The Changing Nonlinear Relationship between Income and Terrorism

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Abstract

This paper reinvestigates the relationship between real per capita GDP and terrorism. We devise a terrorism Lorenz curve to show that domestic and transnational terrorist attacks are each more concentrated in middle-income countries, thereby suggesting a nonlinear income-terrorism relationship. Moreover, this point of concentration shifted to lower income countries after the rising influence of the religious fundamentalist and nationalist/separatist terrorists in the early 1990s. The paper then uses nonlinear smooth transition regressions to establish the relationship between real per capita GDP and terrorism for eight alternative terrorism samples, accounting for venue, perpetrators' nationality, terrorism type, and the time period. Our nonlinear estimates are shown to be favored over estimates using linear or quadratic income determinants of terrorism. These nonlinear estimates are robust to additional controls.

Keywords: Terrorism and poverty, Smooth transition regressions, Domestic and transnational terrorism, Lorenz curves

<center>**The Changing Nonlinear Relationship between Income and Terrorism**</center>

1. Introduction

Following the unprecedented terrorist attacks against US targets on 9/11, many public figures, including President George W. Bush, alleged that terrorism is rooted in low per capita GDP or low development (see, e.g., Piazza 2006).[1] Other public figures made similar allegations. The empirical literature, surveyed in Section 2, established no clear-cut connection between terrorism and various income measures. In all but a few instances, the extant literature used a linear specification and either focused on total or transnational terrorist incidents for one extended period. In so doing, the literature generally ignored the possibility that per capita GDP may have a different impact on domestic as opposed to transnational terrorism, or that this impact may have morphed over time.

In a novel study, Enders and Hoover (2012) investigated the relationship between terrorism and per capita GDP, while distinguishing between the two forms of terrorism for a short recent period, 1998–2007. These authors hypothesized that potential terrorists in most very poor countries possess little means for supporting terrorism, while rich countries have ample resources for crushing resident terrorists. This reasoning then implies a nonlinear relationship with terrorist attacks rising to a peak at some intermediate per capita GDP level. This peak level was found to differ between the two kinds of terrorism, but these authors offered no theoretical explanation for this difference.

The relationship between per capita GDP and terrorism is not static.[2] As the composition of terrorist groups changed to include fewer leftists and many more religious fundamentalists

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[1] Low per capita GDP is the preferred proxy for poverty in the literature (e.g., Krueger and Maleckova 2003; Piazza 2011). We do not use the Human Development Index because it does not lend itself to our nonlinear methods, nor does it allow for a clear comparison to much of the literature.

[2] In a different context, Meierrieks and Gries (2013) showed that the growth-terrorism relationship changed after the end of the Cold War. Our current paper is not about economic growth.

around the early 1990s (Enders and Sandler 2006; Hoffman 2006; Rapoport 2004), the causal link between per capita GDP and terrorism is likely to have changed. This follows because the leftists staged many of their attacks in rich countries during the 1970s and 1980s, while the religious fundamentalists directed their attacks against targets of opportunities in poor countries after the early 1990s (e.g., Americans in the Middle East or Asia). As homeland security improved following 9/11, these transnational terrorist attacks shifted to poorer countries with less border security, where foreign interests were targeted (Enders and Sandler 2006, 2012).

The purpose of the current paper is to investigate the nexus between per capita GDP and terrorism for various scenarios using a flexible nonlinear empirical specification that includes linear, quadratic, and other functional forms. This paper differs from Enders and Hoover (2012) in a number of essential ways. First, the current paper examines a much longer time period that runs from 1970 to 2010. This longer time frame allows us to ascertain changes, if any, in the nonlinear income-terrorism relationship for two important subperiods – 1970–1992 and 1994–2010 – that correspond to the greater dominance of the leftist and fundamentalist terrorists, respectively.[3] We indeed uncover a shift in the income-terrorism relationship after 1993 that not only involves per capita GDP associated with the most terrorism, but also the nature of the nonlinearity. Second, unlike Enders and Hoover (2012), we distinguish between the location (i.e., venue) of the attack and the perpetrators' country for transnational terrorist attacks. By so doing, we uncover a stronger link between low per capita income and transnational terrorism when the perpetrators' country is the focus. This finding has policy relevance in terms of risk assessment. Third, the current paper develops a modified Lorenz curve to display visually the dispersion between terrorist attacks and per capita GDP for various subsamples. Enders and

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[3] We leave out 1993 because the data for this year is incomplete in the *Global Terrorism Database*. The diminished influence of the leftists in the late 1980s was documented in Alexander and Pluchinsky (1992).

Hoover (2012) relied, instead, on hard-to-read scatter plots. Fourth, the current paper establishes that the nonlinear relationship between per capita GDP and terrorism cannot be captured by a quadratic representation for any of the eight terrorism series examined. This finding raises questions about earlier works, mentioned later, that tried to capture the nonlinearity with a simple quadratic per capita GDP representation. The clustering of terrorist incidents that we find for some series is more complex than that for the two short series in Enders and Hoover (2012). Fifth, the paper provides a much greater in-depth econometric analysis with more controls than Enders and Hoover (2012). Finally, unlike this earlier paper, we provide a theoretical foundation for our anticipated findings.

Our analysis strongly suggests that the myriad findings in the literature stem from the different time periods used, the aggregation of terrorist attacks, and the generally, but not universally, assumed linear specification. The changing mix of terrorist ideologies may affect how per capita GDP impacts terrorist attacks. In addition, the country's viewpoint may make a difference in how per capita GDP impacts terrorism. The low per capita GDP justification for terrorism appears more descriptive of the perpetrators' country than of the venue country. No clear findings characterize the literature because too many confounding considerations are aggregated in the empirical tests, which relied on an inflexible functional form.

2. Preliminaries

2.1 On Terrorism

Terrorism is the premeditated use or threat to use violence by individuals or subnational groups to obtain a political objective through the intimidation of a large audience beyond that of the immediate victim (Enders and Sandler 2012). Consistent with the literature, this definition views

the perpetrators as below the state level in order to rule out state terrorism. Other key ingredients of this definition are violence, political objectives, and the audience. Two distinct categories of terrorism are relevant: domestic and transnational terrorism. Domestic terrorism is a single-country affair where the victims and perpetrators hail from the venue country, where the attack occurs. If the nationalities of the victims or the perpetrators involve more than one country, or if the venue country differs from that of the victims or perpetrators, then the terrorist attack is a transnational incident. For transnational terrorism, a researcher must decide whose (victim or perpetrator) countries' economic, political, and demographic variables to include in the empirical investigation.[4]

2.2 Terrorist event data

Two terrorist event datasets are used in our statistical analysis. The *International Terrorism: Attributes of Terrorist Events* (ITERATE) records the incident date, venue country, casualties, perpetrators' nationalities (up to three), victims' nationalities (up to three), and other variables for just transnational terrorist incidents (Mickolus et al. 2012). Currently, ITERATE covers 1968–2011. ITERATE and other terrorist event databases rely on the news media for their variables.

A second event dataset is the *Global Terrorism Database* (GTD), which records both domestic and transnational terrorist incidents (National Consortium for the Study of Terrorism and Responses to Terrorism (START) 2012). Unfortunately, GTD does not distinguish between domestic and transnational terrorist incidents. Since the two types of terrorism may be differentially influenced by alternative drivers, this distinction is essential in order to ascertain

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[4] We do not examine victims' nationalities because this falsely presumes that terrorists generally know the nationalities of potential victims of an intended transnational terrorist attack. There is considerable randomness in who become victims. Moreover, there is randomness concerning which of three victims' nationalities are coded when more than three nationalities are involved.

the relationship, if any, between per capita GDP and terrorism. Enders, Sandler, and Gaibulloev (hereafter, ESG) (2011) devised a five-step procedure for distinguishing between domestic and transnational terrorist incidents in GTD for 1970–2007, which was later updated to 2008–2010.[5] Before ESG applied their procedure, they eliminated insurgent and "doubt terrorism" attacks. ESG (2011) also calibrated GTD transnational terrorist attacks to those in ITERATE to address periods of under- and over-reporting of terrorist incidents in GTD. We use ESG's calibrated data in our empirical runs. Although GTD records many of the same variables as ITERATE, a crucial difference is that GTD does not record the countries of perpetrators.

