84.86

Incidents	Sample 1	%[a]	Incidents	Sample 2	%[a]	Incidents	Sample 3	%[a]
37	8	91.27	37	5	87.80	37	3	85.10
38	18	91.66	38	14	88.34	38	12	86.07
39	4	91.74	39	3	88.45	39	2	86.23
40	6	91.87	40	6	88.68	40	1	86.31
41	8	92.04	41	6	88.91	41	4	86.63
42	3	92.11	42	2	88.99	42	1	86.71
43	6	92.23	43	5	89.18	43	3	86.96
44	5	92.34	44	5	89.37	44	4	87.28
45	6	92.47	45	5	89.56	45	2	87.44
46	6	92.60	46	5	89.75	46	4	87.76
47	7	92.75	47	4	89.90	47	1	87.84

[a] Percentage is cumulative.

Sample 1 contains 147 states with data from 1970 to 2005. There are a total of 4687 state-year observations in Sample 1. Sample 1 is the largest sample of countries and years of domestic and transnational terrorism that have been used in the literature thus far to test the instability – terrorism relationship. The summary statistics for Sample 1 are shown in table 4.

Terrorism incidents

Terrorism is a count variable. The minimum is 0 incidents per country-year which constitutes 50.3% of the sample of country-years. The maximum is 645 incidents, which 0.02% of the sample of country-years experienced. The average number of terrorism incidents experienced in Sample 1 is 14.293. The standard deviation is 49.17, demonstrating that there is a good deal of variation in the sample. The distribution of terrorism incidents is highly skewed to the right. Nearly 11% of the country-years in the sample record only 1 incident, followed by 6% of the sample with a record of 2 incidents. 75% of the sample of country-years experienced fewer than 5 terrorism incidents per

Table 4. Summary statistics for sample 1

Variables	Measurement	Sample 1: Mean	Sample 1: *SD*	Sample 1: Minimum	Sample 1: Maximum
Terrorism incidents	Count	14.293	49.17	0	645
Instability					
H1: instability	1/0	0.172	0.377	0	1
H2: instability type					
Complex instability (complex singular and same-year)	1/0	0.137	0.344	0	1
Ethnic war	1/0	0.014	0.117	0	1
Genocide	1/0	0	0	0	0
Adverse regime change	1/0	0.007	0.086	0	1
Revolutionary war	1/0	0.014	0.116	0	1
H3 & H4: multiple instability & timing					
Stability	1/0	0.828	0.377	0	1
Complex singular instability	1/0	0.08	0.272	0	1
Non-complex singular instability	1/0	0.035	0.184	0	1
Same-year complex instability	1/0	0.057	0.231	0	1
<u>Model 1: governance, contiguity & country demographics</u>					
Governance					
Full autocracy	1/0	0.377	0.485	0	1
Full democracy	1/0	0.399	0.49	0	1
Transitional	Reference	0.224	0.417	0	1
Contiguous state instability	1/0	0.431	0.495	0	1
<u>Country demographics</u>					
Total population	Continuous (divided by 100,000)	357.966	1225.21	1.225	13037.2
Population change	Continuous	1.929	1.599	-7.855	17.738
Population density	Continuous	90.8	127.991	1.116	1177.546
Urbanity	Continuous	46.89	23.202	2.4	95.4
Land area	Continuous (divided by 1,000,000)	0.835	1.888	0.001	16.390
Data collection agency					
Gtd2 period	1/0	0.250	0.433	0	1

year. 90% of country-years in Sample 1 recorded fewer than 29 terrorism incidents. The full distribution of terrorism incidents is contained in table 13 in the Data Appendix; here, I present the distribution up to 47 incidents in table 3 to save space.

Instability

I operationalize instability as a series of dichotomous variables for the four hypotheses. Hypothesis 1 uses a dichotomous measure that simply measures when instability occurs at the state-year level. 17% of the sample, or 806 state-years, are instability state-years. For Hypothesis 2, I use a series of dichotomous measures for instability by type. Complex instability, which includes instabilities that occurred in the same year as well as instabilities that occurred within five years of one another but not during the same year, constitutes the modal type of instability; there are 642 instances of complex instability. Ethnic war occurs less frequently than complex instability; only 65 of the 4687 state-years had an ethnic war occurring for that year. There are no genocide years of instability, because this instability type never occurred on its own. Genocide always occurred during other instabilities so that genocide is always contained in the complex category. Adverse regime change is very rare; there are only 35 country-years of adverse regime change. Finally, there are 64 country-years of revolutionary war.

For hypotheses 3 and 4, I use the same operationalizations of instability. Stability is the reverse coding of instability so that there are 3881 observations of instability of the 4687 total. Complex singular instability, when multiple instabilities occur within the same five-year period but not within the same year, constitutes 376 observations. There are 164 instances of non-complex singular instability, when instability occurs only once during a five year period. Finally, there are 266 occurrences of same-year complex instability, which is when multiple instabilities occur within the same year. I turn now to

Sample 2. Note that I will review the Model 1 control variables later in this section, when I compare the samples.

Summary Statistics Review for Sample 2

Terrorism incidents

Sample 2 contains data for 116 nations from 1981 to 2005. The summary statistics for Sample 2 are shown in table 5. There are 2624 country-year observations in Sample 2. The minimum of terrorism incidents in Sample 2 is 0 incidents, which is experienced by 42% of the sample or 1105 country-years. The maximum is 645 incidents, 0.04% of the sample or one country-year. The mean of terrorism incidents for Sample 2 is 20.195, with a standard deviation of 60.095 incidents. The distribution of incidents has a clear right skew. Approximately 42% of the sample experiences no terrorism incidents in that year. 299 country-years or 11% of the sample report just 1 terrorism incident. 75% of the sample experiences fewer than 9 terrorism incidents. 90% of the sample of country-years reports fewer than 48 incidents. I turn now to the distribution of instability for Sample 2. The distribution of terrorism incidents is contained in table 3.

Instability

As in Sample 1, the instability variables are measured as dichotomous indicator variables. For Hypothesis 1, I use a dichotomous indicator for the occurrence of instability. Sixteen percent of Sample 2, or 426 observations, are country-years of instability. For Hypothesis 2, the dichotomous variables measure the occurrence of the different types of instability. Complex instability is the most common form of instability; 12% of the sample, or 311 observations, are country-years of complex instability. Ethnic war occurred in 52 country-years, or just less than 2% of Sample 2. Genocide is only experienced as part of a complex instability so it has 0 observations. Adverse regime

Table 5. Summary statistics for sample 2

Variables	Measurement	Sample 2: Mean	Sample 2: *SD*	Sample 2: Minimum	Sample 2: Maximum
Terrorism incidents	Count	20.195	60.095	0	645
Instability					
H1: instability	1/0	0.162	0.369	0	1
H2: instability type					
Complex instability (complex singular and same-year)	1/0	0.119	0.323	0	1
Ethnic war	1/0	0.02	0.139	0	1
Genocide	1/0	0	0	0	0
Adverse regime change	1/0	0.005	0.07	0	1
Revolutionary war	1/0	0.019	0.137	0	1
H3 & H4: multiple instability & timing					
Stability	1/0	0.838	0.369	0	1
Complex singular instability	1/0	0.078	0.268	0	1
Non-complex singular instability	1/0	0.044	0.205	0	1
Same-year complex instability	1/0	0.041	0.198	0	1
<u>Model 1: governance, contiguity & country demographics</u>					
Governance					
Full autocracy	1/0	0.258	0.438	0	1
Full democracy	1/0	0.501	0.5	0	1
Transitional	Reference	0.241	0.428	0	1
Contiguous state instability	1/0	0.444	0.497	0	1
<u>Country demographics</u>					
Total population	Continuous (divided by 100,000)	448.885	1459.057	3.608	13037.2
Population change	Continuous	1.778	1.377	-7.855	11.181
Population density	Continuous	106.969	149.154	1.498	1177.546
Urbanity	Continuous	49.337	22.324	4.48	92.3
Land area	Continuous (divided by 1,000,000)	0.891	2.018	0.001	16.389
Data collection agency					
Gtd2 period	1/0	0.3536585	0.4781959	0	1

Variables	Measurement	Sample 2: Mean	Sample 2: *SD*	Sample 2: Minimum	Sample 2: Maximum
Model 2: population age structure and social and economic development.					
Population age structure					
% Population aged 0-14	Continuous (Percentage)	34.617	10.578	13.884	51.462
% Population aged 15-65	Continuous (Percentage)	59.001	6.767	46.184	79.048
% Population aged 65+	Reference	6.382	4.557	1.083	19.747
Social and economic development					
Telephone lines	Continuous (per 100 people)	14.061	18.113	0.012	74.462
GDP per capita	Continuous (divided by 10,000)	0.529	0.811	0.008	4.419
Change in GDP per capita	Continuous	1.395	5.108	-47.085	37.573
Food production index	Continuous	89.062	19.639	11.18	199.39
CO2 emissions	Continuous (divided by 10,000)	16.529	59.591	0	577.643

change is quite rare in Sample 2. There are only 13 country-years of adverse regime change, or 0.5% of the sample. There are 50 country-years of revolutionary war, or 1.9% of Sample 2.

Hypotheses 3 and 4 utilize the same set of dichotomous measures of instability. There are 2198 instances of stability, the reverse of instability; this constitutes 83.77% of Sample 2. Complex singular instability, when just one instability occurs within a year but more than one instability occurs within a five year period, accounts for 7.7% of the sample, or 204 country-years. Non-complex singular instability, just one instability in a five-year period, accounts for 4.4% of the sample, which is 115 state-years. Same-year complex instability, which is when multiple instabilities occur within the same year, constitutes 107 observations in Sample 2, which is 4.1% of the country-years. I turn now to Sample 3.

Summary Statistics for Sample 3

Terrorism incidents

Sample 3 contains data from 82 nations, from 1990 to 2005, with a total of 1242 observations. The descriptive statistics for Sample 3 are shown in table 6. Thirty-five percent of these observations, 434 country-years, record 0 terrorism incidents. The maximum observation, as in the prior samples is 645 incidents in one country-year, which constitutes 0.08% of the sample. The mean for terrorism incidents in Sample 3 is 22.415, with a standard deviation of 58.83 incidents. Approximately 11% of the sample, or 136 country-years, report 1 incident. Seventy-five percent of the sample experiences less than 14 incidents per country-year while 90% of the sample experiences less than 64 terrorism incidents per country-year. I turn to the distribution of instability for this sample.

Instability

Instability is distributed as follows in Sample 3. Seventeen percent of the 1242 observations in Sample 3 experience instability, which constitutes 214 country-years of instability. This is the measure for Hypothesis 1. For Hypothesis 2, instability by type, 157 state-years, or nearly 13% of Sample 3 experiences complex instability. Ethnic war occurs in 34 country-years, or 2.74% of Sample 3. As before, genocide never occurs on its own but only nested within the complex category. Adverse regime change is the rarest of the instability types with only 5 occurrences, a scant 0.4% of Sample 3. Finally, revolutionary war constitutes 1.45% of the sample and occurs 18 times.

Table 6. Summary statistics for sample 3

Variables	Measurement	Sample 3: Mean	Sample 3: *SD*	Sample 3: Minimum	Sample 3: Maximum
Terrorism incidents	Count	22.415	58.83	0	645
Instability					
H1: instability	1/0	0.172	0.377	0	1
H2: instability type					
Complex instability (complex singular and same-year)	1/0	0.126	0.332	0	1
Ethnic war	1/0	0.027	0.163	0	1
Genocide	1/0	0	0	0	0
Adverse regime change	1/0	0.004	0.63	0	1
Revolutionary war	1/0	0.014	0.12	0	1
H3 & h4: multiple instability & timing					
Stability	1/0	0.828	0.377	0	1
Complex singular instability	1/0	0.09	0.287	0	1
Non-complex singular instability	1/0	0.046	0.209	0	1
Same-year complex instability	1/0	0.036	0.187	0	1
Model 1: governance, contiguity & country demographics					
Governance					
Full autocracy	1/0	0.17	0.376	0	1
Full democracy	1/0	0.595	0.491	0	1
Transitional	Reference	0.235	0.424	0	1
Contiguous state instability	1/0	0.483	0.5	0	1
Country demographics					
Total population	Continuous (divided by 100,000)	599.03	1778.27	4.93	13037.2
Population change	Continuous	1.488	1.381	-7.855	11.181
Population density	Continuous	112.95	167.652	1.712	1177.55
Urbanity	Continuous	53.298	21.414	5.4	92.3
Land area	Continuous (divided by 1,000,000)	1.171	2.482	0.001	16.389
Data collection agency					
Gtd2 period	1/0	0.528	0.499	0	1

Variables	Measurement	Sample 3: Mean	Sample 3: *SD*	Sample 3: Minimum	Sample 3: Maximum
Model 2: population age structure and social and economic development.					
Population age structure					
% Population aged 0-14	Continuous (Percentage)	32.481	10.541	13.884	51.348
% Population aged 15-65	Continuous (Percentage)	60.548	6.542	46.184	71.919
% Population aged 65+	Reference	6.971	4.728	2.23	19.747
Social and economic development					
Telephone lines	Continuous (per 100 people)	16.25	18.211	0.018	74.462
Gdp per capita	Continuous (divided by 10,000)	0.507	0.806	0.008	3.897
Change in gdp per capita	Continuous	1.942	5.166	-47.09	37.573
Food production index	Continuous	97.117	14.725	46.58	199.39
Co2 emissions	Continuous (divided by 10,000)	24.119	74.606	0.001	577.643
Model 3: ethnic minority group characteristics					
Religious restrictions					
None	Reference	0.825	0.38	0	1
Informal	1/0	0.097	0.296	0	1
Some	1/0	0.06	0.237	0	1
Sharp	1/0	0.019	0.135	0	1
Political discrimination					
None	Reference	0.084	0.277	0	1
Neglect with help	1/0	0.164	0.371	0	1
Neglect	1/0	0.147	0.355	0	1
Social exclusion	1/0	0.273	0.446	0	1
Formal exclusion	1/0	0.332	0.471	0	1
Economic discrimination					
None	Reference	0.168	0.374	0	1
Neglect with help	1/0	0.11	0.312	0	1
Neglect	1/0	0.197	0.398	0	1

Variables	Measurement	Sample 3: Mean	Sample 3: *SD*	Sample 3: Minimum	Sample 3: Maximum
Social exclusion	1/0	0.359	0.48	0	1
Formal exclusion	1/0	0.166	0.372	0	1
Protest					
None	Reference	0.366	0.482	0	1
Verbal	1/0	0.14	0.347	0	1
Symbolic	1/0	0.209	0.406	0	1
Small	1/0	0.224	0.417	0	1
Medium	1/0	0.046	0.209	0	1
Large	1/0	0.16	0.126	0	1
Group spatial distribution					
Dispersed	Reference	0.206	0.405	0	1
Urban	1/0	0.147	0.355	0	1
Regional	1/0	0.184	0.388	0	1
Concentrated	1/0	0.462	0.499	0	1

For Hypotheses 3 and 4, I examine the effects of stability, complex singular instability, non-complex singular instability and same-year complex instability. Stability is the norm, with 83% of country-years or 1028 observations. There are 112 observations of complex singular instability, which is 9% of Sample 3. Non-complex singular instability constitutes 4.59% of the sample, or 57 country-years. Same-year complex instability is observed 45 times in the sample and makes up 3.62% of Sample 3. I turn to a comparison of the three samples with respect to terrorism, instability and the control variables that are common across the models.

Comparing the Samples

Introduction

I compare the samples used in this study here via their distributions on terrorism, instability and the control variables that are common across all 3 samples, which are the country demographics, governance and contiguity characteristics. The purpose of comparing across the samples is to understand the important similarities and differences between them. This will help to inform my analyses and the extent to which the differences between models may be due, in part, to any differences across samples. In addition, if the samples are very similar, any model results that differ cannot be attributed solely to the observed differences across samples.

Terrorism

A close examination of the distribution of terrorism incidents in table 3 demonstrates that although the samples decrease in size, they increase in terrorism. In Sample 1, 50% of the sample experiences no terrorism incidents. In Sample 2, this is down to 42% of country-years. In Sample 3, only 35% of the sample observes 0 incidents. Interestingly, the percentage of observations that report 1 incident remains constant across the 3 samples at approximately 11%. That is where the similarities end, however. The number of incidents at the seventy-fifth percentile increases steadily when I look across samples. In Sample 1, 75% of the country-years experience less than 5 incidents; in Sample 2, this increases to less than 8 incidents. In Sample 3, this has increased to less than 14 incidents. Further, the 90th percentile shows the same pattern. In Sample 1, this threshold occurs at less than 30 incidents; for Sample 2, it increases to less than 48 incidents. For Sample 3, this threshold is at fewer than 64 incidents. In addition, although the minimums and maximums remain the same, the means increase across the samples. The mean of terrorism incidents increases monotonically across the samples, from 14 incidents in Sample 1 to 22 incidents in Sample 3. Interestingly, the change in standard deviations is not a monotonic increase; Sample 2 evidences the largest variability in terrorism incidents with a standard deviation of 60.095 incidents. These statistics demonstrate that the loss of country-years as I change samples concentrates terrorism by primarily deleting country-years in which no incidents occur. These samples become more serious with regards to their average levels and overall distribution of terrorism incidents. It is unknown exactly what effect this increasing seriousness of terrorism across samples will have on my analyses. I turn now to examine the changes for instability as I look across samples.

Instability

Examination of the summary statistics for instability across the three samples shows little change in the means of each dichotomous indicator. This shows that the loss of country-years from sample to sample pulled from observations of both stability and instability. The proportion of instability to stability country-years remained roughly the same even though the absolute number of observations decreased dramatically. Across the samples, roughly 17% of observations were instability country-years. The distributions by type of instability did vary a bit, particularly for Sample 2. Roughly speaking, complex instability was the most common in Sample 1. Ethnic war country-years as a percentage of all of the country-years were most common in Sample 3 and least in Sample 1. The opposite was true for adverse regime change. Revolutionary war country-years were more consistent in distribution across the three samples, with Samples 1 and 3 being the most similar. Complex singular instability was least common for Sample 2. Non-complex singular instability and same-year complex instability evidenced monotonic changes in distribution in opposite directions across the samples; Sample 1 experienced the least non-complex singular instability percentagewise and the most same-year complex instability. Although there are some variations by type, instability is distributed quite similarly in the three samples. This should mean that the effects of instability ought to remain roughly consistent across the changes in samples.

Model 1 Control Variables: Country Demographics, Governance and Contiguity Characteristics

Table 7 contains summary statistics for the Model 1 control variables for the three samples. These are the control variables that have data for all three samples. These show a clear and monotonic pattern across the three samples. Sample 1 shows that, on average, it has less populous, less densely packed populations, less urban and smaller land area observations. On average, it contains more observations of full autocracy and less of full democracy and fewer years of contiguity to an unstable state. On the other hand, Sample 3 is made up of more populous, more densely packed, more urban and larger land area observations, on average. They also generally show more variation on these characteristics. Sample 3 observations are least likely to be fully autocratic and show a clear trend towards full democracy, on average. They are also more likely to be contiguous to an unstable state, on average. For any of these control variables, Sample 2 is usually in the middle of the two samples. Overall, Samples 1 and 2 are the most similar of the three. Sample 3 demonstrates some important differences from both Samples 1 and 2.

Conclusions

Several important differences and similarities have been demonstrated across the three samples. Interestingly, the changes are generally monotonic across the samples; as the sample size decreases, the differences become apparent in order from Sample 1 to 2 to 3. The most important difference for this analysis is that they vary quite a bit with regards to terrorism. Sample 3 has a much lower percentage of observations with no

Table 7. Summary statistics of the model 1 control variables for all 3 samples: Governance, contiguity and country demographics

	Total Population	Population Change	Population Density	Urbanity	Land area	Full Autocracy	Full Democracy	Transitional Government	Contiguous State Instability	GTD2 period
Measurement	Continuous (divided by 100,000)	Continuous	Continuous	Continuous	Continuous (divided by 1,000,000)	1/0	1/0	Reference	1/0	1/0
Sample 1: Mean	357.966	1.929	90.8	46.89	0.835	0.377	0.399	0.224	0.431	0.250
Sample 2: Mean	448.885	1.778	106.969	49.337	0.891	0.258	0.501	0.241	0.444	0.354
Sample 3: Mean	599.026	1.488	112.951	53.298	1.171	0.17	0.595	0.235	0.483	0.528
Sample 1: Std. Dev.	1225.209	1.599	127.991	23.202	1.888	0.485	0.49	0.417	0.495	0.433
Sample 2: Std. Dev.	1459.057	1.377	149.154	22.324	2.018	0.438	0.5	0.428	0.497	0.478
Sample 3: Std. Dev.	1778.265	1.381	167.652	21.414	2.482	0.376	0.491	0.424	0.5	0.499
Sample 1: Min	1.225	-7.855	1.116	2.4	0.001	0	0	0	0	0
Sample 2: Min	3.608	-7.855	1.498	4.48	0.001	0	0	0	0	0
Sample 3: Min	4.93	-7.855	1.712	5.4	0.001	0	0	0	0	0
Sample 1: Max	13037.2	17.738	1177.546	95.4	16.390	1	1	1	1	1
Sample 2: Max	13037.2	11.181	1177.546	92.3	16.389	1	1	1	1	1
Sample 3: Max	13037.2	11.181	1177.546	92.3	16.389	1	1	1	1	1

recorded terrorism incidents than either Samples 1 or 2. The mean of terrorism incidents is the highest in Sample 3. Thus, terrorism is more concentrated, that is, with fewer no-terrorism observations, in Sample 3 than in Sample 1. With terrorism more common in Sample 3, it is possible that it will be easier to see an effect in the instability variables as well as in the control variables in that sample. It may be more difficult to see an effect in Sample 1. Instability is more similarly distributed between the three samples although this breaks down a bit by type. For example, adverse regime change is least likely to occur in Sample 3 while same-year complex instability is proportionally more likely to occur in Sample 1. The overall instability indicator remains quite steady across the samples, which should mean that the overall instability effect will not vary much across the samples. However, there will likely be variation across type of instability in Hypotheses 2, 3 and 4, because the distribution of these indicators varies across samples.

Demographically, Sample 3 is distilled down to the most populous, most urban, largest and most democratic state-years. These differing demographics across the samples potentially means that there will be differing model results across the three samples. These differences and similarities show that it is important to be cautious when comparing model results. These samples vary enough that differential results may be due to sample selection bias. The comparison across the three samples revealed important differences across samples for terrorism, type of instability and the Model 1 control variables. These differences suggest that we should be cautious in extrapolating any results between models, because they may be due to sample selection. This will be discussed in further depth later in the chapter. I turn now to the results for my hypotheses for Model 1.

Results for Hypothesis 1

Introduction

In this section, I review the results of the first hypothesis for all samples. The samples varied from 147 nations from 1970 to 2005 in Sample 1 to 116 nations from 1981 to 2005 in Sample 2 and finally, in 82 nations from 1990 to 2005 in Sample 3. I first review the results of the first hypothesis from Model 1, which contains the country demographics, governance and contiguity characteristics control variables. I then turn to Model 2, which has population age structure and social and economic development control variables in addition to the country demographics, governance and contiguity characteristics. I then examine Hypothesis 1 for Model 3, which contains the ethnic minority group control variables in addition to the earlier control variables. I then conclude by summarizing the support for Hypothesis 1 across the three models. Please note that the results for the control variables and the Model 1 replications across samples are reviewed later in this chapter.

Model 1: Country Demographics, Governance, and Contiguity Characteristics: Hypothesis 1

Theoretical variable of interest

Hypothesis 1 states that increases in instability status will be accompanied by increases in terrorism. I expect this because as the rapid social change of political instability sets in, the ties that bind individuals to society may disintegrate. As this process sets in fully, the actions of individuals in the state may be uncontrolled, and they may do non-routine collective action. This non-routine collective action may take the form of terrorism. This means that I expect that during times of instability, a state will experience more terrorism than when the state is stable. Instability is operationalized in its simplest form for Hypothesis 1; it is a dichotomous indicator where 1 is coded when instability occurred in that year and a 0 when it did not. Recall that because I use the fixed effects negative binomial regression model (FENBRM), the proper interpretation of results involves changes in instability on changes in terrorism within-country, rather than across. I present the results for instability, the theoretical variable of interest first, followed by incidence rate ratios and the predicted counts of terrorism incidents. I turn to the results now, which are contained in table 8.

This model shows, first, that instability is important. Instability is accompanied by statistically significantly greater levels of terrorism. This increase in levels of terrorism is made up of a 2.6 times greater rate of terrorism. Thus, increases in instability result coincide with increasing terrorism levels within a state.

I have broken down the predicted counts of terrorism incidents from this model as follows. Because governance type and instability in contiguous states have been demonstrated as important predictors of terrorism and instability (Eyerman, 1998; Li, 2005; Iqbal and Starr, 2008), I present the predicted counts over various combinations of these binary variables, while holding the continuous control variables constant at their medians.[24] The largest increase in the expected count of terrorism incidents when instability is present in a state is for a fully democratic state that is contiguous to an unstable state while the smallest increase in the expected count of terrorism incidents is for a fully autocratic state without an unstable contiguous state. In the former, when a state experiences instability, terrorism is predicted to increase by 0.19 terrorism incidents

24. There are 568 country-years in which a full democracy is contiguous to an unstable nation. The list of nations who satisfy both conditions is long and varied. It includes India, Israel, Pakistan, Venezuela, Greece and Finland, among other nations.

Table 8. Model results for hypothesis 1 for all three models

	Sample 1: 147 states				Sample 2: 116 states				Sample 3: 82 states			
	B		*SE*	IRR	*B*		*SE*	IRR	*B*		*SE*	IRR
Hypothesis 1												
Instability	0.943	***	0.058	2.566	1.048	***	0.079	2.853	0.997	***	0.130	2.711
<u>Model 1: governance, contiguity and country demographics</u>												
Governance & contiguity												
Full autocracy	-0.663	***	0.067	0.515	-0.675	***	0.092	0.509	-0.845	***	0.167	0.430
Full democracy	0.086		-0.064	1.090	0.152		0.079	1.164	0.283	*	0.113	1.328
Contiguous state instability	0.206	***	0.052	1.229	0.228	**	0.071	1.256	-0.137		0.100	0.872
Country demographics												
Total population	0.000	**	0.000	1.000	0.000	*	0.000	1.000	0.000		0.000	1.000
Population change	-0.018		0.019	0.982	-0.066		0.034	0.936	0.049		0.044	1.050
Population density	0.001	*	0.000	1.001	0.000		0.000	1.000	0.000		0.000	1.000
Urbanity	0.023	***	0.002	1.023	0.015	***	0.003	1.015	0.008		0.004	1.008
Land area	-0.009		0.018	0.991	-0.051	*	0.026	0.950	0.067		0.042	1.069
Data collection indicator												
Gtd2 period	0.145		0.224	1.156	-1.016	***	0.201	0.362	-1.112	***	0.218	0.329
Constant	-2.949	***	0.213		4.405	*	2.166		7.851	*	3.291	
<u>Model 2: population age structure and social and economic development.</u>												
Population age structure												
% Population aged 0-14					-0.052	*	0.020	0.949	-0.082	**	0.030	0.921
% Population aged 15-65					-0.062	*	0.026	0.940	-0.071		0.039	0.932

	Sample 1: 147 states				Sample 2: 116 states				Sample 3: 82 states			
	B		*SE*	IRR	*B*		*SE*	IRR	*B*		*SE*	IRR
Social and economic development												
Telephone lines					-0.002		0.006	0.998	-0.004		0.008	0.996
Gdp per capita					-0.011		0.110	0.989	-0.317	*	0.155	0.728
Change in gdp per capita					-0.011	*	0.005	0.989	0.008		0.007	1.008
Food production index					-0.001		0.002	0.999	-0.013	***	0.003	0.988
Co2 emissions					0.003	**	0.001	1.003	0.002		0.001	1.002
Model 3: ethnic minority group characteristics												
Religious restrictions												
Informal									-0.239		0.128	0.787
Some									0.359	*	0.149	1.431
Sharp									0.790	**	0.289	2.204
Political discrimination												
Neglect with help									0.202		0.273	1.224
Neglect									0.179		0.274	1.196
Social exclusion									0.732	**	0.261	2.079
Formal exclusion									0.799	**	0.266	2.223
Economic discrimination												
Neglect with help									-0.549	*	0.232	0.577
Neglect									-0.580	**	0.216	0.560
Social exclusion									-0.613	**	0.202	0.541
Formal exclusion									-0.513	*	0.221	0.599
Protest												
Verbal									-0.238		0.124	0.788

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Symbolic							0.194 *	0.096	1.214
Small							0.099	0.091	1.104
Medium							0.095	0.133	1.100
Large							0.093	0.225	1.098
<u>Group spatial distribution</u>									
Urban							-0.070	0.166	0.932
Regional							-0.182	0.182	0.833
Concentrated							-0.518 ***	0.147	0.596

***=p<.000

**=p<.01

*=p<.05

(p<.000). In the latter, when instability occurs, only 0.07 more incidents are predicted (p<.000). Although the predicted increase in the expected count of incidents is small, countries that experience instability have a much higher average level of terrorism in general. The mean of terrorism incidents for unstable country-years is 39.3 incidents while the mean for stable country-years is 9.1 incidents. These are non-trivial differences in terrorism incidents between instability and stability. I turn now to my conclusions for Hypothesis 1 in Model 1.

Conclusions

Overall, Model 1 demonstrates that instability matters when it comes to terrorism. When instability occurs, terrorism also increases, and this increase is of a substantial magnitude. I turn now to the results for Model 2.

Model 2: Population Age Structure and Social and Economic Development Variables: Hypothesis 1

Introduction

I test the first hypothesis, that increases in instability should be accompanied by increases in terrorism with an expanded set of control variables in this model. There are 116 states with data from 1981 to 2005 in Sample 2.

Theoretical variable of interest

In this smaller sample of countries and years with the expanded set of controls, state instability still matters. Instability is accompanied by statistically significant increases in terrorism incidents. The rate of terrorism is expected to increase by 2.85 times during instability. I turn now to the predicted counts of incidents for Model 2.

I present the predicted counts of incidents as before, with the governance and contiguous instability control variables varying from 0 to 1 and all of the continuous social and economic demographics held constant at their medians. As in Model 1, the Model 2 predicted counts are highest for a full democracy with an unstable contiguous state and lowest for a full autocracy without an unstable contiguous state. When instability occurs in a full democracy with an unstable contiguous state, terrorism is predicted to increase by 0.74 terrorism incidents ($p<.000$). For a full autocracy without an unstable contiguous state, the occurrence of instability is predicted to result in 0.26 more terrorism incidents ($p<.000$). The magnitude of the instability effect appears to be slightly greater in Sample 2 than in Sample 1. The increase in the magnitude of the instability effect for a smaller sample of countries and years but a larger set of social and economic demographic control variables is an interesting effect and suggests that the change in sample may strengthen the effect of instability in Model 2. However, given that instability was positive and statistically significant in Model 1, the continued robustness of instability in the face of more rigorous controls suggests that it is an important effect.

Conclusions

Overall, Model 2 demonstrated the robustness of the instability effect in a smaller sample of countries with more extensive control variables. Instability remained a positive and statistically significant predictor of terrorism incidents. There was an increase in the magnitude of its effects on terrorism incidents though at least some of this increase in the size of the effects can surely be attributed to the change in samples. The change in samples allowed me to subject the instability effect to an even wider host of controls. As the instability effect survived this more rigorous test, I am more confident in my results that instability is related to terrorism. I turn now to Model 3.

Model 3: Ethnic Minority Group Characteristic: Hypothesis 1

Introduction

I examine the results of the first hypothesis, that increases in state instability is associated with increased terrorism levels with a set of control variables that measure the distribution and characteristics of ethnic minority groups within their state. To be clear, the following analysis only includes a sample of states with an ethnic minority group at risk and thus, applies only to this group of states. Unfortunately, the MAR data do not allow for comparison between countries with minorities at risk with those that do not have minorities at risk, because the MAR team only collected data on a sample of countries that contain MARs and did not assess all nations for MARs (Pate, 2000, personal communication). This means that this analysis cannot provide information about the risk of terrorism due to the occurrence of instability for a state with MARs versus a state without MARs. I turn now to the results for the theoretical variable of interest; all model results are shown in table 8.

Theoretical variable of interest

In Sample 3, state instability is still an important predictor of terrorism. Instability is accompanied by a positive and statistically significant increase in terrorism levels. The occurrence of instability in a state is associated with a 2.71 times larger rate of terrorism incidents. I turn now to the predicted counts of incidents for Model 3.

Again, I present the predicted counts of terrorism incidents broken down by governance type and instability in a contiguous state with the continuous variables held at their medians. However, since some of the ethnic minority group characteristics proved quite important, I added these significant factors into the calculation as well, rather than simply holding them at their medians, and I obtained the highest and lowest predicted counts of incidents. The highest predicted count of incidents is for a fully democratic state that is contiguous to an unstable state in which an ethnic minority group there is the victim of the highest level of political discrimination and is not subject to economic discrimination; terrorism is predicted to increase by 2.46 incidents in such an unstable period ($p<.01$). The lowest predicted count of incidents is for a fully autocratic state that is not contiguous to an unstable state and subjects an ethnic minority group within its boundaries only to economic discrimination (social exclusion from the economic sphere). In this scenario, terrorism levels are predicted to increase by .22 additional incidents during instability ($p<.01$). Instability remains a robust and statistically significantly positive predictor of terrorism events even in this third sample of countries and years with the largest set of control variables.

In the end, the most important result through all of the changes in models and samples, is that instability, the main theoretical variable of interest, remains positive and statistically significant. This means that the instability effect is quite robust. I turn now to the presentation of the results of the control variables for Models 1, 2 and 3 as well as the Model 1 replications. These results will allow me to comment on the effects of omitted variable and sample selection biases in my results.

Results for Control Variables and Model 1 Replications

Introduction

In this section, I review two sets of results. First, for each model, I review the results for the control variables. Then, I review the results of Model 1 replicated using Samples 2 and 3. Taken together, these two sets of analyses will help to clarify the degree to which sample selection bias and omitted variable bias may affect my substantive and theoretical results. I turn now to a presentation of the Model 1 control variables on Sample 1.

Model 1, Sample 1: Control Variables

Governance and contiguity control variables

First, governance type does matter. Compared to a transitional government, a fully autocratic regime is statistically significantly likely to have fewer terrorism incidents. However, relative to a transitional government, a fully democratic regime does not experience statistically significantly different levels of terrorism though the relationship is positive.[25] A state that is contiguous to one that is currently experiencing instability is statistically significantly likely to experience more terrorism incidents than when there are no contiguous unstable nations.

Country demographics

Total population size is a positive and statistically significant predictor of terrorism incidents. Change in a state's population is negative but statistically insignificant. Note that this variable actually captures deviations from the country-specific average changes in population given the fixed effects modeling approach. An increase in the population density of the state is a statistically significant predictor of terrorism incidents. Increases in the urbanity of the state, which measures increases in the percentage of citizens living in cities, is statistically significantly concomitant with increases in terrorism. Total land area is negative but is statistically non-significant.

Data collection agency

In Model 1, the indicator for the later GTD2 period collected by CETIS (1998-2005) was positive and statistically non-significant. This means that the 1998-2005 time period was no more likely to report terrorism incidents than the period from 1970-1997.

25. When the model is run with full democracy as the reference category and the transitional democracy category as the included effect, the incidence rate ratio for transitional democracy is 0.917, indicating a small decrease in terrorism incidents. This effect is not statistically significant in this model.

The IRR implied a 1.16 factor increase in the rate of terrorism incidents for the period from 1998-2005. I turn now to the results of the Model 1 replication on Sample 2; the original Model 1 results and all replication results are shown in table 9.

Model 1 Replication on Sample 2

The purpose of reviewing the results of the Model 1 replication on Sample 2 (116 countries from 1981 to 2005) is to gain an understanding of the role of sample selection bias based on the degree of difference between the results from Sample 1 to Sample 2. If the results are basically the same from Sample 1 to Sample 2, I feel safer making statistical inferences about the effects of the variables. I turn now to these results.

Theoretical variable of interest

Most importantly, the theoretical variable of interest, the dichotomous indicator of instability, is positive and statistically significant. This is also of a similar magnitude as it is in Model 1. Political instability remains a robust predictor of terrorism incidents, even on a smaller sample of countries and year. I turn now to the results for the control variables.

Control variables

When Model 1 is replicated using Sample 2, there is some similarity. Full autocracy, relative to a transitional government, remains negative and statistically significant. Instability in a contiguous state remains a statistically significant predictor of more terrorist incidents in Sample 2. In addition, total population remains positive and statistically significant while total land area remains negative and statistically insignificant. Urbanity is a positive and statistically significant predictor of terrorism incidents in Sample 1 as in Sample 2.

Table 9. Model 1: Replication on all three samples

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Hypothesis 1									
Instability	0.943 ***	0.058	2.566	1.019 ***	0.077	2.770	0.990 ***	0.118	2.691
Model 1: Governance, contiguity and country demographics									
Governance & contiguity									
Full autocracy	-0.663 ***	0.067	0.515	-0.690 ***	0.091	0.502	-0.904 ***	0.153	0.405
Full democracy	0.086	-0.064	1.090	0.175 *	0.077	1.191	0.126	0.114	1.135
Contiguous State instability	0.206 ***	0.052	1.229	0.169 *	0.068	1.184	-0.008	0.098	0.992
Country demographics									
Total population	0.000 **	0.000	1.000	0.000 ***	0.000	1.000	0.000 ***	0.000	1.000
Population change	-0.018	0.019	0.982	-0.114 ***	0.029	0.892	-0.043	0.037	0.958
Population density	0.001 *	0.000	1.001	0.000	0.000	1.000	0.000	0.000	1.000
Urbanity	0.023 ***	0.002	1.023	0.016 ***	0.002	1.017	0.009 **	0.003	1.009
Land area	-0.009	0.018	0.991	-0.005	0.023	0.995	0.025	0.028	1.025
Data collection indicator									
GTD2 period	0.145	0.224	1.156	-1.065 ***	0.185	0.345	-1.325 ***	0.192	0.266
Constant	-2.949 ***	0.213		-1.220 ***	0.193		-0.469 ***	0.253	

***=p<.000

**=p<.01

*=p<.05

There are four main changes in Model 1 results between Samples 1 and 2. In Sample 2, being a full democracy relative to a transitional government does attain statistical significance, and it is positive.[26] This governance paradox has been discussed extensively in the academic literature (see Eyerman, 1998; Li, 2005). The basic idea is that although democracies provide more outlets for legitimate political activity, they also provide more opportunities to succeed at a terrorist incident for those who wish to do violent political action. This is because of government restraints on the infringement of civil liberties in a full democracy, thereby increasing the levels of terrorism in full autocracies relative to transitional governments and full autocracies. Change in population stayed negative but attained statistical significance. Population density stayed positive but lost its statistical significance. Further, the indicator for the data collection agency is negative and statistically significant, which demonstrates that within country, less terrorism is predicted in the 1998-2005 period. There is a 0.34 factor decrease in the rate of terrorism during this time period. It is possible that this decline is partly due to a real trend down in terrorism incidents as well as a data artifact. These changes demonstrate the potential of sample selection bias in the smaller Sample 2 relative to the larger Sample 1 when the same Model 1 is run on both samples.

Although there are important similarities here, there are also differences. The differences are clearly substantial enough so that it would be unwise to make across-sample statistical inferences. In the end, though, what is most important is that my main

---

26. When the Model 1 replication for Sample 2 is run with full democracy as the reference category and transitional government included in the model, the incidence rate ratio indicates a moderate magnitude effect. The terrorism rate decreases by a factor of 0.839 in a transitional government relative to full democracy. This effect is statistically significant ($p<.05$). A full autocracy experiences a 0.421 factor decrease in the terrorism rate relative to a transitional government ($p<.000$).

variable of interest, instability, remains positive and statistically significant in the face of sample changes, year fixed effects and an indicator for the GTD2 period data collection agency. I feel confident that the instability effect is not due to the chosen sample. However, the effects of the control variables in any of the samples ought to be viewed with caution since they may be due to sample selection effects. I turn now to the Model 2 results.

Model 2, Sample 2: Control Variables

Population age structure control variables

Both of the population age structure variables are statistically significant. These variables refer to the percentage of the population of the state within a certain age-range. The reference category is the percentage of the population greater than age 65. A decrease in the percentage of the population from age 0 to 14 and a decrease in the percentage of the population from age 15 to 64 are both associated with statistically significant increases in terrorism incidents relative to the percentage of the population greater than 65. This finding requires some unpacking; a declining youthful and middle-aged population relative to the older population is associated with more terrorism incidents. I turn now to the results of the social and economic development variables.

Social and economic development control variables

Having more telephone lines per 100 people predicts less terrorism, but it is not a statistically significant effect. Although telephone lines are a very basic indicator of social development, this model cannot provide support for the idea that less terrorism may occur in more socially developed societies. The economic development control variables are presented next.

The first economic control variable, GDP per capita, is intended to capture the current size of the state's economy; it exerts a negative influence on terrorism levels, but this effect is not statistically significant.[27] In contrast, the change in GDP per capita is negative and statistically significant. Recall that this variable actually measures deviations from the within-country average change in GDP per capita. This effect suggests that a declining economy occurs alongside increases in terrorism incidents. The food production index is an attempt to capture whether the economy is more agriculturally based, and it demonstrates a negative but statistically non-significant relationship with terrorism incidents. Further, a higher volume of carbon dioxide emissions, representing a more industrialized or an industrializing economy coincides with statistically significantly more terrorism incidents. Overall, these results demonstrate that the economic domain may be important. I turn now to the governance and contiguity control variables.