2.3 On the changing nature of terrorism

In an important contribution, Rapoport (2004) distinguished between the changing nature of terrorism. In the 1970s and 1980s, the secular leftists, including the nationalist Palestinian and Irish groups, were the dominant transnational terrorist influence (Hoffman 2006; Rapoport 2004). These leftist terrorist groups' grievances were often against rich countries that pursued unpopular foreign policy (e.g., the Vietnam War or support of Israel). The leftists also included the anarchists and communist groups that desired the overthrow of rich capitalist systems and the governments that ruled them. There were also leftist terrorist groups – e.g., Direct Action in France – that specialized in domestic terrorism. With the decline of communism in Eastern Europe, many European leftist terrorist groups – e.g., Red Army Faction, Italian Red Brigades, Popular Forces of 25 April, and Direct Action – either ended operations or were annihilated by the authorities (Alexander and Pluchinsky 1992). The very active Shining Path, a leftist terrorist group in Peru, became much less active after the arrest of its leader, Abimael Guzmán, in September 1992. By the early 1990s, religious fundamentalist terrorists gained ground as a

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[5] The interested reader should consult ESG (2011) for details.

dominant terrorist force (Enders and Sandler 2000; Hoffman 2006). Unlike the leftists who generally wanted to limit collateral damage,[6] the fundamentalists wanted to maximize death tolls as 9/11 and the Madrid commuter train bombings demonstrated. The number of active nationalist/separatist terrorist groups also increased after 1993.[7] In any study of the relationship between per capita GDP and terrorism, there must be recognition of this changing nature of terrorism, which we place at 1994 and beyond.

2.4 On the poverty and terrorism literature

Prior to the Enders and Hoover (2012) study, the literature on poverty and terrorism displayed some noteworthy characteristics. First, the underlying empirical models generally hypothesized and tested a linear relationship between per capita GDP and terrorism (e.g., Abadie 2006; Krueger and Maleckova 2003; Piazza 2006). However, articles by de la Calle and Sánchez-Cuenca (2012) for total terrorism (1970–1997), Freytag et al. (2011) for total terrorism (1971–2007), and Lai (2007) for transnational terrorism (1968–1998) used a quadratic per capita GDP term, whose negative and significant coefficient implied an inverted U-shape relationship between per capita GDP and terrorism. Second, some studies investigated micro-level data (e.g., Benmelech and Berrebi 2007; Benmelech et al. 2012), others examined macro-level data (e.g., Li and Schaub 2004; Piazza 2011), and still others analyzed both micro- and macro-level data (Krueger and Maleckova 2003). Third, this literature typically used transnational or total terrorist data, with the notable exception of Piazza (2011), who used ESG's (2011) division of

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[6] This was not true of Shining Path, which killed many people.
[7] Using RAND terrorist event data, we can track 586 active terrorist groups during 1970–2007. Before 1993, there were 45 active religious terrorist groups, while, after 1993, there were 111 active religious terrorist groups. Thus, the number of these terrorist groups more than doubled after 1993. There were 140 active left-wing terrorist groups before 1993 and 123 active left-wing terrorist groups after 1993. Moreover, the activity level of these leftist terrorist groups declined in the latter period. Active nationalist/separatist terrorist groups increased somewhat from 127 before 1993 to 145 after 1993. Active right-wing terrorist groups numbered 15 before 1993 and 16 after 1993.

GTD. Fourth, these earlier studies analyzed varied samples of countries for alternative time periods. For example, Blomberg et al. (2004a) examined 127 countries for 1968–1991 during the dominance of the leftists and found a positive long-run relationship between per capita GDP in the venue country and transnational terrorist attacks. This finding is consistent with reduced per capita GDP decreasing terrorism. Fifth, most of these articles focused on the venue country (e.g., Abadie 2006; Li and Schaub 2004; Piazza 2006), with the exception of Krueger and Laitin (2008) and Gassebner and Luechinger (2011). Krueger and Laitin (2008) distinguished between venue and perpetrators' countries, whereas Gassebner and Luechinger (2011) distinguished venue, perpetrators', and victims' countries. Neither of these two studies ran separate regressions for domestic and transnational terrorist incidents. In fact, Krueger and Laitin (2008) only investigated transnational terrorist attacks, while Gassebner and Luechinger (2011) examined transnational and total terrorist attacks.

In terms of the relationship between per capita GDP and terrorism, these earlier studies found diverse results. Krueger and Maleckova (2003) showed that there was no relationship between per capita income and transnational terrorism once political freedoms were introduced into the regressions. Similarly, Abadie (2006) demonstrated that the risk of terrorism was not greater in poor countries once political freedoms and other country-specific controls (e.g., ethnic fractionalization) were introduced. Krueger and Laitin (2008) showed that political repression, not GDP measures, encouraged transnational terrorism. Piazza (2006) also found that economic variables (e.g., the Human Development Index) did not affect the level of transnational terrorism. More recently, Piazza (2011) uncovered that higher levels of per capita GDP increased domestic terrorism. This positive relationship is inconsistent with the low per capita GDP cause of terrorism. Gassebner and Luechinger (2011) also reported a robust positive relationship between per capita GDP and terrorism when using the viewpoint of victims' countries. The relationship

was not robust from the venue or perpetrator countries' viewpoints. In their study of globalization and terrorism, Li and Schaub (2004) showed that higher per capita GDP in the venue country reduced the amount of transnational terrorism for some models. Their sample included 112 countries for 1975–1997, which was primarily before the prevalence of the fundamentalist terrorists (see footnote 7). Subsequently, Li (2005) also found a negative relationship between per capita GDP and transnational terrorism when additional control variables were introduced.

Except for the two articles by Li, there was little empirical support that low per capita GDP encouraged terrorism. Even the micro-level studies did not support this view. Rather, some micro-level studies found that reduced economic conditions (e.g., greater unemployment) allowed terrorist leaders to recruit more skilled operatives (see, especially, Benmelech et al. 2012; Bueno de Mesquita, 2005), but this is not the same as arguing that low per capita GDP is the root cause of terrorism. A puzzle concerns the alternative empirical findings regarding per capita GDP as a cause of terrorism. We believe that these diverse findings come from the lack of linearity between per capita GDP and terrorism[8] and from their changing relationship as different terrorist motives came to dominate the world stage. The latter suggests that the sample period is an important consideration. Other contributing factors to past findings arise from the country viewpoint assumed and the type of terrorism investigated.

3. Theoretic Discussion

We draw from the literature and our own insights to hypothesize a nonlinear relationship between per capita GDP and terrorism that possesses two key characteristics: (i) a concentration

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[8] Even those few studies that used a quadratic specification could not capture the more complicated relationship between per capita GDP and the alternative terrorism series displayed in Sections 7 and 8.

of terrorist attacks at some intermediate per capita GDP level; and (ii) a smaller potential concentration of terrorist attacks at a very low per capita GDP level. In particular, we identify a number of considerations that give rise to this nonlinear relationship from the venue or perpetrators' countries' viewpoint. There is no reason to expect the per capita GDP influence to be symmetric, as reflected in previous explanations behind an inverted U-shape parabolic relationship (de la Calle and Sánchez-Cuenca 2012; Freytag et al. 2011; Lai 2007).

An initial peak in terrorism at a very low per capita GDP level may arise from terrorist groups' welfare grievances, particularly in the perpetrators' homeland. This motivating factor is reinforced by the venue or perpetrators' state's inability to mount much of a counterterrorism offensive, because tax revenues to support such operations would be greatly limited. Additionally, such poor countries lack administrative, law-enforcement abilities, and military might to address the terrorism (Fearon and Laitin 2003; Lai 2007). Another contributing factor to this low income spike in terrorism may arise from opportunity cost considerations – namely, terrorists have few market opportunities to sacrifice by becoming terrorists (Freytag et al. 2011).