Governance and contiguity control variables

A fully autocratic state is expected to experience statistically significantly less terrorism relative to a transitional government. However, a fully democratic state is not expected to experience higher terrorism levels relative to a transitional government although the effect is not statistically significant at the traditional .05 level ($p<.10$). Instability in a contiguous state remains a positive and statistically significant predictor of terrorism incidents. I turn now to the results for country demographics.

27. GDP per capita does not achieve statistical significance despite extensive sensitivity analyses including sequentially excluding the three other economic measures. In this context, GDP per capita does not appear to be significantly related to terrorism. However, across sensitivity analyses, both carbon dioxide emissions and change in GDP both significantly predicted terrorism.

Country Demographics

There are some important similarities in the effects of the country demographics as compared to their effects in Sample 1. Total population size remained positive and statistically significant as did urbanity. Change in population size remained negative and statistically insignificant. However, there were also important differences between Models 1 and 2 for these control variables. The data collection indicator was negative and statistically significant in this sample, indicating a 0.36 factor decrease in the terrorism rate for the 1998-2005 period. Population density switched signs, from positive to negative and lost its statistical significance. Total land area switched signs, from positive to negative and just barely attained statistical significance ($p<.05$). I turn now to my conclusions for Model 2.

Conclusions

Model 2 featured an additional batch of control variables that tested new domains, such as the age effect at the state level and the effects of social and economic development. In Model 2, many of these control variables were statistically significant. The statistical significance of this new batch of control variables suggested that there is omitted variable bias in Model 1 as well as many of the models in the literature that do not include them. Despite the effects of omitted variable bias on Model 1, Model 2 continued to support the instability effect for Hypothesis 1 and shows that this effect is not sensitive to the increase in the number of control variables and the reduction in sample size. I turn now to the results of the Model 1 replication on Sample 3.

Model 1 Replication on Sample 3

The purpose of reviewing the results of Model 1 on Sample 3, that is the sample of 82 nations with coverage on the ethnic minority group distribution variables from the

MAR dataset from 1990 to 2005, is to assess the degree to which there may be sample selection issues at work. If there are substantial similarities in the model results across samples, then it is safe to conclude that these are fairly robust effects and are not the result of the sample I have chosen. If there are substantial differences, then, it is not safe to conclude that the effects are robust and the effects may in fact be due to the chosen sample. I turn now to these results.

Theoretical variable of interest

As in all previous models, the effect of instability is positive and significant. In this reduced sample of countries and years, instability accompanies an increase in the levels of terrorism in that year. The robustness of this finding across the models is reassuring and demonstrates that the effect cannot simply be written off to sample selection. The main theoretical variable of interest in this study, instability, remains robust no matter the chosen sample. I turn now to the results for the control variables.

Governance and contiguity control variables

The effects of the governance and state-level demographic control variables are not uniformly as robust as the instability effect. Full autocracy relative to a transitional government does retain a negative, statistically significant effect, and full democracy relative to a transitional government remains positive and statistically insignificant. Yet, instability in a contiguous nation changes signs to negative and loses its statistical significance.

Country demographics

Total population size remains positive and statistically significant and change in population remains negative and statistically insignificant. In addition, urbanity remains positive and statistically significant. Several of the other country demographics change effects. Population density remains positive but loses its statistical significance. Total land area switches signs from negative to positive but continues to be statistically non-significant.

Data collection agency

The indicator for the collection agency is negative and statistically significant. This shows that for this sample, statistically significantly less terrorism was reported for the 1998-2005 period. For the period 1998-2005, the terrorism rate decreases by a factor of 0.27.

The Model 1 replication on Sample 3 demonstrates that for the control variables there may be serious sample selection issues at work. From the comparison of three samples conducted earlier, I know that Sample 3 is composed of the most populous, largest land area, most urban and most densely populated observations of the three samples. This likely plays a role in explaining the differences between Model 1 run on Sample 1 and replicated on Sample 3. It is heartening that in the face of these potential sample selection issues, the main theoretical variable of interest remains a robust predictor of terrorism. I turn now to the results of control variables for the full Model 3.

Model 3, Sample 3: Control Variables

Ethnic minority group characteristics

There are three domains of MAR control variables. The first is the degree to which the group suffers political, economic and religious discrimination. The set of discrimination variables is measured as a series of dichotomous variables, in which the reference category is always no discrimination regardless of the type. Overall, the discrimination domain shows that discrimination matters in some interesting ways.

First, political discrimination of all types against an ethnic minority at risk, relative to no discrimination, coincides with more terrorism incidents. This effect is statistically significant at the higher levels of political discrimination, which are social exclusion from the political sphere and formal exclusion from the political sphere. In contrast, economic discrimination exerts a negative influence on terrorism incidents, all of which are statistically significant. Finally, both some restrictions and sharp restrictions on a group's practice of its religion are statistically significantly related to terrorism, and these effects are positive. Overall, there are important discrimination effects, and their results are opposite. When a state denies an ethnic minority group access to the political sphere or restricts a group's practice of their religion, there is increased risk of terrorism while economic discrimination is associated with a decrease in terrorism. These divergent effects are interesting. I turn now to the second domain of ethnic minority group control variables, political protest activity.

The political protest set of binary variables measure the effects of the full gamut of political protest, from only verbal protest to physical gatherings of people with more than 100,000 participants. The reference category again is no protest activity. All but the verbal protest category have positive effects on terrorism, but only symbolic protest is able to achieve statistical significance. Symbolic protest activity, like sit-ins are statistically significantly associated with higher levels of terrorism incidents relative to no protest. Vocal protest like letter writing and small, medium or large protests are not statistically significantly associated with changes in terrorism. I turn now to the effects of the final domain of ethnic minority group characteristics, concentration of the ethnic minority group in geographic space.

The final ethnic minority group characteristic measures how the ethnic minority group lives within the state. For example, the reference category is dispersion, meaning that the ethnic group resides all over the state. The categories included in the model all show a negative relationship with terrorism. However, only concentration, that is an ethnic minority group which lives concentrated in one region, evidences a statistically significant relationship with terrorism; this effect is negative, relative to a dispersed population. I turn now to the population age structure and social and economic development variables.

Population age structure control variables

The population age structure variables demonstrate some predictive utility in Model 3. The population demographics, relative to the over-65 age group, remain negative, but only the youngest age group retains statistical significance at the traditional .05 level ($p<.10$). Overall, the effects of the population age structure control variables stayed the same in this model but did not both retain statistical significance. I turn now to the social and economic development control variables.

Social and economic development control variables

Regarding social development, the amount of telephone lines per 100 people retains a negative and statistically insignificant relationship with terrorism. The economic control variables demonstrate mixed effects in Model 3. GDP per capita attains statistical significance, and this effect remains negative while change in GDP switches signs from negative to positive and loses its statistical significance. On the other hand, the alternative economic measures switch statistical significance while retaining their original signs. Higher food production in a state predicts statistically significantly less terrorism. Higher carbon dioxide emissions continue to be associated with higher terrorism levels, but this effect loses statistical significance. I turn now to the governance and contiguity control variables.

Governance and contiguity control variables

The governance and contiguity control variables experience some similarities and some changes from Model 1. Full autocracy remains a negative and statistically significant predictor of terrorism incidents. However, full democracy is a positive and statistically significant predictor of terrorism for the full Model 3.[28] Instability in a contiguous state switches signs from positive to negative and loses its statistical significance. I turn now to the results of the country demographics.

Country demographics

The country demographics retain no statistical significance in Model 3. Total population size remains positive, as do urbanity and population density. Total land area and change in population size both switch signs and are positive now. As predictors of terrorism, the country demographics do not fare well in Model 3.

Data collection agency

The indicator that measures the 1998-2005 data collection agency (GTD2) is negative and statistically significant. The terrorism rate decreases by a factor of 0.33

28. Interestingly, full democracy does not attain statistical significance in the Model 1 replication on Sample 3 but does so in the full Model 3. These results seem to be due to a combination of multicollinearity with total population, population density, change in population and urbanity in the Model 1 replication and a suppression effect in Sample 3 that requires the inclusion of infringement of the MAR's practice of their religion and the political discrimination variables in the full Model 3 for the variable to attain statistical significance. I determined this through extensive sensitivity analyses. The lack of robustness of the full democracy effect to changes in samples and the inclusion and exclusion of sets of variables demonstrates that the results for this operationalization of full democracy suffer from both sample selection and omitted variables bias. Thus, the findings for full democracy ought to be viewed with skepticism.

during the GTD2 time period.[29] I turn now to a discussion of the changes in effects for the Model 3 control variables.

Omitted variable bias, multicollinearity and sample selection bias

There are some distinct differences in the results, both in direction and significance when I replicated the Model 1 analysis using Samples 2 and 3. To explore the differences, particularly those found in the Sample 3 replication, I conducted extensive sensitivity analyses, including sequentially excluding variables, particularly highly intercorrelated variables, and replicating Model 2 on Sample 3. After extensive analyses and model comparisons, I conclude that these differences are due to a combination of omitted variable bias in the earlier models and sample selection bias in the case of the Sample 3 analyses.

Although there is a non-trivial amount of intercorrelation and potential multicollinearity between many of my control variables, such as land area and carbon dioxide emissions, through the sensitivity analyses, I have determined that it is unlikely that these correlations are the *only* cause of the changes. In fact, despite sequentially excluding the highly correlated variables and then, excluding whole sets of control variables, including all of the ethnic minority group control variables (essentially running Model 2 on Sample 3), I have been unable to replicate Model 1 results using Sample 3. This leads me to believe that the differential behavior of these variables is *partly* due to the differences between samples. Recall that Sample 3 contains only 43% of the years

29. Although the time fixed effects are necessarily correlated with the data collection agency indicator (which is 1 during the period between 1998-2005), the correlations never rise above 0.3 (negative or positive). This demonstrates a moderate correlation. However, it is necessary to include the time fixed effects due to the vast amount of changes that have occurred over the time series that must be controlled. In addition, it is also necessary to include the indicator for the data collection agency since there were non-trivial differences between the GTD1 and GTD2 collection efforts. To obtain the best model, I include both and conclude that this is an acceptable amount of correlation.

and 46% of the countries in Sample 1 and that of these, Sample 3 contains the most populous, most democratic, largest land area, most urban and most densely populated observations. In addition to the potential of sample selection bias, omitted variable bias may also be responsible for the changes from the earlier models to Model 3. There are many significant results in Model 3 which are of high magnitude. This means that the results of the earlier models must have suffered from omitted variable bias since these models did not include those variables. It is clear that it was both useful and informative to utilize the multi-stage analysis technique in order to find a balance between omitted variable bias and sample selection bias.

In the end, the most important result through all of the changes in models and samples, is that instability, the main theoretical variable of interest, remains positive and statistically significant. This means that the instability effect is quite robust and is unchanged by the omitted variable bias and sample selection bias that has influenced the results for many of the other variables. I turn now to the chapter conclusions.

Conclusions

In this chapter, I have presented many results. First, I presented the descriptive statistics for terrorism and instability for each sample. I also compared the samples on their distributions and summary statistics for terrorism and instability. I compared the samples using the common control variables across the samples, the country demographics, governance and contiguity characteristics. Second, I presented the results of the first hypothesis for all three models. Across all of these models, even with the additional control variables, instability continued to be a positive and statistically significant predictor of terrorism incidents. Third, I presented the results for each sample’s control variables. I also reviewed the results of the Model 1 replication on

Samples 2 and 3. This enabled me to begin to understand the role that omitted variables and sample selection biases may have played in the results. These results have continued to support an instability effect for Hypothesis 1. I turn now to the next chapter in which I present the results for Hypotheses 2-4.

Results for Hypotheses 2, 3, and 4

In this chapter, I present the results first for Hypothesis 2 for each sample. Hypothesis 2 suggests that the effects of instability should vary by type. I also present the results for the third set of hypotheses for each sample. These hypotheses explore whether complex singular instability episodes and same-year complex instability episodes have differing effects on terrorism levels compared to non-complex singular instability. I turn next to the results for the fourth set of hypotheses. These hypotheses suggest that the temporal density of multiple instabilities ought to have differing effects on terrorism. For Hypotheses 3 and 4, there is also the question of the effects of stability on terrorism. Finally, I conclude the final chapter of model results. I turn now to the results for Hypothesis 2.

Results for Hypothesis 2

In the following section, I review the results of the rest of the second set of hypotheses for all three samples. The second hypothesis proffers that the effects of instability on terrorism ought to vary by instability type. I also hypothesize that increases in the adverse regime change instability type ought to be associated with small increases in terrorism incidents while increases in the ethnic and revolutionary war types should be associated with large increases in terrorism incidents. I turn now to the results of the second hypothesis for Model 1, which are contained in table 10.

Model 1: Hypothesis 2, Hypothesis 2a, and Hypothesis 2b

Theoretical variables of interest

In order to assess the effects of the different kinds of instability on terrorism, I use stability as the reference category in this analysis. These results are shown in table 10. First, all four instability types statistically significantly predict increased levels of terrorism relative to stability in Sample 1. In terms of magnitude, I turn to the incidence rate ratios and present those results from highest magnitude to lowest. Revolutionary war results in a 5.73 times greater rate of terrorism incidents, the largest rate increase in of any of the types, relative to stability. The occurrence of ethnic war is accompanied by a 2.68 times greater rate of terrorism incidents relative to stability. When adverse regime change instability occurs, a 2.37 times increased rate of terrorism incidents relative to stability. When a complex instability is ongoing, that is when more than one of the types occurred within the same year or within five years of the last, there is also a 2.37 times greater rate of terrorism relative to stability. Again, all of these effects are statistically significant.

In addition, I conducted Wald tests for the differences between coefficients in order to assess whether they were statistically different from one another. I found that all four types were statistically significantly different from one another (in all cases, $p<.0000$). However, I also conducted equality of regression coefficients tests per Paternoster et al. (1998) who provide a corrected formula for this test and argue that this is the proper test for assessing the equality of regression coefficients. Using this test, only the revolutionary war type is statistically distinguishable from the other types in terms of increases in terrorism. Specifically, revolutionary predicts statistically significantly more terrorism than the other types, including ethnic war and adverse regime change (all

Table 10. Results for hypotheses 2, 2a, and 2b for all three models

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Hypothesis 2									
Complex instability (same-year & complex singular)	0.863 ***	0.065	2.370	0.995 ***	0.092	2.704	1.026 ***	0.159	2.791
Ethnic war	0.986 ***	0.167	2.681	0.907 ***	0.196	2.476	0.785 **	0.249	2.193
Adverse regime change	0.864 ***	0.227	2.373	0.604	0.326	1.829	0.431	0.592	1.539
Revolutionary war	1.746 ***	0.170	5.733	1.781 ***	0.192	5.938	1.648 ***	0.385	5.194
Model 1: Governance, contiguity and country demographics									
Governance & contiguity									
Full autocracy	-0.678 ***	0.067	0.507	-0.700 ***	0.092	0.497	-0.826 ***	0.170	0.438
Full democracy	0.074	0.064	1.077	0.138	0.079	1.148	0.255 *	0.116	1.290
Contiguous state instability	0.217 ***	0.053	1.242	0.243 **	0.072	1.276	-0.123	0.101	0.884
Country demographics									
Total population	0.000 **	0.000	1.000	0.000 *	0.000	1.000	0.000	0.000	1.000
Population change	-0.021	0.019	0.979	-0.069 *	0.034	0.933	0.051	0.043	1.052
Population density	0.001 *	0.000	1.001	0.000	0.000	1.000	0.000	0.000	1.000
Urbanity	0.023 ***	0.002	1.023	0.015 ***	0.003	1.015	0.007	0.004	1.007
Land area	-0.009	0.019	0.991	-0.048	0.026	0.954	0.073	0.043	1.075
Data collection indicator									
GTD2 period	0.111	0.224	1.118	-1.017 ***	0.199	0.362	-1.11 ***	0.218	0.329
Constant	-2.906 ***	0.213		5.067 *	2.168		8.834 **	3.307	

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Model 2: Population age structure and social and economic development.									
Population age structure									
% Population aged 0-14				-0.058 **	0.020	0.944	-0.091 *	0.031	0.913
% Population aged 15-65				-0.070 **	0.026	0.932	-0.082 *	0.040	0.921
Social and economic development									
Telephone lines				-0.003	0.006	0.997	-0.003	0.008	0.997
GDP per capita				-0.013	0.110	0.987	-0.340 *	0.155	0.712
Change in GDP per capita				-0.010	0.005	0.991	0.007	0.007	1.007
Food production index				-0.001	0.002	0.999	-0.012 ***	0.003	0.988
CO2 emissions				0.003 **	0.001	1.003	0.002	0.001	1.002
Model 3: Ethnic minority group characteristics									
Religious restrictions									
Informal							-0.240	0.129	0.787
Some							0.359 *	0.149	1.433
Sharp							0.758 **	0.289	2.134
Political discrimination									
Neglect with help							0.169	0.271	1.184
Neglect							0.169	0.273	1.184
Social exclusion							0.699 **	0.261	2.012
Formal exclusion							0.788 **	0.265	2.199
Economic discrimination									
Neglect with help							-0.533 *	0.234	0.587
Neglect							-0.542 *	0.219	0.582

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Social exclusion							-0.612 **	0.203	0.542
Formal exclusion							-0.498 *	0.221	0.608
Protest									
Verbal							-0.241	0.123	0.786
Symbolic							0.167	0.097	1.182
Small							0.077	0.092	1.080
Medium							0.089	0.131	1.093
Large							0.097	0.228	1.102
Group spatial distribution									
Urban							-0.048	0.168	0.953
Regional							-0.149	0.185	0.861
Concentrated							-0.501 **	0.152	0.606
***=p<.000									
**=p<.01									
*=p<.05									

p<.01). However, the other types are not statistically distinguishable from one another in their effects on terrorism incidents. This evidence generally supports the second hypothesis and the sub-hypotheses, although it does not demonstrate that all of the types are different from one another. Instability is important overall, but the type of instability that occurs seems to matter, particularly with reference to revolutionary war. Revolutionary war seems to be a singularly dangerous form of instability with respect to terrorism incidents. I turn to the final piece of evidence, the presentation of the changes in the predicted counts of incidents.

As before, I present the predicted counts of incidents from Model 1 broken down by governance type and contiguity of an unstable nation with all continuous country demographics held at their medians. I also present the predicted counts by instability type from highest to lowest. When revolutionary war occurs in a fully democratic regime which is contiguous to an unstable state and with all other control variables held at their medians, terrorism is predicted to increase by an additional 0.36 incidents relative to stability (p<.000). For ethnic war, the increase is predicted to consist of 0.20 more incidents relative to stability (p<.000). The smallest predicted increases in terrorism incidents were for adverse regime change and for complex instability, both of which are predicted to be associated with 0.18 additional incidents relative to stability (p<.01).

On the other end of the spectrum, for full autocracies that are not contiguous to an unstable state, the inference remains the same but the magnitude differs. Revolutionary war instability is predicted to have the largest increase in terrorism incidents per year, but the magnitude is only 0.13 more incidents relative to stability (p<.000). Ethnic war in a state follows with a predicted count of 0.08 more incidents relative to stability (p<.000) which is followed by the incidence of complex instability in a country and the occurrence of 0.07 more incidents relative to stability ($p<.000$). When a state experiences adverse regime change, the model predicts an increase of 0.07 more incidents relative to stability ($p<.000$).

Conclusions

The second hypothesis and the two sub-hypotheses are somewhat supported. Both the incidence rate ratios and the predicted counts of terrorism incidents demonstrate some clear differences between the types of instability and their effects on terrorism levels, relative to stability. Further, the Wald tests demonstrate that these differences are statistically significant and the Paternoster et al. (1998) test demonstrated that revolutionary war is statistically significantly associated with more terrorism than any of the other types. Ultimately, all of the instability types are associated with statistically significant increases in terrorism levels. The occurrence of adverse regime change instability is associated with small increases in the amount of predicted terrorism incidents, though these are of similar magnitude as those experienced for complex instability, while the happenings of revolutionary war and ethnic war are consistently predicted to be associated with the large increases in terrorism incidents. Clearly, the type of instability does matter relative to stability. I turn now to the results of the second hypothesis for Model 2, which contains more rigorous control variables such as the population age structure and the social and economic development variables.

Model 2: Hypothesis 2, Hypothesis 2a, and Hypothesis 2b

Theoretical variables of interest

In Model 2, all four instability types except for adverse regime change are positive and statistically significant relative to stability. That is, three of the four types are expected to coincide with an increase in the levels of terrorism within a state, relative to stability. With regards to magnitude, in this sample, as in Sample 1, the incidence rate ratios show that revolutionary war is associated with the largest increase in terrorism relative to stability followed by complex instability. Ethnic war has the third highest magnitude. This partially contradicts Hypothesis 2b, which suggested that both revolutionary war and ethnic war instabilities ought to exert the most influence on terrorism. Adverse regime change has the smallest magnitude and does not attain statistical significance at the traditional .05 level ($p<.10$). However, it should be noted that adverse regime change is particularly rare in this sample, with only 13 country-years of occurrence. This suggests that the lack of statistical significance for adverse regime change may at least be partially due to its rarity.

Specifically, when revolutionary war occurs in a nation, it is accompanied by a 5.94 times increase in the terrorism rate. Complex instability within a state follows with an increase of 2.70 times the terrorism rate relative to stability. For the occurrence of ethnic war in a state, the rate of terrorism also increases by 2.47 times relative to stability. This partially contradicts Hypothesis 2b, which suggested that both revolutionary war and ethnic war instabilities ought to exert the most influence on terrorism. Finally, the occurrence of adverse regime change demonstrates the smallest increase in the terrorism rate at 1.83 times relative to stability; in addition, this rate increase is not statistically significant. Further, utilizing the Wald test for the differences between the coefficients shows that all of the types are statistically significantly different from one another (all $p<.0000$). These results demonstrate that Hypothesis 2 and its sub-hypotheses are at least partially supported even though adverse regime change did not attain statistical significance.

I also conducted tests to assess the statistical significance of the regression coefficients against one another using the formula offered by Paternoster et al. (1998). The Paternoster et al. formula for equality of regression coefficients demonstrates that the only statistically significant differences between regression coefficients are between revolutionary war and all the other types. According to this test, revolutionary war predicts significantly more terrorism than any other type including ethnic war (all $p<.01$). The other coefficients are not statistically distinguishable from one another. For example, the ethnic war type is not statistically distinguishable from the adverse regime change type in terms of terrorism. Overall, the significance of the revolutionary war types provides some support for the sub-hypotheses. I turn now to the prediction of counts of terrorism incidents to further assess the sub-hypotheses.

The sub-hypotheses proffer that the occurrence of adverse regime change instability ought to be associated with the smallest increase in incidents while revolutionary war and ethnic war ought to be associated with the largest increase relative to stability. As before, I assess the predicted counts at the largest and smallest changes. For a full democracy that is contiguous to another unstable state and with all continuous control variables held at their medians, the occurrence of revolutionary war is predicted to increase the count of terrorism incidents in a state by 1.24 additional incidents relative to stability ($p<.000$). Complex instability within a country is predicted to increase terrorism by 0.69 more incidents than stability ($p<.000$). Ethnic war in a nation follows with 0.63 additional incidents ($p<.000$). Adverse regime change is predicted to have the fewest additional incidents, 0.42 additional incidents relative to stability, which is unsurprising since the effect is not statistically significant ($p<.10$). The order remains the same for full autocracies without an unstable contiguous state. Revolutionary war is predicted at 0.42 additional incidents relative to stability ($p<.000$) followed by complex instability with 0.23 additional incidents ($p<.000$). Ethnic war within a state is predicted at 0.21 more incidents than stability ($p<.000$) while adverse regime change is predicted to be accompanied by an increase of 0.14 incidents relative to stability ($p<.10$).

Conclusions

Hypothesis 2 and the sub-hypotheses are partially supported in Model 2, which adds the population age structure and social and economic development control variables. The instability effect is shown to be robust in this model. Instability type does matter in terms of the size of the effects. The war types, revolutionary war and ethnic war, are associated with increases in terrorism relative to stability. However, only revolutionary war predicts statistically significantly more terrorism than the other types. In addition, when adverse regime change occurs, there is a statistically insignificant increase in terrorism. This does not support Hypothesis 2a. There is some evidence that this may be due to the rarity of adverse regime change in Sample 2. Hypothesis 2 and the sub-hypotheses are partially supported. I turn now to the results of Hypothesis 2 for Model 3, which contains the largest suite of control variables in the analyses.

Model 3: Hypothesis 2, Hypothesis 2a, and Hypothesis 2b

Theoretical variables of interest

I examine the results of Model 3 for hypotheses 2, 2a and 2b. As it was in Model 2, the effect of an adverse regime change on terrorism is statistically indistinguishable from the effects of stability on terrorism though it remains positive. Otherwise, the rest of the instability types all show positive and statistically significant effects on terrorism incidents. With regards to magnitude, when revolutionary war instability sets in, there is a 5.19 times greater rate of terrorism incidents relative to stability. The occurrence of ethnic war sees a 2.19 times greater rate of terrorism incidents relative to stability. However, the magnitude of the ethnic war effect is surpassed by the magnitude of the onset of complex instability, which demonstrates a slightly larger increase at a 2.79 times greater terrorism rate relative to stability. As in Model 2, this partially contradicts Hypothesis 2b, which suggested that both revolutionary war and ethnic war instabilities ought to exert the most influence on terrorism. Using the Wald test again, I find that all of the types of instability have statistically significantly different coefficients from one another (all $p<.000$). However, the Paternoster et al. (1998) equality of regression coefficients do not demonstrate any statistically significant differences between the types for this sample. I turn now to the presentation of the predicted counts of terrorism incidents by type for Model 3.

I present the highest and lowest predicted counts of terrorism incidents by instability type from Model 3. The highest predicted counts corresponds to a full democracy contiguous to an unstable nation in which the ethnic minority group at risk there suffers the highest level of political discrimination but no economic discrimination with all other variables held at their medians. Under these conditions, once again, the revolutionary war type is predicted to have the largest effect, with a predicted increase of 3.85 incidents ($p<.01$). Complex instability is expected to have an increase of 2.4 incidents relative to stability ($p<.01$). Ethnic war is expected to involve an increase 1.84

incidents relative to stability ($p<.05$). Adverse regime change is expected to result in an additional 1.00 incidents, but this effect is far from statistically significant.

The lowest predicted counts occur in a full autocracy without an unstable contiguous state in which the ethnic minority group at risk is subject to only economic discrimination rather than political. The predicted count for revolutionary war instability is still the highest at 0.36 additional incidents relative to stability ($p<.05$). Complex instability follows with an expected increase of 0.23 additional incidents ($p<.01$). Ethnic war is predicted to occur alongside an additional 0.17 incidents relative to stability ($p=.05$).

Conclusions

Model 3 demonstrates quite similar results as Model 2. All of the instability types, save for adverse regime change resulted in statistically significant and positive effects on terrorism. As in Sample 2, adverse regime change is quite rare in Sample 3, with only 5 state-years. There are only 18 state-years of revolutionary war and 34 of ethnic war. The rarity of the individual types may help to explain how the Paternoster el al. (1998) coefficients were unable to detect statistically significant differences between the types.

In the model itself, however, the effects of all but adverse regime change are positive and statistically significant. Further, if I rely on the incidence rate ratios, I can conclude that Hypothesis 2b is partially supported in that revolutionary war has the largest magnitude effect on terrorism incidents. Perhaps because there are only 5 state-years of adverse regime change in Sample 3, it is statistically indistinguishable from stability in its effects on terrorism. Although Model 3 clearly suffers because certain of the instability types are very rare, it is reasonable to conclude that the second set of hypotheses are partially supported.

Conclusions

The results for the second set of hypotheses demonstrate that they are partially supported. These hypotheses were examined in all three models, meaning they were tested with a large set of control variables. They were also tested in decreasing sample sizes. Overall, instability types do differ to varying degrees with regards to terrorism levels. Generally speaking, when revolutionary or ethnic war occurs, both low-control instability types, there will be more terrorism incidents; this effect is statistically significant for revolutionary war in 2 of the 3 models. When a high-control and generally short-term instability like adverse regime change occurs, the increases in terrorism incidents will generally be smaller or statistically insignificant. I turn now to the results for the third set of hypotheses.

Results for Hypothesis 3

I assess the results of Hypothesis 3 and its sub-hypotheses for all models and their associated samples below. The third hypothesis proffers that increases in terrorism will be more likely to occur when a state experiences increases in complex singular instability as opposed to non-complex singular instability. Complex singular instability refers to the occurrence of two or more instability episodes within five years of one another but not within the same year. For example, a revolutionary war followed by an adverse regime change two years later would constitute two complex singular instabilities: complex-revolutionary war and complex-adverse regime change. A non-complex singular instability is the occurrence of ethnic war, or any other type, without any other form of instability occurring in that five-year period. The first purpose of this hypothesis is to delve into whether there are qualitative differences in the level of terrorism experienced by just one instability event within five years relative to more than one. I derived this expectation from breakdown theory, because one instability episode should be associated with a non-zero level of terrorism, but two in a short period of time should be associated with even higher levels of terrorism. The sub-hypotheses build on these ideas. First, increases in same-year complex instability should be associated with more terrorism than just one instability in a five-year period. Second, increases in stability should be clearly associated with less terrorism because breakdown has not occurred in a stable state. I turn now to the results for Hypothesis 3 in Model 1.

Model 1: Hypothesis 3, Hypothesis 3a and Hypothesis 3b

In order to test Hypothesis 3, I have run my models changing the reference category from stability to non-complex singular instability so as to test whether complex singular instability and non-complex singular instability are significantly different from one another. I also do this to test whether same-year complex instabilities are statistically significantly different from non-complex singular instability. Finally, I also examine whether stability is significantly different from non-complex singular instability as it ought to be if breakdown theory is to be believed. The results for the third set of hypotheses are shown in table 11, along with the results for the fourth set of hypotheses.

Theoretical variables of interest

For Model 1, I find that complex singular instability predicts significantly *less* terrorism than non-complex singular instability. When a complex singular instability occurs, there is also a 0.68 factor decrease in the rate of terrorism relative to a non-complex singular instability. As before, I present the predicted counts of terrorism broken down by governance type and contiguity of an unstable nation. For a full democracy that is contiguous to an unstable nation and all other values held at their medians, complex singular instability is predicted to be associated with 0.26 fewer incidents relative to a

Table 11. Results for hypotheses 3 and 4 for all samples

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Hypothesis 3: Complex singular instability v. Non-complex singular instability									
Complex singular instability	-0.390 **	0.124	0.677	-0.283	0.157	0.753	0.052	0.242	1.054
Hypothesis 3a: Same-year complex instability v. Non-complex singular instability									
Same-year complex instability	-0.254	0.130	0.775	0.039	0.166	1.040	0.293	0.261	1.341
Hypothesis 3b: Stability v. Non-complex singular instability									
Stability	-1.206 ***	0.107	0.299	-1.181 ***	0.130	0.307	-0.935 ***	0.197	0.393
Hypothesis 4: Same-year complex instability v. Complex singular instability									
Same-year complex instability	0.136	0.089	0.775	0.322 **	0.112	1.380	0.241	0.152	1.273
Hypothesis 4a: Stability v. Complex singular instability									
Stability	-0.816 ***	0.074	0.299	-0.898 ***	0.100	0.407	-0.987 ***	0.164	0.373
Model 1: Governance, contiguity and country demographics									
Governance & contiguity									
Full autocracy	-0.659 ***	0.067	0.517	-0.680 ***	0.092	0.507	-0.821 ***	0.168	0.440
Full democracy	0.103	0.064	1.108	0.199 *	0.081	1.220	0.304 **	0.114	1.355
Contiguous state instability	0.212 ***	0.053	1.236	0.234 **	0.071	1.264	-0.148	0.099	0.863
Country demographics									
Total population	0.000 **	0.000	1.000	0.000 *	0.000	1.000	0.000	0.000	1.000
Population change	-0.015	0.020	0.985	-0.062	0.035	0.940	0.051	0.044	1.052

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Population density	0.001 *	0.000	1.001	0.000	0.000	1.000	0.000	0.000	1.000
Urbanity	0.023 ***	0.002	1.023	0.014 ***	0.003	1.014	0.008	0.004	1.008
Land area	-0.012	0.018	0.988	-0.050	0.026	0.952	0.075	0.043	1.078
Data collection indicator									
GTD2 period	0.158	0.224	1.172	-1.028 ***	0.200	0.358	-1.116 ***	0.217	0.328
H3 constant	-1.764 ***	0.230		5.452 *	2.172		9.312 **	3.305	
H4 constant	-2.154 ***	0.218		5.169 *	2.179		9.364 **	3.330	
<u>Model 2: population age structure and social and economic development</u>									
Population age structure									
% population aged 0-14				-0.052 *	0.020	0.950	-0.088 **	0.031	0.916
% population aged 15-65				-0.061 *	0.026	0.941	-0.077	0.040	0.925
Social and economic development									
Telephone lines				-0.002	0.006	0.998	-0.004	0.008	0.996
GDP per capita				-0.016	0.110	0.984	-0.336 *	0.155	0.715
Change in gdp per capita				-0.010 *	0.005	0.990	0.010	0.007	1.010
Food production index				-0.001	0.002	0.999	-0.012 ***	0.003	0.988
CO2 emissions				0.003 **	0.001	1.003	0.002	0.001	1.002
<u>Model 3: Ethnic minority group characteristics</u>									
Religious restrictions									
Informal							-0.243	0.128	0.785
Some							0.350 *	0.149	1.419
Sharp							0.756 *	0.292	2.130

	Sample 1: 147 states			Sample 2: 116 states			Sample 3: 82 states		
	B	*SE*	IRR	*B*	*SE*	IRR	*B*	*SE*	IRR
Political discrimination									
Neglect with help							0.171	0.273	1.187
Neglect							0.160	0.274	1.174
Social exclusion							0.713 **	0.261	2.040
Formal exclusion							0.793 **	0.265	2.210
Economic discrimination									
Neglect with help							-0.513 *	0.232	0.599
Neglect							-0.573 **	0.216	0.564
Social exclusion							-0.595 **	0.201	0.552
Formal exclusion							-0.526 *	0.219	0.591
Protest									
Verbal							-0.237	0.124	0.789
Symbolic							0.195 *	0.096	1.215
Small							0.093	0.091	1.097
Medium							0.107	0.133	1.113
Large							0.098	0.226	1.103
<u>Group spatial distribution</u>									
Urban							-0.049	0.165	0.952
Regional							-0.163	0.182	0.850
Concentrated							-0.500 **	0.146	0.607

***=p<.000

**=p<.01

*=p<.05

non-complex singular instability (p<.05). For a full autocracy that is not contiguous to an unstable nation, complex singular instability in a state is predicted to lower that state's terrorism by 0.09 fewer incidents relative to a non-complex singular instability (p<.05). These results demonstrate that there is a statistically significant difference between the effects of a complex singular instability and a non-complex singular instability, but it is in the opposite direction than that predicted by Hypothesis 3. That is, multiple instabilities within a five-year period are individually associated with statistically significantly less terrorism than one instability during a five-year period. With the first part of Hypothesis 3 completely unsupported, I turn to the rest of the results from this model for the sub-hypotheses.

A state which experiences multiple instabilities within a year, same-year complex instabilities, does not experience levels of terrorism that are statistically significantly distinguishable from a state which experiences non-complex singular instability. This contradicts Hypothesis 3a, which stated that same-year complex instabilities would be associated with significantly more terrorism than non-complex singular instability. In addition, the effects are in the opposite direction than that predicted by Hypothesis 3b. The effect size is relatively small.

Hypothesis 3b is supported, however. Stability is statistically significantly associated with less terrorism than complex singular instability; stability relative to non-complex singular instability is associated with a 0.29 factor decrease in the rate of terrorism incidents. A stable full democracy that is contiguous to an unstable nation (and all other controls held at their medians) is predicted to have a decrease of 0.24 incidents relative to non-complex singular instability (p<.000). A stable full autocracy that is not contiguous to an unstable state (and all other controls held at their medians) is expected to have a predicted decrease of 0.09 incidents relative to a non-complex singular instability ($p<.000$). I turn now to my conclusions for Hypothesis 3 for Model 1.

Conclusions

Hypothesis 3 is completely unsupported. The results show that the effect is in the opposite direction than that expected in my extrapolation from breakdown theory. Further, Hypothesis 3a is unsupported as well; there is no statistically significant difference between same-year complex instability and non-complex singular instability in the effects on terrorism. However, Hypothesis 3b is supported; stability is statistically significantly associated with less terrorism than non-complex singular instability. Of three hypotheses, only one is supported in this model.

These results suggest two things. One, when instability occurs one time in a state, there is enough breakdown to produce terrorism and potentially, increased terrorism relative to two or more instabilities within a five year period. This means that it is not necessarily the states that are having more problems that experience more terrorism. These results also imply that the impact of instability does not appear to be additive. Second, these results suggest that for terrorism to occur, perhaps the state cannot be completely broken down, such as when same-year complex instabilities occur. These ideas will be explored further in the presentation of Hypothesis 4 and the discussion chapter. For now, I conclude that Hypotheses 3 and 3a are unsupported in Model 1 while Hypothesis 3b is supported. I turn now to Model 2 for Hypotheses 3, 3a and 3b.

Model 2: Hypothesis 3, Hypothesis 3a and Hypothesis 3b

Theoretical variables of interest

In this model, complex singular instability demonstrates a negative and statistically non-significant effect on terrorism relative to non-complex singular instability ($p<.10$). That is, when a state experiences instability that occurs along with one or more other instabilities in five years, there also occurs less terrorism than that experienced during one instability in a five-year period, but this effect is not statistically significant. The confidence interval around the coefficient includes zero (-0.59-.02). For Model 2, Hypothesis 3 is still unsupported, as it predicts the opposite direction for the relationship though this effect is not statistically significant.

As in Model 1, the occurrence of same-year complex instability within a state is not statistically distinguishable from non-complex singular instability in its effects on terrorism. Though not statistically significant, same-year complex stability is predicted to increase terrorism incidents relative to non-complex singular instability in Model 2. Also, as in Model 1, stability in a state is associated with statistically significantly fewer terrorism incidents than non-complex singular instability. For stability, there is also a 0.31 factor decrease in the rate of terrorism than that experienced during non-complex singular instability. For a full democracy that is contiguous to an unstable nation and all other variables held at their medians, the occurrence of stability in a nation is predicted to be accompanied by 0.87 fewer incidents relative to non-complex singular instability ($p<.000$). For a full autocracy that is contiguous to only stable nations and all other continuous control variables held at their median, a stable state is predicted to have 0.28 fewer incidents relative to non-complex singular instability within a state ($p<.000$).

Conclusions

The findings discussed above demonstrate that Hypotheses 3 and 3a are completely unsupported while Hypothesis 3b is supported. Regarding Hypothesis 3, although there is not a statistically significant difference between the effects of complex singular instability and non-complex singular instability on terrorism, it is in the opposite direction than that predicted by Hypothesis 3. Interestingly, a state which experiences one instability within five years is predicted to experience no difference in terrorism levels than multiple instabilities within five years. In addition, there was no statistically significant difference between the effects of same-year complex instability and non-complex singular instability. This model suggests that one instability episode within five years is just as detrimental as multiple instabilities within the same year. Finally, stability, as should be expected, demonstrated a negative and statistically significant effect on terrorism relative to non-complex singular instability. I turn now to the results of Hypotheses 3, 3a and 3b from Model 3, which contains even more control variables, including the ethnic minority group characteristics. I turn to Model 3 now.

Model 3: Hypotheses 3, 3a and 3b

Theoretical variables of interest

I examine the results of Hypotheses 3, 3a and 3b in Model 3. The experience of complex singular instability is not statistically distinguishable from non-complex singular instability with respect to terrorism, but the direction is positive. The confidence interval around the coefficient includes zero (-0.42-0.53). Same-year complex instability remains statistically indistinguishable from non-complex singular instability though in Model 3, it is positive relative to non-complex singular instability. The only statistically significant instability variable is the experience of stability itself relative to non-complex singular instability. During stability, there is also a 0.39 factor decrease in the terrorism rate ($p<.000$). For a full democracy that is contiguous to an unstable nation and which has ethnic minorities at risk which are subject to political discrimination but not economic discrimination, a stable state is predicted to have 2.23 fewer terrorism incidents relative to a non-complex singular instability ($p<.05$). In contrast, a full autocracy without a contiguous unstable nation and which has an ethnic minority group that is subjected to only economic discrimination is predicted to have 0.21 fewer incidents during stable times relative to non-complex singular instability.

Conclusions

The results of Model 3 demonstrate that Hypotheses 3 and 3a are completely unsupported. Hypothesis 3b is supported. In Model 3, the only statistically significant theoretical variable was stability, relative to non-complex singular instability. This instability effect remained robust. I turn now to the conclusions for Hypothesis 3.

Conclusions

In the end, the only important finding that emerges from this set of hypotheses is that instability itself matters; the number of instabilities within a five year period, whether in the same year or in different years, is unable to consistently predict the level of terrorism experienced by that state. Overall, it seems that the clearest take-away from all of the models for Hypothesis 3 is that the occurrence of instability itself is the most important. Whether there are multiple instabilities or not, when instability occurs, there are concomitant increases in terrorism incidents. I turn now to examine the results for Hypothesis 4, the final hypothesis in this dissertation.