A second much more pronounced peak is anticipated at some intermediate income level, whose location depends on the time period, type of terrorism, and country viewpoint (see below).[9] For all forms of terrorism, as per capita GDP rises to some middle level in the venue or perpetrators' countries, terrorists and their supporters have greater resources to mount a larger sustained terrorist campaign (see especially Freytag et al. 2011). However, a threshold per capita GDP will eventually be reached where still higher GDP levels will set in motion terrorism-curbing influences. After some threshold per capita GDP level, terrorists and their supporters must sacrifice much in the way of opportunity cost (Freytag et al. 2011). Also, potential

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[9] Blomberg, Hess, and Weerapana (2004b) put forward a dynamic model, in which terrorism increases during economic downturns in rich powerful countries. The interface between their model and our analysis is imperfect, because we are not looking at economic shocks or downturns per se. We are, instead, relating terrorism to income per capita for a cross-section of countries.

grievances are apt to dissipate as a perpetrator's economy becomes richer, where government expenditures can serve more varied interests (Lai 2007). The capacity of the government to quash terrorist groups or to harden potential targets will be formidable at high per capita GDP levels in either the venue or perpetrators' countries. Moreover, education levels, which are positively correlated with per capita GDP, can bolster terrorist attacks at an intermediate income level by providing terrorist groups with operatives with sufficient human capital (Benmelech and Berrebi 2007). But after some per capita GDP, opportunity cost considerations will curb these skilled operatives' enthusiasm in the venue and perpetrators' countries.

For both venue and perpetrators' nation-states, our theoretical discussion not only implies the possibility of multiple uneven peaks, but also nonsymmetrical rises and falls on either side of these peaks. For example, if a targeted government relies on defensive measures, then the reduction of terrorism beyond some peak intermediate per capita GDP level is apt to be gradual. In contrast, a government's reliance on proactive measures to annihilate the terrorist groups at home or abroad could, if successful, result in a steep drop in terrorism beyond its apogee. The rise to the peak level of terrorist activity may be gradual or steep depending on how grievances or other terrorism-supporting factors build. Asymmetry may also arise from the multiple underlying considerations, which need not be in sync as per capita GDP rises or falls. The important point is that there is no reason to expect a single symmetric peak terrorism level, associated with a quadratic per capita GDP term. This suggests the need for a flexible nonlinear form, as used here, that allows for the quadratic representation as a special case.

Next, we turn to why the per capita GDP and terrorism relationship is anticipated to differ for alternative terrorism samples. Domestic terrorism is expected to be more motivated by economic grievances (Piazza 2011, 2013), while transnational terrorism is more motivated by grievances tied to foreign policy decisions by rich democracies (Savun and Phillips 2009).

Consequently, the peak level of domestic terrorism will correspond to a lower per capita GDP than that for transnational terrorism, especially before 1993. After 9/11, transnational terrorists faced tighter international borders, which would have restricted their movement, thereby affecting attack venues in the latter part of 1994–2010. These security measures should keep the peak levels of domestic and transnational terrorism at similar per capita GDP levels after 1993 as transnational terrorist attacks increasingly targeted foreign interests at home (Enders and Sandler 2006).

Based on the perpetrators' nationality, there is an expected *shift* in the per capita GDP associated with the most transnational terrorist attacks before and after 1993. In the pre-1993 period, the leftist groups were a strong terrorist influence. Many of their members resided in wealthy countries. In contrast, the religious fundamentalists were generally located in poor Middle Eastern and Asian nations after 1993 (Enders and Sandler 2006). Thus, we should anticipate the greatest concentration of transnational terrorist attacks at a higher per capita GDP in the earlier than in the later period, based on the perpetrators' nationality. This prediction is reinforced by the resurgence of nationalist/separatist terrorists in relatively poor countries after 1993 (see footnote 7). This same predicted shift should apply to the venue country owing to the greater presence of leftists before 1993. In addition, increased security measures in rich countries after 9/11 should reinforce this shift during the last half of 1994–2010.

4. Examining the Terrorism Series

Throughout the analysis, our terrorist series involve at least one casualty. Because the pre-1993 sample is longer than that of the post-1993 period, we use the average number of terrorist incidents within a country for 1970–1992 and 1994–2010 for comparison purposes. In total, we have eight terrorism incident series: GTD domestic terrorism casualty events before and after

1993; GTD transnational terrorism casualty events before and after 1993; ITERATE casualty events by location before and after 1993; and ITERATE casualty events by perpetrator's country before or after 1993. We choose our two periods to reflect the predominance of the leftists and religious fundamentalists, respectively, while taking advantage of discarding 1993, for which GTD has no data.[10]

[Table 1 near here]

The usual normality assumption is inappropriate because many countries experienced no terrorism and most countries experienced no more than a single incident. As shown in Table 1, in the pre-1993 period, 53 of the 166 usable sample countries experienced no domestic casualty incidents, while 54 experienced no transnational casualty incidents. There was a slight increase in the number of incidents over time insofar as the typical per-year average of domestic casualty incidents was 3.20 in the pre-1993 period and 3.78 in the post-1993 period. Notably, the standard error of each series is at least twice its mean, and, although not reported in Table 1, all series fail the Jarque-Bera test for normality. When the mean of the process is properly specified, quasi-maximum likelihood estimates, assuming normality, are asymptotically unbiased and can be used to assess the effects of per capita GDP on terrorism. However, since the resultant coefficient estimates are likely to be inefficient with incorrect standard errors, hypothesis testing can be misleading. Hence, we estimate the various incident series as counts using the Poisson and the negative binomial distributions.

Prior to a rigorous econometric analysis, we devise a straightforward modification of a

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[10] The pre-1993 and post-1993 runs included a different set of countries, since some of the 166 countries were not in existence for the entirety of both sample periods. A country that did not exist during one of the subperiods was excluded from the analysis of that period. Similarly, countries not in existence for the preponderance of a subperiod were excluded from the analysis for that period. For example, since Macedonia came into existence in 1991, it was excluded from the pre-1993 runs. For each variable, we used per-year country averages. As such, a country in existence for, say, 12 of the 17 years of the post-1993 period could be compared to the other countries in the sample. A complete discussion of the sources and the variables used in the study is contained in the online Appendix.

Lorenz curve to illustrate the relationship between terrorism and per capita GDP (or income). A standard Lorenz curve shows the cumulative shares of total world income accounted for by the cumulative percentiles of countries, ranked from poorest to richest. Instead, our modified Lorenz curves show the cumulative shares of total world terrorism accounted for by the cumulative percentiles of states, ranked from poorest to richest. For example, in Panel 1 of Figure 1, the horizontal axis shows the cumulative percentiles of countries ranked by income, while the vertical axis shows the cumulative percentage of total world domestic casualty incidents. As such, points along the diagonal line represent the line of equality for the pre-1993 data set. The 20th, 40th, 60th, and 80th income percentiles correspond to real per capita GDP levels of $366 (Nigeria), $1,028 (Honduras), $2,410 (Chile), and $7,947 (Slovenia).

[Figure 1 near here]

If there were a uniform distribution of terrorism among all countries, our so-called terrorism Lorenz curve would lie along the diagonal; instead, the cumulative terrorism percentiles lie below the diagonal in Panel of Figure 1 until the 55th income percentile is reached. In fact, the poorest 25% of nation-states accounted for about 18% of total domestic casualty incidents and the next 25% accounted for about 16% of these incidents, so that the lowest 50% accounted for 34% of domestic terrorism incidents with casualties. However, there are sharp increases in the amount of terrorism in the next 20% of the states; the countries in the 51st through 70th percentiles of the income distribution experienced 38% of domestic terrorism. Hence, during the pre-1993 period, domestic terrorism seems to be clustered in the nation-states with income levels that are slightly to well above average. This pattern is consistent with the prevalent leftist and nationalist/separatist terrorists directing attacks at their relatively wealthy homelands (e.g., France, Spain, the United Kingdom, West Germany, Turkey, and Portugal).

Panel 2 of Figure 1 shows a different pattern of domestic terrorism for the post-1993

period, where the rapid increase in terrorism occurred at a much lower income percentile than that shown in Panel 1. Specifically, for the post-1993 period, the poorest 20% of countries ranked by per capita GDP levels only sustained about 7% of the domestic terrorist incidents with casualties, whereas the next 30% accounted for about 65% of these incidents. Because the next 10% of countries suffered about 18% of the domestic terrorism, the richest 40% experienced only 10% of these incidents. For the post-1993 data set, the 20th, 40th, 60th, and 80th percentiles correspond to real per capita GDP levels of $287 (Ghana), $1,431 (Paraguay), $4,133 (Lithuania), and $14,531 (Spain). Terrorism was clustered in the middle-income countries although the point at which the rapid increases in terrorism occurred shifted toward the lower end of the real per capita income spectrum. According to our priors, this marked shift after 1993 is likely due to the much greater prevalence of religious fundamentalist terrorists, who generally resided in low- and middle-income countries. This era was also marred with many internal conflicts in low- and middle-income countries. Such conflicts, orchestrated by nationalist/separatist motives, are often associated with terrorism (Sambanis 2008).