Results for Hypothesis 4

In the previous hypotheses, I tried to determine whether the occurrence of multiple instabilities was associated with more terrorism compared to one instability. In the next hypothesis, I try to determine whether the temporal density of those multiple instabilities is important. In Hypothesis 4, I hypothesize that increases in terrorism will be more likely to occur when a state experiences increases in same-year complex instabilities relative to two or more instability episodes within a five-year period (but not in the same year). I derived from breakdown theory that a state experiencing two or more instability episodes in the same year should be in a downward spiral of negative consequences, of which terrorism ought to be prevalent. Both same-year complex instability and complex singular instability involve multiple instabilities, and Hypothesis 4 tries to determine whether the temporal density of the multiple instability episodes matters. Theoretically, more than one instability in a year should produce more breakdown and then, more breakdown should produce more terrorism. Hypothesis 4a examines whether stability is associated with less terrorism than complex singular instability, as it should if breakdown is empirically supported. I turn now to testing this in the context of Model 1. These results are shown in table 11 with the Hypothesis 3 results.

Model 1: Hypothesis 4 and 4a

Theoretical variables of interest

In Model 1, same-year complex instabilities are not statistically distinguishable from complex singular instability regarding terrorism. The effect is positive but small. In contrast, when stability occurs, there is also a decrease in terrorism incidents, and this decrease is statistically significant and of a substantial magnitude. There is a 0.44 factor decrease in the terrorism rate for stability relative to complex singular instability. For a full democracy that is contiguous to an unstable nation and all else held at the median, the predicted count of terrorism for stability is expected to decrease by 0.16 incidents relative to complex singular instability ($p<.000$). For a full autocracy that is not contiguous to a nation experiencing instability and all else at the median, the expected count for stability is predicted to decrease by 0.06 incidents ($p<.000$).

Conclusions

Hypothesis 4 is not supported while Hypothesis 4a is supported in Model 1. This model demonstrates that the temporal density of instability may not matter with respect to terrorism. It may be enough that instability has occurred to observe differences in the rate and predicted count of terrorism incidents. I turn now to the results for these hypotheses in Model 2.

Model 2: Hypotheses 4 and 4a

Theoretical variables of interest

For Model 2, the temporal density of multiple instabilities does play a role in the distribution of terrorism incidents. The occurrence of same-year complex instability accompanies an increase of 1.38 times the rate of terrorism incidents relative to complex singular instability. For a full democracy that is contiguous to an unstable nation and with all else held at the median, the occurrence of multiple instabilities within a year is predicted to coincide with 0.58 additional terrorism incidents in a state relative to complex singular instability ($p<.01$). For a full autocracy that is not contiguous to an unstable nation and all else held at the median, a country in which there are multiple instabilities within the same year is predicted to experience 0.19 additional terrorism incidents relative to complex singular instability ($p<.01$). Interestingly, for this sample, Hypothesis 4 is supported. A country experiencing multiple instabilities within the same year is also victimized by more terrorism when compared to multiple instabilities over five years but never within the same year. I turn now to the results of Hypothesis 4a.

A stable country experiences statistically significantly less terrorism relative to a country with complex singular instability. The rate of terrorism incidents is expected to decrease by a factor of 0.41 for stability relative to complex singular instability. When a full democracy that is contiguous to an unstable nation and all other control variables held at the median experiences stability, it is predicted to be victimized by 0.65 fewer incidents relative to more than one instability per five-year period ($p<.000$). When a full autocracy that is contiguous to only stable nations and all other control variables held at their medians is stable, the predicted count of terrorism incidents is reduced by 0.22 incidents relative to complex singular instability ($p<.000$).

Conclusions

For this sample of 116 nations from 1981 to 2005, both Hypotheses 4 and 4a are supported. Temporal density does seem to matter for this sample, such that when there are multiple instabilities within the same year, there is a predicted increase in terrorism incidents. When a country experiences stability, it is also expected to decrease in terrorism incidents relative to a complex singular instability. Since the temporal density of the multiple instabilities did not statistically significantly predict more terrorism in Model 1, I am cautious with regards to these results as they may be the result of sample selection. I turn now to the results for Model 3 for these Hypotheses.

Model 3: Hypotheses 4 and 4a

Theoretical variables of interest

In Model 3, the occurrence of same-year complex instability is not statistically distinguishable from complex singular instability. The coefficient is positive, but the magnitude is quite small. However, stability is statistically significantly different from complex singular instability. A stable state is also expected to have a 0.37 factor decrease in the rate of terrorism incidents. For a full democracy in which an ethnic minority group at risk which is subject to political discrimination but not economic discrimination in a state that is contiguous to an unstable nation, when the state is stable, it is predicted to have 2.35 fewer terrorism incidents relative to a state in complex singular instability ($p<.01$). Meanwhile, a stable full autocracy that is not contiguous to any unstable states and in which there is only economic discrimination against an ethnic minority group at risk is predicted to experience 0.22 fewer terrorism incidents ($p<.01$).

Conclusions

In Model 3, only Hypothesis 4a is supported. This model shows that the temporal density of instabilities is unable to meaningfully distinguish between the effects of multiple instabilities. Models 1 and 3 demonstrate that the Model 2 finding, that the temporal density of multiple instabilities matters, may be the result of sample selection. It also demonstrates the strength of the multi-pronged analytical approach utilized here. By running my models on multiple samples, I am able to detect unexpected results and weigh them against the results of the other models. I conclude that it is likely that Hypothesis 4 is unsupported while Hypothesis 4a is supported. The temporal density of multiple instabilities is not a consistent predictor of increased levels of terrorism. The occurrence of instability itself, rather than how many or when, is far more consistently associated with increased levels of terrorism. I turn now to the chapter conclusions.

Conclusions

In this chapter, I have presented many results. I presented results that demonstrated that the effects of instability on terrorism differ to some degree based on the type that occurs. For example, for two of the three models, revolutionary war instabilities were associated with the largest statistically significant predicted increases in terrorism incidents while adverse regime change was associated with either the smallest increase or lacked statistical significance. These findings generally supported the second set of hypotheses. Further, I presented results in this chapter that contradicted the third set of hypotheses. Specifically, there does not appear to be a greater risk of terrorism when a state experiences two or more instability episodes within five years relative to just one episode. In addition, there is likely no additional risk of terrorism incidents when two or more instabilities occur within the same year relative to one instability in five years. Stability always demonstrated a negative relationship with terrorism. Only one hypothesis from the third set was supported. The fourth set of hypotheses showed slightly inconsistent results across models, which appear to be the result of sample selection. In Sample 2 alone, the temporal density of instability demonstrated positive and statistically significant power. For all other models, there was no statistically distinguishable effect of two or more instability episodes within one year on terrorism relative to one instability episode within a year. Finally, the occurrence of stability always predicted less terrorism incidents relative to complex singular instability. For the most part, breakdown theory was supported by the results presented in this chapter, but the theoretical extensions were not. I turn now to a discussion of the many models I have presented here.

Chapter 5

Discussion and Conclusions

Introduction

In this chapter, I discuss my findings regarding the relationship between political instability and terrorism. I review the results of each of the hypotheses across the three samples. I also summarize my thoughts on the roles that omitted variable and sample selection biases may have played in this study. I then summarize the state of the support for breakdown theory and the cases that do not fit breakdown theory. I also review the limitations of this study. I then consider the policy implications of this study. I end with some suggestions for future research topics regarding political instability and some final conclusions. I turn now to a discussion of my findings regarding instability and terrorism.

Discussion

Instability and Terrorism

In this dissertation, I sought to complete an exhaustive test of the instability and terrorism relationship. I examined the relationship between instability and terrorism over four sets of hypotheses and three different models and samples. The samples varied from 147 nations from 1970 to 2005 in Sample 1 to 116 states from 1981 to 2005 in Sample 2 and finally, in 82 states from 1990 to 2005 in Sample 3. These changes in samples also included the addition of an increasing number of control variables as I moved from the larger to the smaller samples. The first set of control variables included the country demographics, governance and contiguity characteristics. In Model 2, the control variables included the population age structure and the social and economic development variables. In Model 3, I added characteristics of ethnic minority groups at risk in a sample of states that have MARs. I utilized a multi-stage analytical strategy so as to balance the risks of omitted variables bias, by including as many control variables as possible, and sample selection bias, by starting with the largest sample of countries and years and reducing the sample size from that starting point.

The most important element of this test was the multi-sample analytical strategy. By testing the instability effect in three different samples of countries and years, I was able to demonstrate both sample selection bias and omitted variables bias in action. Further, I demonstrated that the instability effect was most likely not a result of sample selection bias, because the effect was not beholden to the sample I chose. It is a shame that more studies in the literature do not employ such an analytical strategy since many of the control variables used in this study changed signs and statistical significance depending on the sample. Clear examples of this included the effects of GDP per capita and the effects of governance type, specifically full democracy relative to a transitional government. Differing sample composition is likely a clear factor in the divergent effects found for some of these concepts in the literature. More tests are needed that utilize the multi-sample technique before conclusions can be drawn regarding the importance of these contested domains.

One such contested domain that I tested in this dissertation was governance type. As I found in this study, it is generally agreed upon that the relationship between terrorism and full autocracies is negative, though surely some of this relationship is accounted for by underreporting in autocratic states. However, it was unclear in this study whether transitional democracies or full democracies were expected to experience different levels of terrorism. Depending on the sample and the model chosen in this study, there was either no statistically significant difference between them or full democracies were expected to experience more terrorism. Because of the divergent effects, I was unable to make a final statement on the role of democracy and terrorism. All I was able to state with confidence is that full autocracies likely report less and are victimized less by terrorism. Further, I am unable to comment on whether the promotion of democracies would result in decreasing levels of terrorism. Democracy brings with it many social goods, but it is clear to me that the evidence is mixed on whether one of those goods is decreased terrorism. Until further research utilizes the multi-sample strategy that I exploited in this dissertation, the literature on democracy and terrorism is likely to be threatened by an unknown quantity of sample selection bias.

The instability effect was robust over changes in samples and despite the inclusion of demographic, governance, social development, economic development and ethnic minority group control variables. In addition, the models I presented above demonstrated that there was ample support for the instability effect in a statistically rigorous model, such as the fixed effects negative binomial regression model. This model only used within-country variation to estimate the coefficients such that the results I have demonstrated "control out" time-stable differences between countries. The time fixed effects also controlled for changes over time. As such, it provided a particularly conservative test of the effects of changes in instability on changes in terrorism. This conservativeness allowed me to be more confident in the results. Specifically, the results indicate that when instability in a nation increased, terrorism in that nation also increased. This is a classic sociological finding that would please Durkheim. The society is more than just the sum of its individual parts, and it has explanatory power above and beyond the actions of its individuals. I turn now to a review of the results.

Hypotheses

Hypothesis 1 suggested that the increases in instability ought to increase the number of terrorist attacks within a country. In fact, this hypothesis was strongly supported in all samples and in all analyses. Specifically, a state experiencing instability also experiences increased terrorism attacks.

In Hypothesis 2, I argued that the effects of instability on terrorism ought to vary by type, that revolutionary war and ethnic war should be associated with the largest increases in terrorism and that adverse regime change ought to be associated with the smallest increases in terrorism. In one of the three models, these hypotheses were clearly supported. In Models 2 and 3, possibly due to the rarity of certain types of instability in the sample, adverse regime change was not statistically distinguishable from stability with regards to terrorism. In addition, the equality of regression coefficients tests demonstrated that revolutionary war predicted statistically significantly more terrorism incidents than any other type for Models 1 and 2. Overall, I conclude that the weight of the evidence across the models generally supports Hypotheses 2 and 2b while Hypothesis 2a is likely unsupported. Revolutionary war at least is associated with a large increase in terrorism and adverse regime change is likely not statistically distinguishable from stability with respect to its effects on terrorism.

For Hypothesis 3, I examined a theoretical extension to breakdown that suggested that there should be observable differences in terrorism between increases in instability that occurs once within a five-year period and instability that occurred more than once in both a five-year and a one-year period. The most important finding that emerged from the models that addressed the third set of hypotheses was that the occurrence of instability itself mattered the most; this was tested with stability in the model and the reference category as non-complex singular instability. There were varying results with regards to whether multiple instabilities were important relative to one instability. The varying results made the uniform results regarding the difference between stability and non-complex singular instability stand out in stark contrast. When instability occurs in a state, the state seems to be at heightened risk of terrorism, but this heightened risk does not seem to be further heightened by more instabilities.

In Hypotheses 4 and 4a, I examined another theoretical extension which queried whether the temporal density of the multiple instabilities mattered. That is, this hypothesis questioned whether there is a difference in terrorism levels for multiple instabilities in the same year relative to multiple instabilities within five years. This hypothesis was a logical extension of the breakdown model. The results for Hypothesis 4 varied across models. However, for all models, Hypothesis 4a was supported. The difference between stability in a nation and complex singular instability was important and statistically significant across all models. When instability occurs in a state, again, the state seems to be more vulnerable to terrorism.

Interestingly, the number and temporal density of instabilities looked relatively unimportant when compared to the uniformity of the positive and statistically significant effect of instability in the models. Further, when instability was the reference category as it was in the third and fourth sets of hypotheses, stability was uniformly negative and statistically significant. Over all the changes in models, samples and hypotheses, the instability effect remained a robust predictor of terrorism.

My hypotheses were supported for the most part. State instability was associated with higher levels of terrorism. The effect of instability on terrorism varied somewhat by type, with revolutionary war producing statistically significantly larger expected counts of terrorism. However, the results were more complex with regard to the effects of multiple instabilities in a five-year period and in a one-year period. What did not vary over the latter hypotheses was that instability itself still demonstrated a positive effect on terrorism levels. These results, taken as a whole, demonstrated that it is likely that it is the occurrence of instability itself that is most important.

Omitted Variable Bias and Sample Selection Bias

I attempted to put parameters on the degree of omitted variable bias and sample selection bias present in my analyses through the multi-stage analytical strategy. In this study, there was a very clear balancing act in attempting to minimize each type of bias. In order to minimize omitted variable bias, I needed to include as many control variables that are related to both instability and terrorism as possible. On the other hand, in order to minimize sample selection bias, I needed to include as many states and years as possible in my analysis. Unfortunately, because the desired control variables were not always available with coverage back to 1970, this balancing act was very nuanced for my study. It was made even more difficult given that I attempted to measure the effects of political instability, which is a phenomenon that is most common in the nations that are perhaps least likely to have reliable and valid data on those control variables needed to minimize omitted variables bias. In response to these data challenges, I developed a multi-stage analytical strategy. This strategy involved using three separate samples with increasing numbers of control variables and decreasing sample sizes and replicating the Model 1 analysis on the two smaller samples. Upon reviewing the results for the control variables across the sample changes, I gained an understanding of the potential effects of sample selection and omitted variable bias in this study. I turn now to a discussion of sample selection bias.

Sample selection bias

In order to try to understand the degree of sample selection bias at work, I replicated Model 1, the analysis with the country demographics, governance and contiguity control variables on Samples 2 and 3. Most importantly, instability remained a positive and statistically significant predictor of terrorism incidents across the replications in Samples 2 and 3. This demonstrated that the instability effect is unlikely to be an artifact of sample selection. In the Sample 2 replication, there were a few important differences between the models. However, in the Sample 3 replication of Model 1, there were even more important differences in the control variables. Further, when Model 2 was replicated on Sample 3, the original Model 1 or even Model 2 results could not be replicated. In addition, the descriptive statistics indicated that Sample 3 was composed of the most democratic, most populous, most densely populated, and most urban country-year observations. Sample 3 was also the most concentrated with regards to terrorism incidents, with the highest mean level of terrorism. In conjunction with the lack of Model 1 and 2 replicability, the summary statistics demonstrated that Sample 3 is so different from Samples 1 and 2 that the sample selection issues at work ruled out statistical inferences across models. However, given that instability remained a positive and statistically significant predictor of terrorism even in Sample 3, I am pleased by the robustness of the instability effect. I turn now to addressing omitted variable bias.

Omitted variable bias

I assessed the effects of omitted variable bias by comparing Model 1 to Models 2 and 3. There are important differences between the models in terms of the significance of the Model 1 and 2 variables in Model 3. However, these were made more complicated via the changes in samples across the models. The many statistically significant effects in Models 2 and 3 clearly demonstrated that Model 1 in particular suffers from omitted variable bias by excluding these variables. Overall, the most important missing variables were the economic measures from Model 2 and the political and economic discrimination MAR variables from Model 3. These all showed highly significant effects on terrorism. Overall, the evidence clearly suggested that that there were likely some important omitted variables issues at work, particularly in Model 1. However, what remained most important for this analysis was that instability remained a positive and statistically significant predictor of terrorism even with all of the other important domains of control variables.

I have reviewed the model findings regarding the likely effects of sample selection and omitted variables bias in my analyses. I concluded that both have an impact on the results presented here. It is worth noting that without the multi-sample strategy, the differences across models and samples and the perils of making cross-sample inferences would not have been known. I highly recommend that this strategy be adopted as often as possible in future research on terrorism. I turn now to an assessment of breakdown theory in the light of these findings.

Breakdown Theory

Breakdown theory received empirical support from this study in the robustness of the instability effect. The results are consistent with the central premise of breakdown theory. As a country experiences rapid social change, non-routine collective action in the form of terrorism becomes more likely. Breakdown theory suggests that this occurs due to the loosening of controls on the behavior of individuals as the rapid social change severs the ties of individuals to conventional society. The loosening of bonds is reinforced when less restrained individuals decline to form new conventional commitments to society.

Further, the support for breakdown theory largely extended to the findings that the type of instability influenced the level of terrorism experienced by the state. Lower control instability types, like revolutionary war, were predicted to experience statistically significantly larger increases in terrorism. However, the shorter duration and higher control instability, adverse regime change was not able to attain statistically significant effects in two of the three models, possible due to the rarity of occurrence. Overall, when the rapid social change took the form of a very low-control situation, like war, in which the society itself may have been torn apart, the concomitant increase in terrorism was quite large. These findings are all in line with the tenets of breakdown theory.

However, there was almost no support for the theoretical extensions that I derived from breakdown theory. According to the third and fourth hypotheses, multiple instabilities within a five-year period should coincide with more terrorism than only one instability; further, multiple instabilities in a one-year period should also be associated with even more terrorism than one instability in a one year period (but more than one instability in a five-year period). These were sensible derivations from breakdown theory if the experience of breakdown had additive effects on terrorism. Largely, these hypotheses were not supported in the expected way.

These findings may lend some support to the resource mobilization models suggested by Snyder and Tilly (1972) and the Tillys (1975). Resource mobilization theorists argue that first, collective action of all types is not the result of breakdown and discontent in society. This is primarily because breakdown and discontent, both forms of disorganization, exist in all societies and thus, this type of constant cannot explain a change in collective action. Further, because breakdown and discontent (disorganization) categorically cannot explain collective action in this theory, some type of preexisting organization must be required for collective action to occur. This organization may be in the form of primary, or family, group attachments or secondary attachments, such as to civic groups. Without some type of organization, there cannot be collective action, because discontented and untethered individuals do not suddenly engage in collective (group) actions.

Though this study was not a theory competition between the breakdown and resource mobilization models, since I have no proxy measures for resource mobilization, it appears that some minimum level of organization may be required for terrorism to occur in an unstable state. It is unclear at this point whether primary or secondary group attachments are needed or if there is another type of organization required at the government level. My results can only suggest that perhaps there is such a thing as too much instability (disorganization). In a state experiencing multiple instabilities, particularly in the same year, the resulting chaos and uncertainty may be too much to allow terrorist groups to organize and to act. Von Hippel (2002) actually presented this possibility with respect to transnational terrorism. In the end, though, these are tentative suggestions that require further research.

Since the breakdown model is a non-deterministic model, it is clear that when rapid social change occurs, it will not always be associated with large amounts of terrorism. In addition, terrorism certainly occurs in the absence of rapid social change.

That little to no terrorism occurs during rapid social change in some cases and plenty of terrorism occurs in the absence of rapid social change other times requires some attention. I attempt to offer an explanation of both variants of this problem for the breakdown model below.

I address the occurrence of rapid social change without accompanying terrorism first. In Figure 1, the breakdown model was demonstrated graphically. In that model, there were two stepping points between instability and terrorism. Breakdown needed to stimulate both a macro-level freeing effect via the disintegration of the bond between society and individuals. Then, the loss of controls over individuals needed to manifest itself via non-routine collective action. Perhaps instability does not always result in a macro-level freeing effect or perhaps non-routine collective action is not the result of this societal loss of informal and formal controls. Further, it is possible that individuals in some unstable societies engage in other non-routine collective actions rather than terrorism.

This problem is of particular concern given the lack of support for the third and fourth hypotheses. These hypotheses suggested that increases in multiple instabilities and temporally dense multiple instabilities ought to be accompanied by increases in terrorism. This finding was heavily influenced by sub-Saharan Africa; roughly 40% of the multiple instabilities and same-year complex instabilities occurred in sub-Saharan Africa. Yet, the mean of terrorism incidents for sub-Saharan Africa was only 3.5 incidents while the global average is 13.93 incidents from 1970 to 2005. Surely, some of this difference can be attributed to under-reporting, but it is reasonable to conclude that to some degree, sub-Saharan Africa experienced less terrorism than expected, particularly given the large amount of instability in that region. As mentioned earlier in this discussion, perhaps there does need to be some minimum level of organization present in a society before terrorist groups will form and act. In this context, at least, the effects of instability on terrorism are not as simple as more breakdown leads to more terrorism. Further study is required to better explain this phenomenon.

The reverse problem was also troubling for this test of the breakdown model. The occurrence of political instability simply cannot explain terrorism that occurs in its absence. However, that does not mean that the breakdown model cannot begin to explain terrorism that occurs without a preceding rapid social change. At its heart, the breakdown model is a macro-level control theory; when the constraints on individuals' behaviors are loosened, on average, non-routine collective action should be the result. Thus, if there were other reasons why the constraints in society have been loosened, then breakdown theory can offer predictions as to what will result, in this case, more terrorism. An example of this was the left-wing terrorism in the United States in the 1970s; it is not clear what type of rapid social change preceded the formation and actions of the Weather Underground, for example, but it is clear that society was disorganized and controls over individuals' behaviors were likely loosened during this time period.

Further, some terrorism will never fit the breakdown model perhaps because they are better explained by the political grievance model (Gurr, 2000). A good example of this in the United States is anti-abortion terrorism. Clearly, this form of terrorism persists because the individuals and groups who engage in abortion clinic bombing and abortion provider assassinations are attempting to force their preferred resolution to their grievance, which is an end to legal abortion in the United States. The breakdown model does not explain this type of terrorism particularly well, nor is it intended to do so. Thus, breakdown does not offer a complete theory of terrorism.

Overall, breakdown theory received support from this study. It is an adequate explanation for the basic relationship between instability and terrorism though it does not offer a complete theory of terrorism. The extensions to the breakdown model that I derived in Hypotheses 3 and 4 were not supported. Either another theoretical model is needed to explain the idea that one instability is enough instability to observe a relationship with terrorism or my extrapolations were not in line with the tenets of breakdown theory. More than one instability, within a five-year or a one-year period, did not appear to predict more terrorism, and it is not clear which theoretical model can explain this. I turn now to a review of the limitations of the current research.

Limitations of the Current Research

The most pressing limitation of the current research involves the validity of this study's measures. This study was undertaken with only one of many possible operationalizations of state instability, a very broad one, and one operationalization and one measure of terrorism incidents, the GTD's total terrorism incidents. Thus, it is unknown whether the instability effect I have suggested here will survive with narrower definitions of both instability and terrorism. Because of this uncertainty, it is premature to conclude that instability in all of its forms may be related to terrorism in all of its forms. It remains to be seen whether the instability effect can survive a test that uses different instability measures. Further, I examined the effects of instability on only the total number of terrorism incidents reported from the GTD. In future research, I intend to limit the dependent variable to include only fatal terrorism incidents from the GTD, that is, those incidents that claimed one or more fatalities. It remains to be seen whether there are any differences for the instability effect between incidents that claim a fatality and those that do not. I also intend to examine various other operationalizations of state instability and their effects on terrorism. This will be discussed in further detail in the future research section.

The next limitation of this study is that it only addresses a sample of the possible countries and years and thus, generalizability is hindered. Instability and terrorism both existed before 1970, but due to a lack of data, I am not able to examine the relationship prior to this year.[30] Further, although instability and terrorism certainly exist in countries with less than 500,000 in population, I could not examine the relationship between instability and terrorism in these nations due to the PITF's exclusion of these states. Further, due to control variable coverage, my sample of countries was further whittled down to a starting point of 151 nations from 1970 to 2005. Lack of variation on the dependent variable decreased Sample 1 to 147 nations. Although this sample included more states and years of domestic and transnational terrorism than the prior literature contained, it is still a sample. Thus, I can say nothing about the excluded countries, which included Iraq and Afghanistan. The generalizability of this study is quite clearly limited as a result.

Further, although extensive efforts have been made to minimize sample selection bias and omitted variables bias, they still remain a threat to validity. The instability effect was robust across changes in samples and the addition of many new control variables, but that does not mean it would remain robust if the full universe of countries were studied

30. However, Hoffman (1998) has stated that modern terrorism began in 1968 with the Popular Front for the Liberation of Palestine hijacking of the El Al airliner that captured global media attention. In addition, LaFree (2010, personal communication) has argued that the advent of satellite communications during this period opened the door to large-scale terrorism databases that rely on open-source media reports to collect incidents, such as the GTD that I used here.

further back in time. In addition, there may be an unmeasured variable that drives both instability and terrorism, making the potential connection between them completely spurious. Future research may uncover such a third variable. I have done my best in this study to statistically control for time-stable unobserved heterogeneity as well as to balance the need for country-year coverage with the need for control variables. Certainly, others may be able to do this more convincingly in the future to either better establish a connection between instability and terrorism or to question its foundations.

Finally, it should be made clear that I am not able to establish causality. I have simply demonstrated a correlation that is robust to changes in samples, to changes in the formulation of the independent variable of interest, and that makes good theoretical sense. In addition, I am not able to establish that any relationship between instability and terrorism is unidirectional. I cannot rule out the notion that in some states or years, terrorism may drive instability or that the relationship could be a constant feedback loop. This remains to future research to attempt. I turn now to the policy recommendations of this study.

Policy Recommendations

It is interesting to note that the focus on state failure as a threat to international security largely began in the Helman and Ratner (1992) policy article on the need to intervene in these situations to prevent spectacular state failures like that in Somalia. Helman and Ratner systematically addressed the failings of all of the traditional approaches to dealing with state failure, including United Nations trusteeship, conservatorship, and various aid programs directed at social and economic development. In the end, their policy prescription suggested that although state failings and failure would remain a fixture of the international landscape, a triage system should be employed to apply a sliding scale of intervention to failed and failing states. This sage advice seems as useful now as it was then. I lay out a brief sketch of my modifications to their policy recommendations.

Briefly, the suggested program for sliding scale intervention should look something like the following. All unstable states ought to be targeted by programs to foster the promotion of the legitimacy of government and civil liberties, and the promotion of basic human security and public service provisions, regardless of regime type. These states will also need to enter the peace process with any rebel groups they may currently be fighting. Governments in these states should also be assisted in shoring up their borders to prevent the contagion of instability and terrorism across those borders. Further, the United Nations will likely need to step in both militarily with peacekeeping forces and with training, supplies and equipment to help states to deal with ethnic minority group tensions and social and governmental discrimination against ethnic minority groups living in their borders. Although this recommendation was based off the findings here, that only compared countries with MARs to other countries with MARs (rather than to countries that lack defined MARs), it seems reasonable to conclude that dealing with ethnic minority group tension is a good idea.

It should be noted that caution should be applied regarding economic development given the findings of this research. This caution is suggested by the results in this study regarding the Food Production Index and carbon dioxide emissions. Certainly, economic development can bring opportunity and wealth, but it may also bring with it other ills, such as terrorism, as the state modernizes. Further, democracy promotion should be undertaken with caution; democracy certainly brings with it plenty of social goods, but the evidence is still incomplete with regards to its effect on terrorism. At the least, democracy should not be promoted as a way to lessen terrorism levels.

Ideally, this type of policy intervention would be applied along a sliding scale, with the most unstable countries receiving the most treatment. Basic functioning of the state will need to be addressed first and this may require the most time and resources. As it was for Helman and Ratner (1992), this list of policy prescriptions is a massive undertaking and will not uniformly lead to success. I turn now to a future research agenda.

Future Research

There are four main projects that are sorely needed. The first two have been previously discussed. Specifically, the operationalizations of instability and terrorism need to be changed to test whether the relationship suggested here is dependent on the formulation that I used. Ideally, several domains of political instability could be tested against one another; legitimacy of government, social service provision, and basic human security, and collapse of central government, for example, could be tested together to attempt to narrow down the involved mechanisms. In addition, a measure of timing or duration could be explored to see if instabilities that occur at certain points in time or if longer instabilities are more harmful. Further, the measure of terrorism should be varied to substitute the number of fatal attacks for total number of attacks. In the future, transnational and domestic terrorism should be tested separately to determine if the effects differ across type of terrorism.

Future research will need to address the directionality of the potential instability and terrorism relationship. This could be addressed via statistical methods such as path analysis or Granger causality tests (Granger, 1988). Pinning down the directionality of the relationship is important, because it is unrealistic to assume that instability can only lead to terrorism. Further, it is similarly unrealistic to assume that the directionality of the effect cannot change over time in the same state. In some years, instability could conceivably stimulate terrorism while in others the reverse could occur. Without specifying the facilitating conditions that may lead to instability influencing terrorism and those that lead to the reverse, work on instability and terrorism is incomplete. I plan to conduct such research in the future again utilizing the multi-sample strategy used here.

The final future research project that is needed the most is more difficult and ambitious than the changes in operationalizations and statistical modeling outlined above. Put simply, even if there is an actual relationship between instability and terrorism, it is still unknown what the mechanisms involved are and how they work. This is simply not a question that can be answered with quantitative, country-level research. The question of how and why instability and terrorism may be related requires an ambitious qualitative research agenda that includes in-depth case studies of states in stability and states with one instability, with complex singular instability and with same-year complex instabilities. Ideally, these in-depth case studies could follow these states as they transitioned into and out of instability. Further, these case studies require surveys and interviews of the general citizenry to measure the degree of breakdown *felt* in each state (Useem, 1998) as well as interviews with perpetrators of terrorism and instability. The perpetrator interviews ought to delve into the decision-making process that preceded the violent actions and should be conducted at the individual and group-level, if applicable. This qualitative research can help to answer questions regarding the mechanisms of any relationship between instability and terrorism.

In conclusion, future research is most certainly needed to replicate this study. First, alternative operationalizations and measures of both instability and terrorism need to be tested. The ways in which I operationalized both instability and terrorism in this study was quite broad, and it is necessary to test the relationship with different and narrower formulations so as to ensure the findings reported here are not artifacts of the data. Second, research that tests the directionality of any relationship, as well as allowing the directionality to go both ways, between terrorism and instability is needed. Finally, it is necessary to supplement this quantitative, country-level study with qualitative research, such as case studies of states as they transition into and out of instability as well as in-depth individual interviews. It is only by considering both the quantitative and qualitative evidence that true conclusions can be drawn regarding any relationship between instability and terrorism.

Conclusions

This study examined the relationship between political instability and terrorism. Prior research had suggested that political instability and terrorism could be related in a positive way (Marshall, 2002; Piazza, 2007; Piazza, 2008; Tikusis, 2009; LaFree, Dugan and Fahey, 2008). Theoretically, such a relationship made sense in the breakdown framework. Rapid social change had been shown repeatedly to be associated with the occurrence of non-routine collective action at the individual, city and country-level (Useem, 1980; 1985; 1997; 1998; LaFree and Drass, 1997; Lieske, 1978). Political instability constitutes one form of rapid social change and was the principal focus of this study. Political instability was conceptualized primarily as the legitimacy of the state in this study; this addresses the effective functioning of the government to compel conformity in its citizens through the rule of law. Political instability was operationalized using the Political Instability Task Force data; the four types of political instability were revolutionary war, ethnic war, adverse regime change, genocide and any combination of these events. Non-routine collective action, collective action that violates societal norms was conceptualized here as terrorism. Terrorism was operationalized using the Global Terrorism Database and was measured as the total number of terrorism incidents in the sampled countries from 1970 to 2005. This study sought to establish whether the occurrence of political instability in a state coincided with the occurrence of terrorism in that state.

My analysis demonstrated a strong positive relationship between instability and terrorism. When instability occurred, terrorism increased. When certain types of instability occurred, such as revolutionary war and ethnic war, the increases in terrorism were larger. These findings are highly supportive of breakdown theory. However, my logical extensions to breakdown theory were not supported. These extensions included that idea that multiple instabilities within five years should be accompanied by more terrorism incidents than one instability within five years. This was not observed. Further, the theoretical extensions suggested that multiple instabilities within a year should coincide with even more terrorism than one instability within a year. This also was not observed. Thus, breakdown theory explained the basic relationship between terrorism and instability; it is unclear what theoretical framework explains the findings regarding multiple instabilities and temporal density. The most important factor to emerge from this study was that despite the changes in formulations and samples, the occurrence of instability itself was always associated with increased terrorism. I conclude that there is a positive relationship between political instability and terrorism, but future research is required to delineate the boundaries of this relationship.

Appendix

Data

The Political Instability Task Force (PITF) data has issued a set of narratives which describe the basic foundations of their determinations of political instability for each instability event. The instability event types include adverse regime change, genocide, ethnic war and revolutionary war as well as a combination of any of these events called complex. (The complex category is disaggregated into its component parts in the data narratives, which allowed me to deal directly with the four instability types in the following procedure.) After reading the codebook, I discovered that it was possible for terrorism campaigns to be used by PITF as evidence in support of the occurrence of an instability event. Because of this, it is necessary to exclude these events so that no instability events in my independent variable could conceivably appear as a terrorism incident, my dependent variable, which is drawn from the Global Terrorism Database (GTD). I have gone about this in a three-step process. (All event descriptions in this Data Appendix come directly from Marshall, Gurr and Harff, 2009 and can be located via the country name and the instability type for that period).

Step 1

First, I searched for all occurrences of the words “terror”, “terrorize”, “terrorism”, “terrorist”, “terrorists”, etc. in the PITF event narratives and excluded any instability events that included the use of terrorism. This means that I kept the countries in the analysis, but I coded them as if they were not experiencing the instability event. What follows are those events that were excluded based on this rule.

In Syria from 1979 – 1989, a revolutionary war was excluded based on:

Militants of the Muslim Brotherhood initiate a terror and assassination campaign against the Alawite-dominated, Baathist regime.

In Israel from 1987 to the present, an ethnic war was excluded based on:

> Palestinians rebel against Israel's repressive authority in the occupied territories of Gaza and West Bank and in Israel proper (the "intifada"). Violent mass demonstrations and systematic terrorist campaign is largely suspended in October 1998 awaiting the final implementation of the Wye River Accords. Violence begins again in September 2000 as implementation falls short of expectations.

In Peru from 1982-1987, a revolutionary war was excluded based on:

> Maoist guerrillas of Sendero Luminoso (Shining Path) attack government troops, terrorize rural and urban supporters of government.

In the United Kingdom (which includes Northern Ireland in this study) from 1971-1982,

an ethnic war was excluded based on:

> Catholic IRA (Irish Republican Army) uses terror against British forces and militant Protestants in quest for union with Republic of Ireland. Violence begins to subside in late 1970s and early 1980s as all sides search for alternatives to violence, eventually culminating in October 1994 peace agreement.

In Algeria from 1991 to 2004, a revolutionary war was excluded based on:

> Islamic militants and military-government initiate intense terror campaigns designed to undermine each other's support bases.

In China from 1988-1998, an ethnic war was excluded based on:

> Episodic violent protests by Uighurs in Xinjiang Province against Han Chinese control escalate by 1996 into terror campaign; government repression ends open opposition.

In the Philippines, from 1972-1976, a genocide was excluded based on:

> Moro resistance to Christian settlement and support for separatist guerrillas results in military and paramilitary terror tactics in which many Moros die in massacres and napalm bombings.

In Egypt from 1992 – 1999, a revolutionary war was excluded based on:

> Terror campaign by militant Islamic groups against secular government; largely suppressed by mid-1996. Widespread arrests of activists result in March 1999

> renunciation of violence by the Gamaat-I-Islamiya (Egypt's largest resistance group).

In Iran from 1981 to 1983, a revolutionary war was excluded based on:

> Moderates (National Front) and conservatives (IRP Islamic Revival Party) use terror and repression in competition for political control.

Excluding these instability events is a necessary data strategy to avoid confounding my independent and dependent variables.

Step 2

Second, I also excluded any government actions that were a response to the terrorism on the grounds that it is likely that they would not have occurred if the terrorism had not itself occurred in the first place. This excluded government reaction instability events that likely would not have occurred without the terrorism. To be clear, I kept these countries in the analysis, but I coded them as if they were not experiencing the instability events. The events excluded by this rule are provided below.

In Syria, the government responded to a revolutionary war that involved the use of terror (discussed earlier) by conducting a genocide in 1981 and 1982. The following genocide was excluded because it occurred in direct response to the terror campaign discussed above.

> Following a coup attempt in January 1982, government forces move to crush the militants' stronghold in Hama in February 1982.

In Peru in 1992, the government response to the revolutionary war excluded above consisted of a regime change which was then excluded.

> Facing internal warfare and recession, President Fujimori, backed by military, dissolves Congress and suspends Constitution.

In the Sudan from 2003 to the present, an ethnic war and a genocide were each excluded. I exclude the ethnic war, because it was backed by the government. I exclude the genocide, because it was a direct governmental response. [I classify these both as responses because the local Arab militias took on a government role of using terror as they took over the anti-insurgency role from the government.]

> Rebellion breaks out in Darfur region in western Sudan in February 2003 followed by army offensive in March; violence quickly escalates as local Arab militias take over anti-insurgency role [ethnic war]. Government backs local, Arab janjaweed militias and encourages them to terrorize suspected supporters of separatist rebels; victims groups include Fur, Zaghawa, Masaleit, and other non-Arab peoples of the Darfur region [genocide].

In Iran from 1981 to 1992, a revolutionary war was excluded based on the use of terror so the corresponding government response of a genocide by the government was excluded based on:

> To consolidate Islamic revolution, Khomeini government violently suppresses dissident Muslims (Mujahedin) and rebel Kurds, selectively executes prominent Baha'is.

Excluding the government response-instability events to the preceding instability events that included terror is premised on the notion that the government response-instability event would likely not have occurred without the instability event that included terror tactics. It is a conservative data strategy to avoid confounding the dependent and independent variable. It is not without weaknesses, which are discussed later in the appendix.

Step 3

For the third prong of my data strategy, I dropped all terrorism incidents from the Global Terrorism Database in which any of the targets of the incident was military. The reasoning for doing so is as follows. Two of the instability types in the PITF data involve war: ethnic war and revolutionary war. Unfortunately, there are few clear cut boundaries between terrorist incidents that target the military and insurgent acts against the military that are part of a larger campaign in an ethnic war or a revolutionary war. Because of this lack of conceptual clarity, it is conceivable that terrorist incidents included in the GTD may have been used as evidence in support of the determination of an ethnic war or a revolutionary war instability event. For this reason, I exclude all incidents in which any of the targets of the incident are a nation's military to avoid confounding my dependent and independent variables.

I have also removed high casualty incidents (25 or more fatalities) perpetrated in Rwanda from April 1, 1994 until July 31, 1994 from the GTD as these incidents may have been part of the Rwandan genocide. The Rwandan genocide is part of a complex instability in the PITF data; the specific classification of this event is a genocide from 4/1994 to 7/1994. These criteria resulted in the deletion of 4 incidents from the GTD, including the massacre of more than 1000 individuals in a Catholic Church. There were a total of 21 incidents in Rwanda between April 1, 1994 and July 31, 1994. Thus, the contamination of the GTD with individual genocide events is quite low, given that at least 500,000 individuals perished within the 100 days of the Rwandan genocide.

Step 4

A second possible area of concern are when genocides were perpetrated against civilian populations by armed rebel groups as evidenced by the inclusion of events that made up the Rwandan genocide in the GTD as terrorism events. It is possible that these instability events could have been picked up in the GTD and counted as terrorism incidents. For this reason, I exclude all of the genocides that were perpetrated by groups other than the government from the PITF data. This includes genocides perpetrated by armed rebel groups as well as those in which the groups helped the government to carry them out. The following genocides were excluded so as to not run the risk of confounding the independent and dependent variables.

In Angola, two separate genocides were excluded because the rebel group there participated in it.

> Both Union for the Total Independence of Angola (UNITA) rebels and government forces perpetrate destructive campaigns and atrocities against civilians throughout conflict (Genocide: 11/75-11/94).
> Targeting of civilian populations resumes with the break down to civil war (Genocide: 12/98-3/02).

In Bosnia and Herzegovina, a genocide was excluded based on the following.

> Muslim residents of Bosnia are subject to “ethnic cleansing” measures including destruction of property, forced resettlement, and execution mainly by Serb and some Croat forces (Genocide: 5/92-11/95).

In Burundi, a genocide was excluded based on the following narrative.

> Subsequent armed clashes and massacres occur in three waves: Tutsi soldiers against Hutu civilians, Hutus against Tutsis, and Tutsi against Hutus (Genocide: 10/93-12/93).

In Sudan, genocide was perpetrated by rebel militia groups, among others, and so was excluded.