In contrast to Panels 1 and 2, Panel 3 shows that transnational terrorism strongly clustered in the middle- to upper-income countries in the pre-1993 period. The poorest 50% of states had only 24% of transnational terrorism with casualties, whereas the next richer 40% of states sustained 66% of these attacks. Panel 4 shows that this pattern changed dramatically for the post-1993 period. In fact, the shape of this terrorism Lorenz curve is very much like that in Panel 2. The poorest 20% of countries accounted for about 11% of transnational terrorism; however, the next richer 30% of countries accounted for 50% of the incidents. Panel 3 is consistent with the prevalence of the leftist terrorists in the early period, while Panel 4 is consistent with the prevalence of the religious fundamentalist and nationalist/separatist terrorists after 1993. As theorized earlier, the push for homeland security in rich countries after 9/11

would also reinforce the Lorenz pattern in Panel 4, where lower middle-income countries sustained a disproportionately large percent of transnational terrorist attacks and rich countries suffered a disproportionately small percent of transnational terrorist attacks.

In Figure 2 we use ITERATE data to show the terrorism Lorenz curves for transnational casualty incidents measured by location and by the nationality of the incident's perpetrator. Since Panels 1 and 2 measure terrorism by the location of the incident, these two panels correspond to Panels 3 and 4 of Figure 1, constructed using the GTD data. Given that we adjusted the GTD data using the weighting scheme developed in ESG (2011), it is not surprising that the shapes of the corresponding terrorism Lorenz curves are quite similar.

[Figure 2 near here]

In comparing Panels 1 and 3 of Figure 2, we find that the different measures of terrorism have different implications. In the pre-1993 period, the location of terrorism tended to cluster in the upper end of the middle-income countries, whereas the perpetrators tended to hail from the middle-income countries. Comparing pre-1993 and the corresponding post-1993 panels, we see that the clustering of terrorism measured by location or by perpetrators' nationality shifted greatly toward the poorer countries in the post-1993 period. These post-1993 Lorenz patterns agree with our priors about the influence of the changing predominance of religious fundamentalists and nationalist/separatists over leftists during 1994–2010. Terrorist attacks became more concentrated in lower income countries, which were home to the religious fundamentalists in North Africa, the Middle East, and Asia. This agrees with more attacks against Western influences in North Africa, the Middle East, and Asia (Enders and Sandler 2006).

5. Linear Models of Terrorism and Income

Consider the simple linear model,

$$T_i = \alpha_0 + \alpha_1 gdp_i + \varepsilon_i, \tag{1}$$

where T_i denotes the number of terrorist incidents occurring in country i, the αs are parameters to be estimated, gdp_i is a measure of real per capita GDP in country i, and ε_i is the error term. For now, it does not matter whether other control variables are added to (1), what measure of terrorism or sample period is selected, or whether (1) is estimated with ordinary least squares (OLS) or with maximum likelihood estimation (MLE) using a Poisson or negative binomial distribution. The key point is that the specification in (1) does not allow for the type of clustering described in Section 4. In (1), if gdp_i increases by 1 unit, terrorism increases by α_1 units, and if gdp_i increases by 2 units, terrorism increases by $2\alpha_1$ units. However, this is not the pattern observed in Figures 1 and 2, where per capita GDP increases in the poorest and the richest countries had relatively small effects on terrorism.

When we pool all of the ITERATE casualty incidents over the two sample periods, ignore the possibility of nonlinearities, and estimate the model using the negative binomial distribution, we obtain:[11]

$$\hat{T}_i = \exp(-8.32 + 0.30\ lgdp_i + 0.55\ lpop_i)\ ,\quad \eta = 1.38, \tag{2}$$
$$\quad\ (-5.60)\ \ (3.59)\qquad (6.76)\qquad\quad (16.71)$$

where: $\hat{T}_i$ = estimated number of domestic terrorist incidents, $lgdp$ = log of real per capita GDP, $lpop$ = log of population, η^2 = is the variance parameter of the negative binomial distribution, i is a country subscript, and the t-statistics (constructed using robust standard errors to account for

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[11] As in the literature on economic growth, we use long-run cross-sectional data to account for the fact that our dependent variable (terrorism) may have a long and varied cross-country response to our key independent variable (per capita GDP). Even without the added degrees of freedom that a dynamic panel would provide, all of our nonlinear terrorism estimates display a significant response to per capita GDP. Future work could apply our analysis to a dynamic panel.

heteroskedasticity) are in parentheses.[12]

Hence, pooling the ITERATE data over the entire 1970–2010 period implies that there is actually a positive relationship between per capita income and terrorism. In accord with some findings, a linear specification that pools data across a long time span indicates that increasing per capita GDP is not expected to mitigate terrorism (e.g., Piazza 2011).[13]

As a diagnostic check for nonlinearity, we estimated each of the eight terrorism series with an intercept, $lgdp_i$, its square (i.e., $lgdp_i^2$), and $lpop_i$. If there is a nonlinear relationship between terrorism and per capita GDP, the parabolic shape engendered by the squared term might capture the tendency for terrorism to cluster within the middle-income nations, as argued by Lai (2007) and others. This is not to say that the quadratic specification is the most appropriate one to capture the effects of per capita income on terrorism. Clearly, misspecifying the actual nonlinear form of the relationship between terrorism and per capita GDP can be as problematic as ignoring the nonlinearity altogether. The results in Table 2 are instructive, where the first four series use ITERATE (IT) data, while the last four series use GTD data in the pre-1993 (pre) and post-1993 (post) periods. As indicated, the various series allow for venue, perpetrators' nationality, and domestic and transnational incidents. For each of the eight terrorism measures, the point estimate of the coefficient on $lgdp_i$ is positive, while the coefficient on $(lgdp_i)^2$ is negative. This implies that terrorism increases with real per capita income until a maximum is reached, thereafter further per capita income increases act to reduce terrorism. In six of the eight cases, the overall fit of the model with the $(lgdp_i)^2$ term is selected by the AIC over the linear specification. Finally, a χ^2 test indicates that the null hypothesis that both the

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[12] Throughout our analysis, each model is estimated using a Poisson as well as a negative binomial model. Because the Poisson models always show excess volatility, they are not reported. The results do depend on whether per capita GDP is measured in logs or in levels. When we use per capita GDP in levels as opposed to logs, the per capita GDP coefficients are positive and insignificant in (2).
[13] Similar results hold when we use the GTD domestic and transnational terrorism series.

lgdp and $(lgdp)^2$ coefficients jointly equal zero cannot be maintained in five of the eight cases.

[Table 2 near here]

6. ESTR and LSTR Models

As now shown, the relationship between terrorism and per capita income is often more complicated than that of a simple quadratic per capita income term. A specification that captures the tendency of terrorist incidents to cluster in countries with similar GDP levels is the smooth transition regression (STR) model (Teräsvirta 1994). The STR model is a flexible functional form that nests the linear model and can approximate the quadratic model. Since we have count data, the STR model is estimated using a negative binomial distribution. Consider the following specification:

$$\hat{T}_i = \exp\left[\left(\alpha_0 + \alpha_1 lgdp_i + \alpha_2 lpop_i\right) + \theta_i\left(\beta_0 + \beta_1 lgdp_i + \beta_2 lpop_i\right)\right], \tag{3}$$

where α_j and β_j are coefficients $\left(j = 1, 2\right)$ and, in the exponential STR (ESTR) variant of the model, θ_i has the form:

$$\theta_i = 1 - \exp\left[-\gamma\left(lgdp_i - c\right)^2\right], \quad \gamma > 0. \tag{4}$$

The parameter γ is called the "smoothness" parameter, because it determines how quickly θ_i transitions between the two extremes of zero and unity.