> Non-Muslim supporters of secession are targeted for destruction by indiscriminate military attacks, massacres by government-supported tribal militias, and government-induced privation and population displacement; targeting of civilian population ends in October 2002 as part of peace talks and opening of conflict areas to relief agencies (Genocide: 9/83-10/02).

Excluding these instability events is an important, but conservative step to guard against confounding the independent and dependent variable. Since I do not actually know that there was any overlap between, this strategy is not technically necessary, but it is important to ensure that there is little to no chance of confounding instability and terrorism. The weaknesses of this approach will be discussed later in the appendix.

Possibility of False Negatives

Searching for terrorism campaigns in the PITF narratives by searching for "terror" may undercount the amount of terrorism uncovered in the PITF narrative, thus leading to the possibility of false negatives. The false negatives would be instability events that did involve terrorism and should have been excluded. After very careful review of all of the narratives, I determined that the danger of these false negatives was low. However, for the sake of transparency, I have included examples of the instability events that I reviewed and included.

In Laos, a series of instabilities occurred from 1960 to 1979. I start including the instabilities once my observation period begins, 1970. These instabilities were included in my data.

> Kong Le seizes power in an attempt to form a neutralist government; government remains locked in bitter struggle between neutralist, rightists, and communists until the ending of the war in neighboring Vietnam provides opportunity for the Lao People's Revolutionary Party (LPRP; Pathet Lao) to establish one-party rule (Regime Change: 1/60-12/75). Military coup sparks sustained conflict as rebels fight unsuccessfully to overthrow rightist Somsanith regime (Revolutionary war: 9/60-5/62). Hmong (Meo) rebels encouraged to fight Pathet Lao; rebellion is suppressed after Pathet Lao takeover in 1975, no significant guerrilla activity after 1979 (Ethnic war: 7/61-6/79). Neutralists and Conservatives join forces to oppose Communist Pathet Lao forces; resistance by rightist forces continues until 1979 (Revolutionary war: 3/63-3/79).

In Comoros, two separate outbreaks of instability occurred. The first outbreak was in a regime change in 1976 and the second involved two regime changes from 1995 to 1999.

> Twenty-eight days after the declaration of independence a coalition of six political parties known as the United National Front ousts the Abdallah government. Democratic governance ends with the designation of Ali Soilih as head of state.

> Foreign-led mercenaries and disaffected Comorian troops overthrow elected government of President Djohar. French troops sent to the island one week later arrest mercenaries, reinstall elected prime minister, and arrest Djohar. Army Chief

> of Staff, Col. Assoumani Azzali, leads April 30, 1999 coup that dissolves constitution and government; promised transition to new elections based on Antananarivo agreement do not materialize.

In the Central African Republic, from 2003 to the present, there were a series of instabilities.

> Following his dismissal as commander, troops loyal to Gen. Bozize mount challenge to elected government of President Patasse. Gen. Bozize succeeds in seizing power in March 2003 while Patasse is out of the country (Regime change: 3/03). Supporters of ousted President Patasse in the north face retribution from the Bozize regime which draws its support from southerners. Open rebellion breaks out in the northwest in June 2005 and, then, in October 2006 in the northeast (Ethnic war: from 6/05).

I turn now to the weaknesses of excluding data as I have done here.

Weaknesses of the Data Exclusions

Carving out all instability events that were coded based on the use of terror or on government reactions to terrorism is a necessary decision so that I do not include the same types of events in my dependent and independent variable such that any relationship between instability and terrorism could be due to predicting terrorism with terrorism (by another name).

Carving out military targets from the GTD and genocides perpetrated by or in collusion with non-state actors from the PITF data are conservative decisions to guard against counting the same types of events in the independent variable and the dependent variable. To count the same types of events in the independent and dependent variable could mean that any relationship I find between instability and terrorism is spurious due to predicting terrorism with terrorism. To be clear, I do not actually know with certainty that I would be predicting terrorism with terrorism in the military target and armed rebel group genocides, but to minimize the risk of this happening, I have taken this data cleaning step and excluded them from their respective data sets. However, to be clear, it is not without downsides. In a very real way, it does decrease the generalizability of this dissertation. Simply put, my dissertation cannot answer questions about the effects of political instability on terrorism that includes actions against the military nor of the effects of instability with genocides perpetrated by armed rebel groups on terrorism. This is a weakness of this strategy. However, the downside of hampering the generalizability of the study is outweighed by the risks of including events in the independent variable that could conceivably be included in the dependent variable. Finally, it should be noted that I have done more to ensure that my results are not hampered by possible overlap between the independent and dependent variables than others who have studied the instability and terrorism relationship using the PITF data.

Table 12. List of countries and years in sample 1

Sample 1	Years in Sample	Sample 2	Years in Sample	Sample 3	Years in Sample
Albania	1970-2005	Algeria	1981-2005	Bosnia and Herzegovina	1997-2005
Algeria	1970-2005	Argentina	1981-2005	Eritrea	1996-2005
Angola	1975-2005	Armenia	1993-2005	Georgia	1996-2005
Argentina	1970-2005	Australia	1981-2005	Belarus	1995-2005
Armenia	1992-2005	Austria	1981-2005	Moldova	1995-2005
Australia	1970-2005	Azerbaijan	1992-2005	Czech Republic	1994-2005
Austria	1970-2005	Bahrain	1981-2005	Kazakhstan	1994-2005
Azerbaijan	1992-2005	Bangladesh	1981-2005	Kyrgyzstan	1994-2005
Bahrain	1971-2005	Belarus	1995-2005	Macedonia	1994-2005
Bangladesh	1972-2005	Benin	1981-2005	Slovakia	1994-2005
Belarus	1992-2005	Bolivia	1981-2005	Estonia	1993-2005
Benin	1970-2005	Bosnia and Herzegovina	1997-2005	Russia	1993-2005
Bolivia	1970-2005	Botswana	1981-2005	Ukraine	1993-2005
Bosnia and Herzegovina	1992-2005	Brazil	1981-2005	Azerbaijan	1992-2005
Botswana	1970-2005	Burkina Faso	1981-2005	Croatia	1992-2005
Brazil	1970-2005	Burundi	1981-2005	Latvia	1992-2005
Bulgaria	1970-2005	Cameroon	1981-2005	Lithuania	1992-2005
Burkina Faso	1970-2005	Central African Republic	1981-2005	UK	1992-2005
Burma	1970-2005	Chad	1981-2005	Zambia	1992-2005
Burundi	1970-2005	Chile	1981-2005	Algeria	1990-2005
Cambodia	1970-2005	China	1981-2005	Argentina	1990-2005
Cameroon	1970-2005	Colombia	1981-2005	Australia	1990-2005
Canada	1970-2005	Congo-Brazzaville	1981-2005	Bahrain	1990-2005

Sample 1	Years in Sample	Sample 2	Years in Sample	Sample 3	Years in Sample
Central African Republic	1970-2005	Congo-Kinshasa	1981-2005	Bangladesh	1990-2005
Chad	1970-2005	Costa Rica	1981-2005	Bolivia	1990-2005
Chile	1970-2005	Croatia	1992-2005	Botswana	1990-2005
China	1970-2005	Cyprus	1981-2005	Brazil	1990-2005
Colombia	1970-2005	Czech Republic	1993-2005	Burundi	1990-2005
Congo-Brazzaville	1970-2005	Denmark	1981-2005	Cameroon	1990-2005
Congo-Kinshasa	1970-2005	Dominican Republic	1981-2005	Chad	1990-2005
Costa Rica	1970-2005	Egypt	1981-2005	Chile	1990-2005
Croatia	1992-2005	El Salvador	1981-2005	China	1990-2005
Cuba	1970-2005	Eritrea	1993-2005	Colombia	1990-2005
Cyprus	1970-2005	Estonia	1993-2005	Congo-Kinshasa	1990-2005
Czech Republic	1993-2005	Fiji	1981-2005	Costa Rica	1990-2005
Denmark	1970-2005	Finland	1981-2005	Cyprus	1990-2005
Djibouti	1977-2005	France	1981-2005	Dominican Republic	1990-2005
Dominican Republic	1970-2005	Gabon	1981-2005	Egypt	1990-2005
East Timor	2002-2005	Georgia	1996-2005	El Salvador	1990-2005
Ecuador	1970-2005	Germany	1990-2005	Fiji	1990-2005
Egypt	1970-2005	Ghana	1981-2005	France	1990-2005
El Salvador	1970-2005	Greece	1981-2005	Germany	1990-2005
Equatorial Guinea	1970-2005	Guatemala	1981-2005	Ghana	1990-2005
Eritrea	1993-2005	Guinea	1981-2005	Greece	1990-2005
Estonia	1992-2005	Guinea-Bissau	1981-2005	Guatemala	1990-2005
Fiji	1970-2005	Guyana	1981-2005	Guinea	1990-2005
Finland	1970-2005	Haiti	1981-2005	Guyana	1990-2005
France	1970-2005	Honduras	1981-2005	Honduras	1990-2005

Sample 1	Years in Sample	Sample 2	Years in Sample	Sample 3	Years in Sample
Gabon	1970-2005	Hungary	1981-2005	Hungary	1990-2005
Georgia	1992-2005	India	1981-2005	India	1990-2005
Germany	1990-2005	Indonesia	1981-2005	Indonesia	1990-2005
Ghana	1970-2005	Ireland	1981-2005	Israel	1990-2005
Greece	1970-2005	Israel	1981-2005	Italy	1990-2005
Guatemala	1970-2005	Italy	1981-2005	Japan	1990-2005
Guinea	1970-2005	Ivory Coast	1981-2005	Jordan	1990-2005
Guinea-Bissau	1974-2005	Jamaica	1981-2005	Kenya	1990-2005
Guyana	1970-2005	Japan	1981-2005	Korea, South	1990-2005
Haiti	1970-2005	Jordan	1981-2005	Madagascar	1990-2005
Honduras	1970-2005	Kazakhstan	1994-2005	Malaysia	1990-2005
Hungary	1970-2005	Kenya	1981-2005	Mali	1990-2005
India	1970-2005	Korea, South	1981-2005	Mauritania	1990-2005
Indonesia	1970-2005	Kyrgyzstan	1994-2005	Morocco	1990-2005
Iran	1970-2005	Latvia	1992-2005	Namibia	1990-2005
Ireland	1970-2005	Lithuania	1992-2005	Nicaragua	1990-2005
Israel	1970-2005	Macedonia	1994-2005	Niger	1990-2005
Italy	1970-2005	Madagascar	1981-2005	Pakistan	1990-2005
Ivory Coast	1970-2005	Malawi	1981-2005	Panama	1990-2005
Jamaica	1970-2005	Malaysia	1981-2005	Peru	1990-2005
Japan	1970-2005	Mali	1981-2005	Philippines	1990-2005
Jordan	1970-2005	Mauritania	1981-2005	Rwanda	1990-2005
Kazakhstan	1992-2005	Mauritius	1981-2005	Saudia Arabia	1990-2005
Kenya	1970-2005	Mexico	1981-2005	Senegal	1990-2005
Korea, South	1970-2005	Moldova	1995-2005	South Africa	1990-2005

Sample 1	Years in Sample	Sample 2	Years in Sample	Sample 3	Years in Sample
Kyrgyzstan	1992-2005	Morocco	1981-2005	Spain	1990-2005
Laos	1970-2005	Mozambique	1981-2005	Sri Lanka	1990-2005
Latvia	1992-2005	Namibia	1990-2005	Sudan	1990-2005
Lebanon	1970-2005	Nepal	1981-2005	Switzerland	1990-2005
Lesotho	1970-2005	Netherlands	1981-2005	Syria	1990-2005
Liberia	1970-2005	Nicaragua	1981-2005	Thailand	1990-2005
Libya	1970-2005	Niger	1981-2005	United States	1990-2005
Lithuania	1992-2005	Nigeria	1981-2005	Venezuela	1990-2005
Macedonia	1993-2005	Pakistan	1981-2005	Zimbabwe	1990-2005
Madagascar	1970-2005	Panama	1981-2005		
Malawi	1970-2005	Papua New Guinea	1981-2005		
Malaysia	1970-2005	Peru	1981-2005		
Mali	1970-2005	Philippines	1981-2005		
Mauritania	1970-2005	Portugal	1981-2005		
Mauritius	1970-2005	Russia	1993-2005		
Mexico	1970-2005	Rwanda	1981-2005		
Moldova	1992-2005	Saudia Arabia	1981-2005		
Morocco	1970-2005	Senegal	1981-2005		
Mozambique	1975-2005	Slovakia	1993-2005		
Namibia	1990-2005	Slovenia	1992-2005		
Nepal	1970-2005	South Africa	1981-2005		
Netherlands	1970-2005	Spain	1981-2005		
Nicaragua	1970-2005	Sri Lanka	1981-2005		
Niger	1970-2005	Sudan	1981-2005		
Nigeria	1970-2005	Swaziland	1981-2005		

Sample 1	Years in Sample	Sample 2	Years in Sample	Sample 3	Years in Sample
North Korea	1970-2005	Sweden	1981-2005		
Norway	1970-2005	Switzerland	1981-2005		
Pakistan	1972-2005	Syria	1981-2005		
Panama	1970-2005	Tajikistan	1992-2005		
Papua New Guinea	1975-2005	Thailand	1981-2005		
Paraguay	1970-2005	The Gambia	1981-2005		
Peru	1970-2005	Togo	1981-2005		
Philippines	1970-2005	Trinidad and Tobago	1981-2005		
Poland	1970-2005	Tunisia	1981-2005		
Portugal	1970-2005	Turkey	1981-2005		
Qatar	1971-2005	UK	1981-2005		
Romania	1970-2005	Ukraine	1993-2005		
Russia	1992-2005	United Arab Emirates	1981-2005		
Rwanda	1970-2005	United States	1981-2005		
Saudia Arabia	1970-2005	Venezuela	1981-2005		
Senegal	1970-2005	Yemen	1991-2005		
Sierra Leone	1970-2005	Zambia	1981-2005		
Slovakia	1993-2005	Zimbabwe	1981-2005		
Slovenia	1992-2005				
Solomon Islands	1978-2005				
Somalia	1970-2005				
South Africa	1970-2005				
Spain	1970-2005				
Sri Lanka	1970-2005				
Sudan	1970-2005				

Sample 1	Years in Sample	Sample 2	Years in Sample	Sample 3	Years in Sample
Swaziland	1970-2005				
Sweden	1970-2005				
Switzerland	1970-2005				
Syria	1970-2005				
Tajikistan	1992-2005				
Tanzania	1970-2005				
Thailand	1970-2005				
The Gambia	1970-2005				
Togo	1970-2005				
Trinidad and Tobago	1970-2005				
Tunisia	1970-2005				
Turkey	1970-2005				
Uganda	1970-2005				
UK	1970-2005				
Ukraine	1992-2005				
United Arab Emirates	1971-2005				
United States	1970-2005				
Uruguay	1970-2005				
Uzbekistan	1992-2005				
Venezuela	1970-2005				
Vietnam	1976-2005				
Yemen	1990-2005				
Zambia	1970-2005				
Zimbabwe	1970-2005				

Table 13. Full distribution of terrorism incidents for all samples

Incidents	Sample 1	Cumulative Percentage	Incidents	Sample 2	Cumulative Percentage	Incidents	Sample 3	Cumulative Percentage
0	2,358	50.31	0	1,105	42.11	0	434	34.94
1	514	61.28	1	299	53.51	1	136	45.89
2	286	67.38	2	168	59.91	2	98	53.78
3	190	71.43	3	105	63.91	3	51	57.89
4	136	74.33	4	86	67.19	4	38	60.95
5	102	76.51	5	69	69.82	5	39	64.09
6	83	78.28	6	51	71.76	6	29	66.43
7	56	79.48	7	37	73.17	7	18	67.87
8	42	80.37	8	25	74.12	8	11	68.76
9	41	81.25	9	26	75.11	9	10	69.57
10	44	82.18	10	32	76.33	10	17	70.93
11	39	83.02	11	25	77.29	11	17	72.3
12	28	83.61	12	18	77.97	12	10	73.11
13	25	84.15	13	18	78.66	13	7	73.67
14	24	84.66	14	17	79.31	14	8	74.32
15	24	85.17	15	17	79.95	15	10	75.12
16	28	85.77	16	18	80.64	16	7	75.68
17	22	86.24	17	19	81.36	17	13	76.73
18	23	86.73	18	16	81.97	18	9	77.46
19	17	87.09	19	11	82.39	19	7	78.02
20	15	87.41	20	8	82.7	20	4	78.34
21	14	87.71	21	13	83.19	21	8	78.99
22	19	88.12	22	13	83.69	22	10	79.79
23	24	88.63	23	16	84.3	23	8	80.43
24	9	88.82	24	6	84.53	24	1	80.52
25	11	89.05	25	8	84.83	25	7	81.08
26	9	89.25	26	8	85.14	26	5	81.48
27	11	89.48	27	10	85.52	27	6	81.96
28	11	89.72	28	9	85.86	28	4	82.29
29	12	89.97	29	9	86.2	29	7	82.85
30	12	90.23	30	9	86.55	30	8	83.49
31	8	90.4	31	3	86.66	31	1	83.57
32	6	90.53	32	3	86.78	32	1	83.66
33	9	90.72	33	7	87.04	33	5	84.06
34	5	90.83	34	3	87.16	34	2	84.22
35	7	90.98	35	6	87.39	35	4	84.54
36	6	91.1	36	6	87.61	36	4	84.86
37	8	91.27	37	5	87.8	37	3	85.1

Incidents	Sample 1	Cumulative Percentage	Incidents	Sample 2	Cumulative Percentage	Incidents	Sample 3	Cumulative Percentage
38	18	91.66	38	14	88.34	38	12	86.07
39	4	91.74	39	3	88.45	39	2	86.23
40	6	91.87	40	6	88.68	40	1	86.31
41	8	92.04	41	6	88.91	41	4	86.63
42	3	92.11	42	2	88.99	42	1	86.71
43	6	92.23	43	5	89.18	43	3	86.96
44	5	92.34	44	5	89.37	44	4	87.28
45	6	92.47	45	5	89.56	45	2	87.44
46	6	92.6	46	5	89.75	46	4	87.76
47	7	92.75	47	4	89.9	47	1	87.84
48	3	92.81	48	1	89.94	49	2	88
49	4	92.9	49	2	90.02	50	1	88.08
50	2	92.94	50	1	90.05	51	2	88.24
51	3	93	51	3	90.17	52	1	88.33
52	3	93.07	52	1	90.21	53	1	88.41
53	3	93.13	53	1	90.24	54	1	88.49
54	3	93.19	54	3	90.36	56	2	88.65
55	2	93.24	55	1	90.4	57	2	88.81
56	5	93.34	56	3	90.51	58	2	88.97
57	3	93.41	57	2	90.59	59	1	89.05
58	4	93.49	58	3	90.7	60	1	89.13
59	2	93.54	59	2	90.78	61	2	89.29
60	2	93.58	60	2	90.85	62	5	89.69
61	4	93.66	61	4	91.01	63	3	89.94
62	8	93.83	62	8	91.31	64	2	90.1
63	4	93.92	63	3	91.43	65	2	90.26
64	3	93.98	64	2	91.5	66	2	90.42
65	5	94.09	65	4	91.65	68	1	90.5
66	3	94.15	66	3	91.77	70	2	90.66
68	5	94.26	68	3	91.88	72	2	90.82
69	1	94.28	70	2	91.96	73	2	90.98
70	4	94.37	71	1	92	74	3	91.22
71	3	94.43	72	2	92.07	75	1	91.3
72	3	94.5	73	2	92.15	76	2	91.47
73	2	94.54	74	4	92.3	78	4	91.79
74	5	94.64	75	1	92.34	79	4	92.11
75	1	94.67	76	2	92.42	80	2	92.27
76	2	94.71	77	1	92.45	81	3	92.51
77	2	94.75	78	4	92.61	82	3	92.75
78	4	94.84	79	4	92.76	84	1	92.83

Incidents	Sample 1	Cumulative Percentage	Incidents	Sample 2	Cumulative Percentage	Incidents	Sample 3	Cumulative Percentage
79	4	94.92	80	3	92.87	85	2	93
80	5	95.03	81	4	93.03	86	1	93.08
81	7	95.18	82	3	93.14	89	1	93.16
82	3	95.24	84	2	93.22	94	2	93.32
84	3	95.31	85	2	93.29	96	1	93.4
85	4	95.39	86	2	93.37	99	2	93.56
86	2	95.43	87	1	93.41	100	2	93.72
87	2	95.48	89	1	93.45	101	1	93.8
89	1	95.5	92	1	93.48	102	2	93.96
92	1	95.52	93	1	93.52	104	1	94.04
93	1	95.54	94	3	93.64	105	2	94.2
94	4	95.63	95	1	93.67	107	1	94.28
95	1	95.65	96	4	93.83	109	1	94.36
96	4	95.73	98	3	93.94	111	2	94.52
97	1	95.75	99	3	94.05	116	1	94.61
98	3	95.82	100	3	94.17	117	1	94.69
99	3	95.88	101	1	94.21	123	2	94.85
100	3	95.95	102	3	94.32	124	2	95.01
101	2	95.99	104	2	94.4	126	1	95.09
102	3	96.05	105	3	94.51	127	1	95.17
104	2	96.1	106	2	94.59	129	1	95.25
105	3	96.16	107	1	94.63	130	2	95.41
106	2	96.2	108	1	94.66	132	1	95.49
107	5	96.31	109	1	94.7	133	1	95.57
108	2	96.35	111	2	94.78	134	3	95.81
109	1	96.37	113	2	94.86	135	1	95.89
111	2	96.42	114	1	94.89	136	1	95.97
113	2	96.46	116	2	94.97	143	1	96.05
114	1	96.48	117	1	95.01	145	1	96.14
115	1	96.5	119	1	95.05	148	2	96.3
116	2	96.54	120	2	95.12	149	1	96.38
117	1	96.56	123	3	95.24	152	1	96.46
118	1	96.59	124	2	95.31	153	1	96.54
119	2	96.63	125	2	95.39	154	2	96.7
120	2	96.67	126	2	95.46	155	1	96.78
122	2	96.71	127	1	95.5	160	2	96.94
123	3	96.78	129	2	95.58	163	1	97.02
124	2	96.82	130	2	95.66	164	1	97.1
125	2	96.86	132	1	95.69	169	2	97.26
126	2	96.91	133	1	95.73	174	1	97.34

Incidents	Sample 1	Cumulative Percentage	Incidents	Sample 2	Cumulative Percentage	Incidents	Sample 3	Cumulative Percentage
127	1	96.93	134	5	95.92	177	2	97.5
129	2	96.97	135	1	95.96	180	1	97.58
130	2	97.01	136	2	96.04	187	1	97.67
131	1	97.03	138	2	96.11	191	1	97.75
132	1	97.06	139	1	96.15	192	1	97.83
133	1	97.08	141	1	96.19	205	1	97.91
134	5	97.18	143	2	96.27	209	1	97.99
135	2	97.23	144	1	96.3	211	1	98.07
136	2	97.27	145	1	96.34	214	1	98.15
137	1	97.29	146	1	96.38	227	1	98.23
138	2	97.33	147	1	96.42	231	1	98.31
139	2	97.38	148	3	96.53	234	1	98.39
141	2	97.42	149	1	96.57	249	1	98.47
143	2	97.46	151	1	96.61	261	1	98.55
144	1	97.48	152	1	96.65	262	1	98.63
145	1	97.5	153	1	96.68	263	1	98.71
146	1	97.53	154	2	96.76	269	1	98.79
147	1	97.55	155	1	96.8	278	1	98.87
148	3	97.61	156	1	96.84	284	1	98.95
149	2	97.65	157	1	96.87	328	1	99.03
151	1	97.67	160	3	96.99	330	1	99.11
152	1	97.7	163	1	97.03	334	1	99.19
153	2	97.74	164	1	97.07	337	1	99.28
154	3	97.8	165	1	97.1	341	1	99.36
155	1	97.82	167	1	97.14	348	1	99.44
156	1	97.85	169	2	97.22	363	1	99.52
157	2	97.89	174	1	97.26	390	1	99.6
159	1	97.91	177	3	97.37	463	1	99.68
160	3	97.97	180	1	97.41	477	1	99.76
163	2	98.02	182	1	97.45	571	1	99.84
164	1	98.04	186	2	97.52	609	1	99.92
165	1	98.06	187	1	97.56	645	1	100
167	1	98.08	191	1	97.6			
169	3	98.14	192	1	97.64	Total	1,242	
174	2	98.19	195	1	97.68			
177	3	98.25	197	1	97.71			
180	1	98.27	204	1	97.75			
182	2	98.31	205	1	97.79			
184	1	98.34	207	1	97.83			
186	2	98.38	209	1	97.87			

Incidents	Sample 1	Cumulative Percentage	Incidents	Sample 2	Cumulative Percentage	Incidents	Sample 3	Cumulative Percentage
187	1	98.4	211	1	97.9			
191	1	98.42	214	1	97.94			
192	1	98.44	225	1	97.98			
195	1	98.46	227	1	98.02			
197	2	98.51	231	1	98.06			
200	1	98.53	233	1	98.09			
202	1	98.55	234	1	98.13			
204	1	98.57	237	1	98.17			
205	1	98.59	242	1	98.21			
207	1	98.61	243	1	98.25			
209	2	98.66	249	1	98.29			
210	1	98.68	259	1	98.32			
211	1	98.7	261	2	98.4			
214	1	98.72	262	1	98.44			
225	1	98.74	263	1	98.48			
227	1	98.76	269	1	98.51			
231	1	98.78	272	1	98.55			
233	1	98.81	278	1	98.59			
234	1	98.83	283	1	98.63			
237	1	98.85	284	1	98.67			
242	1	98.87	292	3	98.78			
243	1	98.89	302	1	98.82			
244	1	98.91	313	1	98.86			
249	1	98.93	315	1	98.89			
259	1	98.95	317	1	98.93			
261	2	99	319	1	98.97			
262	1	99.02	328	1	99.01			
263	1	99.04	330	1	99.05			
269	1	99.06	334	1	99.09			
272	2	99.1	337	1	99.12			
278	1	99.13	340	1	99.16			
283	1	99.15	341	1	99.2			
284	1	99.17	348	1	99.24			
292	3	99.23	349	1	99.28			
295	1	99.25	351	1	99.31			
296	1	99.27	363	1	99.35			
302	1	99.3	376	1	99.39			
304	1	99.32	390	1	99.43			
313	1	99.34	417	1	99.47			
315	1	99.36	432	1	99.5			

Incidents	Sample 1	Cumulative Percentage	Incidents	Sample 2	Cumulative Percentage	Incidents	Sample 3	Cumulative Percentage
317	1	99.38	442	1	99.54			
319	1	99.4	459	1	99.58			
328	1	99.42	463	1	99.62			
330	1	99.45	477	1	99.66			
334	1	99.47	481	1	99.7			
337	1	99.49	523	1	99.73			
340	1	99.51	540	1	99.77			
341	1	99.53	556	1	99.81			
348	1	99.55	571	2	99.89			
349	1	99.57	593	1	99.92			
351	1	99.59	609	1	99.96			
363	1	99.62	645	1	100			
376	1	99.64						
390	1	99.66	Total	2,624				
417	1	99.68						
432	1	99.7						
442	1	99.72						
459	1	99.74						
463	1	99.77						
477	1	99.79						
481	1	99.81						
523	1	99.83						
540	1	99.85						
556	1	99.87						
571	2	99.91						
593	1	99.94						
602	1	99.96						
609	1	99.98						
645	1	100						
Total	4,687							

References

Abadie, Alberto. 2006. Poverty, political freedom and the roots of terrorism. *The American Economic Review* 96: 50-56.

Allison, Paul. 2009. *Fixed Effects Regression Models.* Thousand Oaks, CA: Sage Publications, Inc.

Angrist, Joshua D., and Jorn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton, NJ: Princeton University Press.

Asal, Victor, and Amy Pate. 2005. The decline of ethnic political discrimination 1950-2003. Pp. 28-38 in *Peace and Conflict 2005*, edited by Monty G. Marshall and Ted Robert Gurr. College Park, MD: Center for International Development and Conflict Management, University of Maryland.

Cameron, A. Colin, and Pravin K. Trivedi. 2009. *Microeconometrics Using Stata.* College

Caplan, Nathan S., and Jeffrey M. Paige. 1968. A study of ghetto rioters. *Scientific American* 219: 15-21.

Charters, David A. 1994. Conclusions: Security and liberty in the balance – Countering terrorism in the democratic context. In *The Deadly Sin of Terrorism: Its effect on Democracy and Civil liberties in Six Countries*, ed. DA Charters. Westport, CT: Greenwood Press.

CIDCM. 2009. *Minorities at Risk (MAR) Codebook Version 2/2009*. Center for International Development and Conflict Management. http://www.cidcm.umd.edu/mar/data/mar_codebook_Feb09.pdf

Cohen, Lawrence E., and Marcus Felson. 1979. Social change and crime rate trends: A routine activity approach. *American Sociological Review* 44: 588-608.

Collier, Paul, and Anke Hoeffler. 1998. On economic causes of civil war. *Oxford Economic Papers* 50: 563-573.

Collier, Paul and Anke Hoeffler. 2002. On the Incidence of civil war in Africa. *The Journal of Conflict Resolution* 46: 13-28.

———. Greed and grievance in civil wars. *Oxford Economic Papers* 56: 563-595.

Correlates of War Project. *Direct Contiguity Data, 1816-2006*. Version 3.1. Data downloaded on 12/01/2009. Online: http://correlatesofwar.org

Dugan, Laura. 2010. Estimating effects over time for single and multiple units. In *Handbook of Quantitative Criminology*, ed. Alex R. Piquero and David Weisburd. New York: Springer New York.

Durkheim, Emile. 1930 [1951]. *Suicide: A Study in Sociology* translated by George Simpson and John A. Spaulding. New York: The Free Press.

Erdman, Donald, Laura Jackson, Arthur Sinko, and SAS Institute Inc. 2008. Zero-inflated poisson and zero-inflated negative binomial models using the COUNTREG procedure. Cary, NC: SAS Institute, Inc. http://www2.sas.com/proceedings/forum2008/322-2008.pdf

Esty, Daniel C, Jack A. Goldstone, Ted Robert Gurr, Pamela T. Surko, and Alan N. Unger. 1995. *Working Papers: State Failure Task Force Report*. Washington, DC: Center for Systemic Peace. http://globalpolicy.gmu.edu/pitf/SFTF%20Phase%20I%20Report.pdf.

Eubank, William Lee, and Leonard Weinberg. 1994. Does democracy encourage terrorism? *Terrorism and Political Violence* 6: 417-443.

———. 1998. Terrorism and democracy: What recent events disclose. *Terrorism and Political Violence* 10: 10.8-118.

———. 2001. Terrorism and democracy: Perpetrators and victims. *Terrorism and Political Violence* 13: 155-164.

Eyerman, Joe. 1998. Terrorism and democratic states: Soft targets or accessible systems. *International Interactions* 24: 151-170.

Fahey, Susan, Gary LaFree, and Laura Dugan. Nov 2007. Terrorism and state fragility. Paper presented at the annual meeting for the American Society of Criminology, November 12-15, 2008, in St. Louis, Missouri.

Gleditsch, Nils Peter, Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg, and Havard Strand. 2002. Armed conflict 1946-2001: A new dataset. *Journal of Peace Research* 39:615-637.

Goldstone, Jack A., Robert H. Bates, Ted Robert Gurr, Michael Lustik, Monty G. Marshall, Jay Ulfelder, and Mark Woodward. A global forecasting model of political instability. Paper prepared for presentation at the Annual Meeting of the American Political Science Association, Washington, DC, September 1-4, 2005.

Granger, C. W. J. 1988. Causality, cointegration, and control. *Journal of Economic Dynamics and Control* 12: 551-559.

Gurr, Ted R, and Monty G. Marshall. 2000. Assessing Risks of Future Ethnic Wars. In *Peoples versus States: Minorities at Risk in the New Century*, ed. Ted Robert Gurr, Chapter 7 and Appendix B. Washington DC: United States Institute of Peace Press.

Gurr, Ted R, Mark Woodward, and Monty G. Marshall. 2005. Forecasting Instability: Are Ethnic Wars and Muslim Countries Different? Political Instability Task Force. McLean, VA: SAIC. http://globalpolicy.gmu.edu/pitf/PITFethnicmuslim.pdf

Gurr, Ted R. 1976. *Rogues, Rebels and Reformers.* Thousand Oaks, CA: Sage Publications.

———. *Minorities at Risk: A Global View of Ethnopolitical Conflicts.* Washington, DC: US Institute of Peace.

———. 2000. *Peoples versus States: Minorities at Risk in the New Century*. Washington DC: United States Institute of Peace Press.

Harff, Barbara. 2003. No lessons learned from the Holocaust: Assessing risks of genocide and political mass murder since 1955. *American Political Science Review* 97: 57-73.

Hehir, Aidan. 2007. The myth of the failed state and the war on terror: A challenge to the conventional wisdom. *Journal of Intervention and Statebuilding* 1: 307-332.

Helman, Gerald B. and Steven Ratner. 1992. Saving failed states. *Foreign Policy* 89: 3-20.

Hilbe, Joseph M. 2008. *Negative Binomial Regression*. Cambridge, UK: Cambridge University Press.

Hoffman, Bruce. 1998. *Inside Terrorism*. New York: Columbia University Press.

Iqbal, Zaryab, and Christopher Zorn. 2003. The political economy of assassination, 1946-2000. Paper prepared for presentation at the Annual Meeting of the Midwest Political Science Association, 3-6 April, Chicago.

Iqbal, Zaryab, and Harvey Starr. 2008. Bad neighbors: Failed states and their consequences. Paper presented at the Annual Meeting of the International Studies Association, March 2008.

LaFree, Gary, and Gary Ackerman. 2009. The empirical study of terrorism: Social and legal research. *Annual Review of Law and Social Science* 5: 347-374.

LaFree, Gary, and Kris Drass. 1997. African American collective action and crime, 1955-1991. *Social Forces* 75: 835-853.

LaFree, Gary, and Laura Dugan. 2007. Introducing the Global Terrorism Database. *Terrorism and Political Violence* 19: 181-204.

LaFree, Gary, and Andromachi Tseloni. 2006. Democratization and crime: A multilevel analysis of homicide trends in 43 nations, 1950 to 2000. *Annals of the American Academy of Political and Social Science* 605:26-49.

LaFree, Gary, and Laura Dugan. 2004. How does studying terrorism compare to studying crime? In Mathieu DeFlem (ed.), *Criminology and Terrorism*. Elsevier.

LaFree, Gary, Laura Dugan, and Susan Fahey. 2008. Global terrorism and failed states. In *Peace and Conflict*, ed. J.J. Hewitt, Jonathan Wilkenfeld, and Ted Robert Gurr. Boulder, CO: Paradigm.

LaFree, Gary. 1999. A summary and review of cross-national comparative studies of homicide. In *Homicide: A Sourcebook of Social Research*, ed. M. Dwayne Smith and Margaret A. Zahn.

———. 2010. Personal communication.

Lieske, Joel A. 1978. The conditions of racial violence in American cities: A developmental synthesis. *American Political Science Review* 72:1324-40.

Lodhi, Abdul Qaiyum, and Charles Tilly. 1972. Urbanization, crime and collective violence in 19th century France. *American Journal of Sociology* 79: 296-318.

Long, J. Scott. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: Sage Publications.

Marshall, Monty G. 2002. *Global Terrorism: An Overview and Analysis.* College Park, MD: University of Maryland. http://www.systemicpeace.org/CSPpaper3.pdf

———. 2008. Fragility, instability, and the failure of states: Assessing sources of systemic risk. *Council on Foreign Relations*.

———. 2009a. Political Instability Task Force Data Page. Center for Systemic Peace. http://globalpolicy.gmu.edu/pitf/

———. 2009b. Email Communication. 8-9/2009.

Marshall, Monty G., and Benjamin R. Cole. 2008. Global Report on Conflict, Governance, and State Fragility 2008. *Foreign Policy Bulletin* 18: 3-21. http://www.systemicpeace.org/Global Report 2008.pdf

Marshall, Monty G., and Keith Jaggers. 2007. POLITY IV Project: Political Regime Characteristics and Transitions, 1800-2007. Dataset User’s Manual. Center for Systemic Peace. http://www.systemicpeace.org/inscr/p4manualv2007.pdf

Marshall, Monty G., Keith Jaggers, and Ted Robert Gurr. 2008. Polity IV Project: Political Regime Characteristics and Transitions, 1800-2008. Dataset. Center for Systemic Peace. http://www.systemicpeace.org/inscr/inscr.htm

Marshall, Monty G., Ted Robert Gurr, and Barbara Harff. 2009. *PITF State Failure Problem Set: Internal Wars and Failures of Governance, 1955-2008.* Center for Systemic Peace. http://globalpolicy.gmu.edu/pitf/pitfcode.htm

McCarthy, John D., and Mayer N. Zald. 1977. Resource mobilization and social movements: A partial theory. *American Journal of Sociology* 82: 1212-1241.

Menkhaus, Ken. 2003. Quasi-states, nation-building, and terrorist safe havens. *Journal of Conflict Studies* 23: 7-23.

Miller, Abraham H., Louis Bolce, and Mark R. Haligan. 1976. The new urban blacks. *Ethnicity* 3: 338-367.

Mosher, Clayton J, Terrance D. Miethe, and Dretha M. Phillips. 2002. *The Mismeasure of Crime.* Thousand Oaks, California: Sage Publications, Inc.

Newman, Edward. 2007. Weak states, state failure and terrorism. *Terrorism and Political Violence* 19: 463-488.

Pate, Amy. 2009. Personal communication.

Paternoster, Raymond, Robert Brame, Paul Mazerolle, and Alex Piquero. 1998. Using the correct statistical test for the equality of regression coefficients. *Criminology* 36: 859-866.

Piazza, James. 2007. Draining the swamp: Democracy promotion, state failure, and terrorism in 19 Middle Eastern Countries. *Studies in Conflict and Terrorism* 30: 521-539.

Piazza, James. 2008. Incubators of terror: Do failed and failing states promote transnational terrorism? *International Studies Quarterly* 52: 469-488.

Piven, Francis Fox, and Richard Cloward. 1977. *Poor People's Movements. Why They Succeed, How They Fail.* New York, Pantheon.

Saideman, Stephen, and David Lanoue. In Process. The (Exaggerated) Perils of Democracy: Analyzing Democracy's Influence on Different Forms of Communal Dissent. Accessed 12/1/2009. http://profs-polisci.mcgill.ca/saideman/Current%20 Research.htm#Political_Institutions_and_Ethnic_Confli

Sambanis, Nicholas. 2001. Do Ethnic and nonethnic civil wars have the same causes? *Journal of Conflict Resolution* 45: 259-282.

Sarkees, Meredith Reid. 2000. The Correlates of War data on war: An update to 1997.*Conflict Management and Peace Science* 18: 123-144.

Schmid, Alex, and Albert Jongman, 2005. *Political Terrorism: A New Guide to Actors, Authors, Concepts, Data Bases, Theories and Literature.* New Brunswick, NJ: Transaction Publishers.

Schneckener, Ulrich. 2004. ‘‘Transnationale Terroristen als Profiteure Fragiler Staatlichkeit.’’ SWP Study S 18. May.

Small, Melvin, and J. David Singer (1982). *Resort to Arms: International and Civil Wars, 1816-1980*. Beverly Hills, Calif.: Sage Publications.

Snyder, David, and Charles Tilly. 1972. Hardship and collective violence in France, 1830 to 1960. *American Sociological Review* 37: 520-532.

START. 2009. Global Terrorism Database: Data Collection Methodology. Accessed 07/21/2009. http://www.start.umd.edu/gtd/using-gtd/

StataCorp LP. 2009. *Stata Longitudinal Data / Panel Data Reference Manual, Release 1.* College Station, TX: Stata Press.

Stinnett, Douglas M., Jaroslav Tir, Philip Schafer, Paul F. Diehl, and Charles Gochman. 2002. The Correlates of War Project Direct Contiguity Data, Version 3. *Conflict Mangagement and Peace Science* 19(2):58-66.

Tikusis, Peter. 2009. On the relationship between weak states and terrorism. *Behavioral Sciences of Terrorism and Political Aggression* 1: 66-78.

Tilly, Charles, Louise Tilly, and Richard Tilly. 1975. *The Rebellious Century, 1830 to 1930.* Cambridge, MA: Harvard University Press.

Useem, Bert. 1980. Solidarity model, breakdown model and the Boston anti-busing movement. *American Sociological Review* 45: 357-369.

Useem, Bert. 1985. Disorganization and the New Mexico prison riot of 1980. *American Sociological Review* 50: 677-688.

———. 1997. The state and collective disorders: The Los Angeles Riot / protest of April 1992. *Social Forces* 76: 357-77.

———. 1998. Breakdown theories of collective action. *Annual Review of Sociology* 24: 215-238.

Van Belle, Douglas A. 1997. Press freedom and the democratic peace. *Journal ofPeace Research* 34: 405-41.

Von Hippel, Karin. 2002. The roots of terrorism: Probing the myths. *The Political Quarterly* 73: 1-39.

World Bank. 2009. *World Development Indicators*. Data downloaded 07/20/2009. http://web.worldbank.org/WBSITE/EXTERNAL/DATASTATISTICS/0,,contentMDK:20398986~menuPK:64133163~pagePK:64133150~piPK:64133175~theSitePK:239419,00.html

Young, Joseph, and Laura Dugan. Forthcoming. Veto players and terror. *Journal of Peace Research.*