The ESTR model is clearly nonlinear because the effect of $lgdp_i$ on terrorism depends on the magnitude of $lgdp_i$ itself. As $lgdp_i$ runs from the lowest to highest values, θ_i goes from 1 to 0 and back to 1. Hence, for countries such that $lgdp_i$ is far below or far above c, the value of θ_i is approximately 1, so that (3) becomes $\hat{T}_i = \exp[(\alpha_0 + \beta_0) + (\alpha_1 + \beta_1)lgdp_i + (\alpha_2 + \beta_2)lpop_i]$. However, for countries with $lgdp_i$ very close to c, the magnitude of θ_i is approximately zero, so

that the relationship in (3) can be written as $\hat{T}_i = \exp(\alpha_0 + \alpha_1 lgdp_i + \alpha_2 lpop_i)$. Because θ_i is a

smooth function of $lgdp_i$, the ESTR specification allows for a smooth transition between these

two extremes. Given that θ_i is symmetric around c, countries with values of $lgdp_i$ close to c will

behave differently from countries with values of $lgdp_i$ much smaller, or much larger, than c.

When, for example, we set $c = 6.5$ and $\gamma = 4$, the solid line in Panel 1 of Figure 3 traces out how

θ_i varies as $lgdp_i$ runs from 5 to 11 (i.e., the approximate range of the $lgdp_i$ values in our sample).

For the lowest values of $lgdp_i$, $\theta_i \cong 1$ (i.e., $1 - \exp[-4(5 - 6.5)^2] = 0.99988$) and as $lgdp_i$

approaches 6.5, the value of θ_i approaches zero. Subsequent increases in $lgdp_i$ act to increase the

value of θ_i from zero towards unity. Once $lgdp_i$ is about 7.5, θ_i is sufficiently close to unity that

further increases in $lgdp_i$ have no substantive impact on the values of θ_i. As shown by the two

dashed lines in Panel 1 of Figure 3, increases in γ act to sharpen the transition.

[Figure 3 near here]

There are two essential features of the ESTR specification for our analysis. First, the U-

shape of the exponential function allows us to capture clustering within closely aligned cohorts

along the income spectrum. If terrorism occurs in countries with $lgdp_i$ levels equal to 6.5 (=

$665 real US dollars), but seldom occurs in the poorest or richest countries, we would then

expect an ESTR model to fit the data such that c is close to 6.5 with γ reflecting the extent of the

clustering. Second, the ESTR model is quite flexible relative to the usual models. For example,

a value of $\gamma = 0$ is equivalent to a linear model, since θ_i is then zero. Moreover, very tight

clustering can be captured by a large values of γ. The type of quadratic specification reported in

Table 2 can be well-approximated by an ESTR model with a small value of γ.

Panel 2 of Figure 3 illustrates the effect of nesting the ESTR model within the negative

binomial framework. As detailed below, for the GTD post-1993 transnational terrorism series,

the coefficient estimates are approximately $c = 6.5$, $\gamma = 10.0$, $\alpha_1 = 11$, and $\beta_1 = -12.5$.

Evaluating $a_0 + a_2 lpop_i$ and $b_0 + b_2 lpop_i$ at the sample mean of $lpop_i$, we obtain -77.0 and 81, respectively. As such, Panel 2 plots the values of T_i against $lgdp_i$, where an increase in per capita GDP is associated with a dramatic increase in the level of terrorism for $lgdp_i$ values sufficiently close to 6.5. The subsequent income-induced drop-off in the number of terrorist incidents causes a substantial clustering within the cohort of countries with values of $lgdp_i$ between 6.2 and 7. Thus, a linear specification or a quadratic specification (see Table 2) cannot capture such extreme clustering.

In the logistic variant of the STR model (LSTR), θ_i has the form,

$$\theta_i = 1 \Big/ \left\{ 1 + \exp\left[-\gamma \left(lgdp_i - c \right) \right] \right\}. \qquad (5)$$

Unlike the U-shape of the ESTR specification, (5) best characterizes a two-regime model. Panel 3 of Figure 3 uses the identical parameters values used in Panel 1. As $lgdp_i$ increases from 5 to 11, θ_i monotonically increases from 0 to 1, so that poorest countries are most dissimilar to the richest countries, in the LSTR specification. The solid curve in Panel 3 is drawn for $\gamma = 4$. As shown by the dashed lines, increases in the value of γ act to sharpen the transition between the low- and high-income countries.

Panel 4 plots the values of T_i against $lgdp_i$. For the poorest states, there is a very small positive effect of $lgdp_i$ on terrorism, whereas, for the richest states, there is a negative effect of $lgdp_i$ on terrorism. An ESTR model captures clustering in the middle of the income cohorts, while an LSTR model best captures discrepancies between the poorest and richest income groups. Since the LSTR model is not well-suited to capture mid-group clustering, we allow for the possibility of squared $lgdp_i$ terms when estimating an LSTR model, such that:

$$\hat{T}_i = \exp\left[\left(\alpha_0 + \alpha_1 lgdp_i + \alpha_2 lpop_i + \alpha_3 lgdp_i^2 \right) + \theta_i \left(\beta_0 + \beta_1 lgdp_i + \beta_2 lpop_i + \beta_3 lgdp_i^2 \right) \right]. \qquad (6)$$

7. Estimates of the ESTR and LSTR Models

We estimate each of the eight incident series as either an ESTR or LSTR process using the negative binomial distribution.[14] The model with the best fit is taken as the most appropriate specification. Given the well-known difficulties in estimating γ, we constrained the upper bound for γ to be no greater than 10.00.[15] The results for each series are shown in Table 3. Perhaps, the most important result is that, as measured by the AIC, the fit of every nonlinear model is superior to that of the corresponding linear *and* quadratic models reported in Table 2. For example, the AIC for the ITERATE series containing incidents by location during the pre-1993 period is −86.40, whereas those for the linear *and* quadratic models are −86.27 and −86.29, respectively. Moreover, as shown in the top line of Table 3, the estimated equation is

$$\hat{T}_i = \exp\left[(21.55 - 5.69lgdp_i + 0.38lpop_i) + \theta_i(92.36 - 3.42lgdp_i + 0.65lpop_i)\right], \qquad (7)$$
$$(10.40)\ (-3.55)\qquad (1.75)\qquad\quad (2.03)\ (-0.68)\qquad (1.03)$$

$$\theta_i = 1 - \exp[-0.02(lgdp_i - 2.72)^2], \quad \eta = 1.57.$$
$$(2.29)$$

For this sample, the poorest countries have a value of θ_i very close to zero, so that the model becomes $\hat{T}_i = \exp(21.55 - 5.69lgdp_i + 0.38lpop_i)$. However, for the very high-income countries in our sample, the value of θ_i is close to 0.7, so that the model becomes[16]

$$\hat{T}_i = \exp\left[(82.20 - 8.08lgdp_i + 8.35lpop_i)\right].$$

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[14] Results using the Poisson distribution are available upon request. We also estimate models using only those countries with nonzero levels of terrorism, but the results are similar to those reported here.

[15] As discussed in Enders (2010) and Teräsvirta (1994), once γ is reasonably large, further increases in γ have little effect on the likelihood function, so that estimation using numerical methods becomes difficult. This can be seen in Panels 1 and 3 of Figure 3, wherein increases in γ from 8 to 12 do little to influence the shape of θ_i. As such, if the transition between regimes is sharp, it is standard to constrain the upper bound of γ. When γ is estimated at its upper bound of 10, the *t*-statistic for the null hypothesis $\gamma = 0$ is meaningless and, thus, not reported.

[16] No country in this sample has an income level sufficiently large to drive θ_i to 1. In Table 3, all equations, except Transnational_pre(GTD), are best estimated in the exponential form of the STR model.

[Table 3 near here]

Since the intercept is positively related to *lgdp*, it is a mistake to think that the negative coefficients on the *lgdp* variables mean that terrorism is always negatively related to *lgdp*. The essential insight is that the relationship between terrorism and per capita income is not monotonic. Given our use of a negative binomial distribution combined with a ESTR model, the interpretation of the coefficients in Table 3 can be difficult since the model is highly nonlinear in its parameters.

[Figure 4 near here]

We rely on Figures 4 and 5 to display the nonlinear relationship between terrorism and the log of real per capita GDP for ITERATE and GTD terrorism samples, respectively. In Panel 1 of Figure 4, we display this relationship for Location_pre (IT), when evaluated at the sample mean for *lpop$_i$*. For the low-income countries, increases in real per capita income cause the level of transnational terrorism to rise until a maximum of about 22 incidents when *lgdp* = 8.63, corresponding to a real per capita GDP of $5,633. Subsequent increases in per capita GDP result in a decline in transnational terrorism. Given the nonlinear shape of the terrorism response function, it is not surprising that simple linear regressions of terrorism on per capita income cannot detect a strong and stable relationship between the two variables.

The effects of the log of per capita GDP on terrorism for the other three ITERATE series are shown in Panels 2 through 4 of Figure 4. In Panel 2, the location-sample response function for the post-1993 period indicates that, except for the very small number of low-income countries [i.e., those with per capita income levels below ln($5.56) = $261], increases in real per capita GDP act to increase the level of terrorism until a per capita income level of about $480. Thereafter, increases in per capita income levels act to gradually reduce the level of terrorism, so that most transnational terrorism is bunched in the lower middle-income countries. Notably, the

clustering of the location of transnational terrorist incidents now occurs at much lower income levels than in the pre-1993 period. This is consistent with the greater dominance of the religious fundamentalist and nationalist/separatist terrorist groups after 1993, and the augmentation of homeland security during the last half of the post-1993 era. In Panel 2, there are two peaks and asymmetric responses around the main peak. This is consistent with our priors that allow for some activity in low-income countries when governments are weak and grievances are high. Clearly, Panel 2 cannot be captured by a quadratic per capita GDP term.

The effects of per capita income on the number of terrorist incidents associated with the nationality of the perpetrators are shown in Panels 3 and 4 of Figure 4. Both response functions have a hump shape, such that the maximum values of terrorist incidents are clustered in the middle-income countries. Again, the maximal values for the post-1993 period occurs at a much lower income levels than those for the pre-1993 period, indicating that transnational terrorists are concentrating their attacks in poorer countries after the start of 1994, consistent with our priors about the changing nature of terrorism and impact of enhanced security. The shapes of the relationship also concur with our priors.

[Figure 5 near here]

Figure 5 shows the results using the GTD data for domestic and transnational casualty incidents. For the pre-1993 period, Panel 1 shows that increases in $lgdp_i$ act to augment domestic casualty incidents until real per capita GDP reaches \$1,762 [i.e., $\exp(7.47) = 1,762$] with a maximum of almost 79 incidents. Further increases in real GDP reduce terrorism. In Panel 2, post-1993 domestic attacks initially fall, then rise to a maximum of almost 28 incidents, and finally decline as $lgdp_i$ increases. In comparing Panels 1 and 2, we discern that there are fewer incidents in the post-1993 period, where the venue of domestic terrorist acts has shifted towards the lower income countries. Panel 3 of Figure 5 greatly resembles Panel 1 of Figure 4,

insofar as both panels measure transnational terrorism by location in the pre-1993 period. In

Figure 5, Panel 4, however, shows a substantial clustering of terrorism in countries with per

capita GDP levels in the range of \$800 to \$1,000 [i.e., $\exp(6.68) \cong 800$ and $\exp(6.91) \cong 1,000$].

Thus, over time there has been a substantial movement of terrorism towards the low-income

countries. For Panels 2 and 4 of Figure 5, the post-1993 shift of the greatest concentration of

domestic and transnational terrorist attacks to a lower per capita GDP level agrees with our

priors. Also, consistent with our priors, domestic terrorism peaks at a smaller per capita GDP

level than transnational terrorism during 1970–1992. Lastly, we note the relatively high

terrorism activity in some poor countries after 1993, which include some failed states. None of

the four panels corresponds to a quadratic relationship.

8. Testing for Nonlinearity in the Presence of Other Determinants of Terrorism

We now address whether $lgdp_i$ remains a determinant of terrorism in the presence of $lpop_i$ and

other explanatory variables that Gassebner and Luechinger (2011), Piazza (2011), and others

identified as potentially important determinants of terrorism. Specifically, we want to determine

whether real per capita GDP levels affect terrorism in the presence of other covariates of

terrorism, such as measures of freedom (POLITY, Freedom House), the Rule of Law, ethnic

tension, religious tension, education, area, income distribution (the Gini coefficient), and

unemployment. Because our goal is to focus on the functional relationship between per capita

GDP and terrorism, we do not include every potential control for terrorism. We do, however,

include many of the most important ones. Because some of the covariates are not available for

all countries over the entire sample period, the covariate measures, used in the study, are the

sample averages over the available dates (e.g., ethnic tension).

The testing methodology is not straightforward because the ESTR and LSTR

specifications are not convenient for testing the null hypothesis of linearity against the alternative of nonlinearity. To explain, we substitute (4) into (3) in order to obtain:

$$\hat{T}_i = \exp\left[\left(\alpha_0 + \alpha_1 lgdp_i + \alpha_2 lpop_i\right) + \left\{1 - \exp\left[-\gamma\left(lgdp_i - c\right)^2\right]\right\}\left(\beta_0 + \beta_1 lgdp_i + \beta_2 lpop_i\right)\right]. \quad (8)$$

The test for linearity entails the restriction that $\gamma = 0$, so that (8) becomes:

$$\hat{T}_i = \exp\left(\alpha_0 + \alpha_1 lgdp_i + \alpha_2 lpop_i\right), \quad (9)$$

where the values of β_0, β_1, β_2, and c are all unidentified under the null hypothesis of linearity. As long as $\gamma = 0$, these four coefficients can take on any value without altering the value of the likelihood function. As Davies (1987) showed, whenever a parameter is unidentified under the null hypothesis, standard inference on the parameters is not possible. We note, however, that the problem does not exist for testing whether $lpop_i$ influences terrorism (i.e., testing whether $\alpha_2 = \beta_2 = 0$), since γ and all of the other parameters of (8) are identified in the null model. Although (8) relies on the ESTR specification, the analogous issue holds for the LSTR specification using (5).

Teräsvirta (1994) indicated how to circumvent this so-called Davies' problem in STR models by relying on a third-order Taylor series approximation for θ_i. To explain briefly, we rewrite (4) as:

$$\theta_i = 1 - \exp\left(-h_i^2\right), \quad (10)$$

where $h_i = \gamma^{0.5}\left(lgdp_i - c\right)$. When we expand (10) using the third-order approximation and evaluate at $h_i = 0$ (so that $\gamma = 0$), we obtain,

$$\theta_i = a_0 + a_1 lgdp_i + a_2 lgdp_i^2 + a_3 lgdp_i^3. \quad (11)$$

Substituting (11) into (3) and collecting terms in the powers of $lgdp_i$ yield the following nonlinear representation of (8):

$$\hat{T}_i = \exp\left[c + \sum_{j=1}^{4} c_j lgdp_i^j + d_0 lpop_i + \sum_{j=1}^{3} d_j lgdp_i^j \left(lpop_i \right) \right].$$ (12)

If it is possible to restrict all values of the c_j and d_j to equal zero, then we can accept the null

hypothesis that terrorism is unaffected by real per capita income levels. As detailed in Enders

(2010), the LSTR specification also yields a model in the form of (12).

Given the large number of parameters that would be necessary to estimate in an

unrestricted model, we estimate the following restricted form of (12):[17]

$$\hat{T}_i = \exp\left[c + \sum_{j=1}^{n} c_j lgdp_i^j + d_0 lpop_i + e_0 z_i \right],$$ (13)

where z_i is one of the previously mentioned covariates. In moving from (12) to (13), we simplify

by setting $d_1 = d_2 = d_3 = 0$ and add the single covariate z_i. That is, we enter the covariates one at

a time in (13) and restrict the nonlinearity to appear only in the $lgdp_i$ variable. The test for the

effect of real per capita GDP on terrorism is straightforward. If, in (13), the null hypothesis that

$c_1 = c_2 = c_3 = c_4 = 0$ cannot be rejected, then we conclude that $lgdp_i$ has no influence on the

terrorism series. If, however, the null hypothesis that $c_2 = c_3 = c_4 = 0$ cannot be rejected, then we

conclude that the effect of $lgdp_i$ on terrorism is linear.

Of the eight terrorism casualty series, we focus on transnational terrorism based on the

perpetrators' nationality and domestic terrorism in the pre- and post-1993 eras. These four series

have displayed interesting shifts in per capita income for maximal terrorism over the two eras;

hence, we are interested in ascertaining which of the standard covariates remain robust for the

two eras. The top portion of Table 4 reports the results for the pre-1993 values of transnational

terrorism, measured by nationality of the perpetrator, and for domestic terrorism. The lower

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[17] Note that the coefficients in (13) are related in the substitution of (11) into (3) as: $c = \alpha_0 + a_0\beta_0$, $c_1 = a_0\beta_1 + a_1\beta_0 + \alpha_1$, $c_2 = a_1\beta_1 + a_2\beta_0$, $c_3 = a_2\beta_1 + a_3\beta_0$, $c_4 = a_3\beta_1$.

portion of the table contains the corresponding results for the post-1993 data. Column 2 reports

the number of observations (Obs.), columns 3 and 6 report the *prob*-values of the *F*-statistic for

the null hypothesis that all values of the $c_j\text{s}(j=1,...,4)$ equal zero. Since the *prob*-values of the

sample *F*-statistic are so small for every case, we can reject the null hypothesis that terrorism is

not affected by real per capita GDP (i.e., we accept the alternative hypothesis that terrorism is

affected by real GDP levels). Although not reported in Table 4, it is always the case that the

prob-values of the test for linearity (i.e., the test that $c_2 = c_3 = c_4 = 0$) are smaller than 0.001, so

that we can reject the linear specification. The fourth and seventh columns report the various

values of e_0, and the fifth and eighth columns report the associated *t*-statistics for the null

hypothesis $e_0 = 0$.[18]

Before discussing Table 4, we introduce two of our control variables. The Freedom

House (2012) indices for political rights and civil liberties vary on a scale from 1 to 7, so that

their sum goes from 2 to 14, with smaller values indicating more freedom. A sum is typically

computed before assigning a dummy value, because the two measures are highly correlated. If

the sum is 5 or less, the country is deemed free and we assign it a dummy value of 1. Otherwise,

we assign the country a dummy of 0. The POLITY index reflects a country's adherence to

democratic principles and varies from −10 (strongly autocratic) to 10 (strongly democratic)

(Marshall and Jaggers 2012). If the POLITY index is 7 or higher, we assign it a dummy value of

1, indicating a relatively democratic country.[19]

[Table 4 near here]

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[18] Since the number of observations for each equation differs by covariate, the AIC cannot be used to assess fit across the different covariates.

[19] Many variables are not available for all countries over the entire sample period. As such, in all instances, each variable used in the study is the sample average over the available dates.

In Table 4, possibly the most interesting result is that, at conventional significance levels, all four measures of terrorism are negatively related to the Freedom House (2012) measure, so that increases in civil and political rights significantly reduce terrorism. The point estimates for POLITY are always negative although POLITY is significant only in the post-1993 period, where greater democracy reduces terrorism. Large values of the Rule of Law, whose index varies from 0 to 6, indicate a strong legal system with impartiality and popular observance of the laws (International Country Risk Guide 2012), while large values of the Ethnic Tension and Religious Tension variables indicate little ethnic division and suppression of religious freedoms, respectively (International Country Risk Guide 2012). Both of the tension indices vary from 0 to 6. Greater Rule of Law limits terrorism, while increased ethnic or religious tensions (reduced values to the index) generally augments terrorism, probably from enhanced grievances. These findings are consistent with the literature – see, e.g., Choi (2010), Gassebner and Luechinger (2011), and Abadie (2006). Education levels (i.e., the number of people receiving secondary education) and the remaining covariates are from the World Bank (2012). Higher education levels are associated with less transnational terrorism in the pre-1993 period, but are statistically insignificant in the other three cases. Greater income inequality (higher Gini coefficient) is positively related to both forms of terrorism in the pre-1993 period during the reign of the leftists, who wanted to right social wrongs. Income inequality is not a significant determinant of terrorism after 1993, which suggests that inequality is not motivating the religious fundamentalist or the nationalist/separatist terrorists. The unemployment rate (as a percent of the total labor force) is positive and marginally significant for post-1993 domestic terrorism, but is not significant in the other three cases. The *essential insight* is that in every case, real per capita GDP always influences terrorism and that this effect remains nonlinear when standard covariates are included in our analysis.

9. Concluding Remarks

This paper establishes a robust nonlinear relationship between per capita income and various terrorist time series during 1970–2010. Unlike most previous articles, this study limits its aggregation of terrorist attacks in order to distinguish domestic and transnational terrorist incidents and the era of leftist prevalence from that of religious fundamentalist and nationalist/separatist prevalence. For transnational terrorism, we also distinguish attacks based on where the attack occurred from where the perpetrators originated from. By so doing, we establish that terrorist attacks are most concentrated at a middle income range that varies in a predictable fashion according to the sample examined. For example, terrorist attacks peaked at a lower per capita income level for the perpetrators' country than for the venue country. Thus, the low per capita GDP rationale for terrorism is more descriptive of the perpetrators' home country. When the leftist terrorists were a greater influence prior to 1993, the peak per capita income level for transnational terrorist incidents was higher than when the religious fundamentalist and nationalist/separatist terrorist groups became a greater influence after 1993. Even when the standard controls are added, our nonlinear relationship remains robust. One reason that the literature failed to uncover a clear and robust income-terrorism relationship is that its aggregation of terrorist incidents and time periods introduced too many confounding and opposing influences. Moreover, the type of nonlinearity present in the identified terrorist-income relationships cannot be readily captured by linear or quadratic estimation techniques, in contrast to the extant literature.

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Figure 1: Lorenz Curve of GTD Casualty Incidents

Panel 1: Domestic Terrorism: Pre-1993

Panel 3: Transnational Terrorism: Pre-1993

Panel 2: Domestic Terrorism: Post-1993

Panel 4: Transnational Terrorism: Post-1993
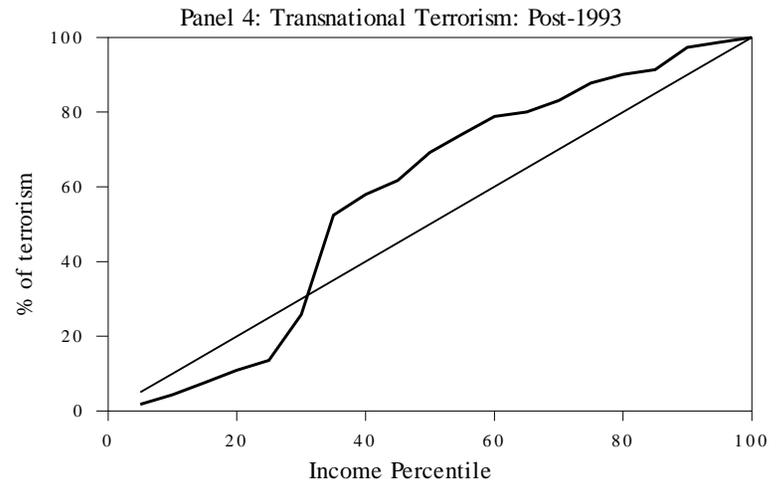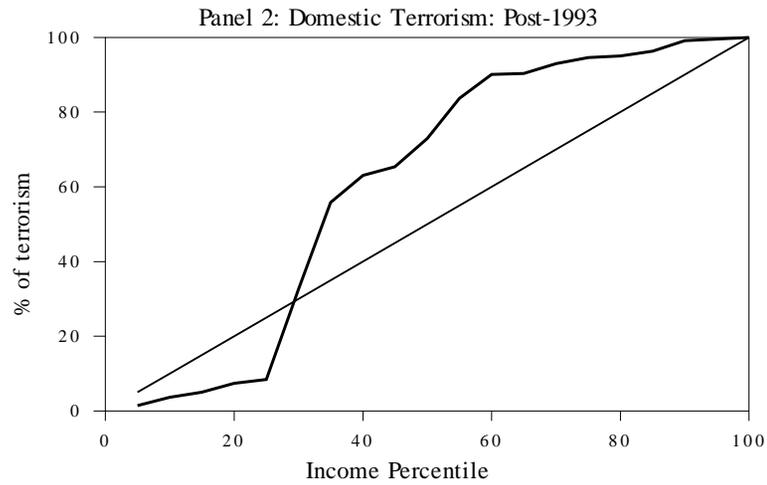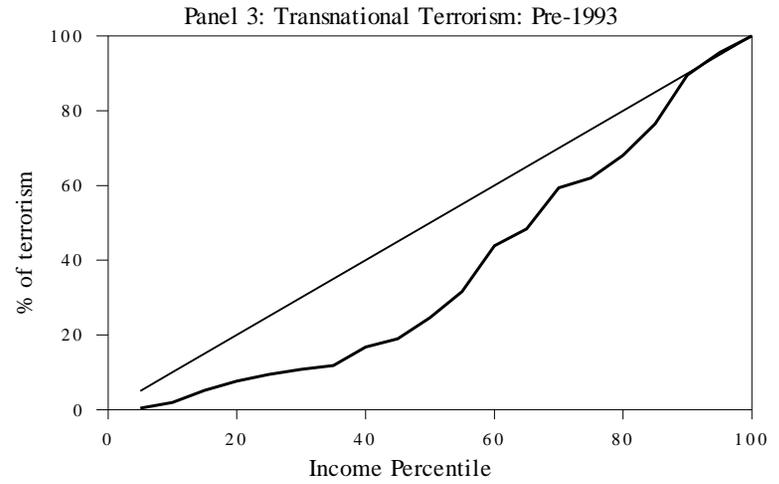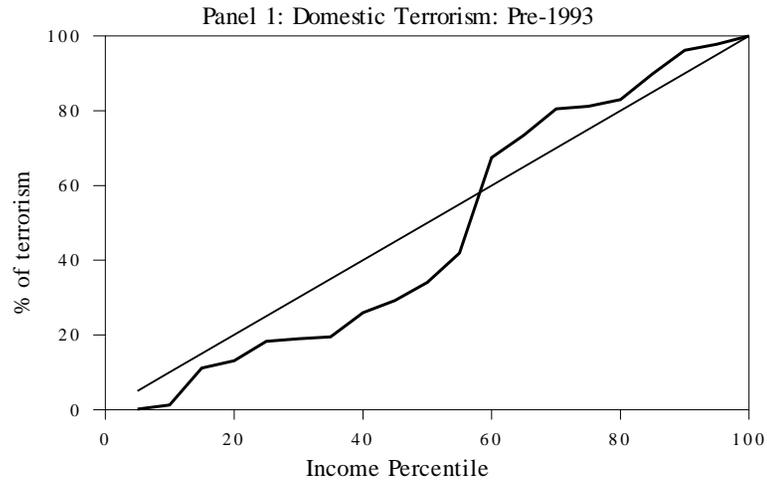
Figure 2: Lorenz Curve of ITERATE Casualty Incidents

Panel 1: By Location: Pre-1993

Panel 3: By Nationality: Pre-1993

Panel 2: By Location: Post-1993

Panel 4: By Nationality: Post-1993
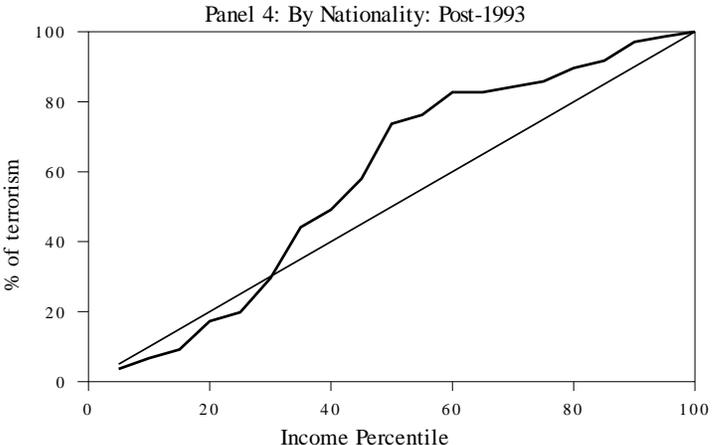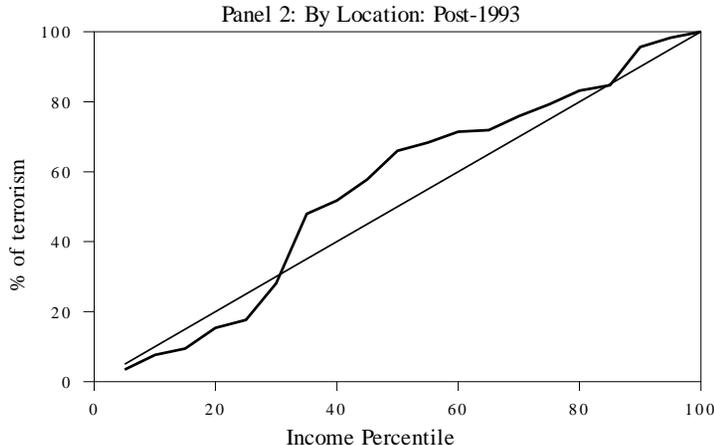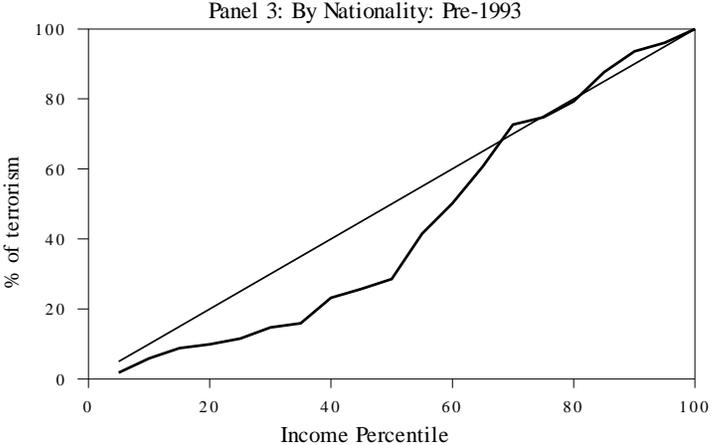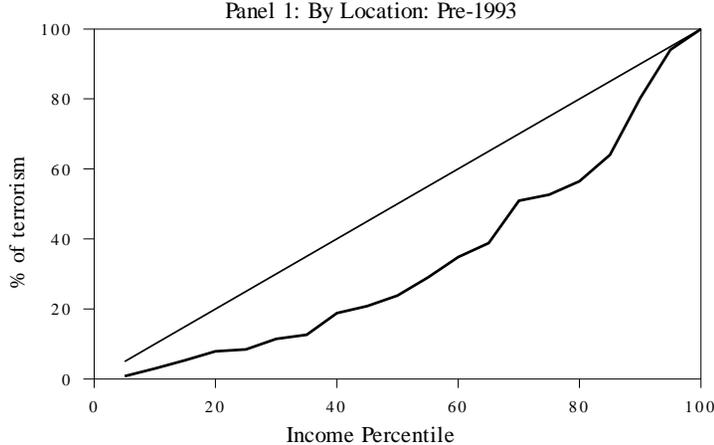
Figure 3: ESTR and LSTR Processes

Panel 1: Theta for Different Values of Gamma

Panel 3: Theta for Different Values of Gamma

Panel 2: A Simulated ESTR Process

Panel 4: A Simulated LSTR Process
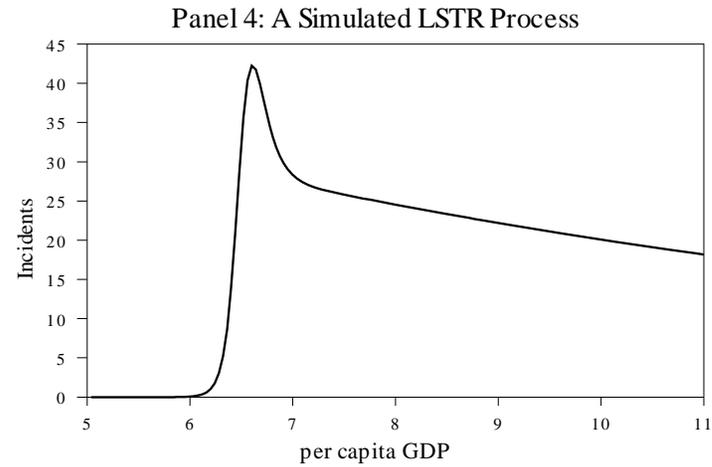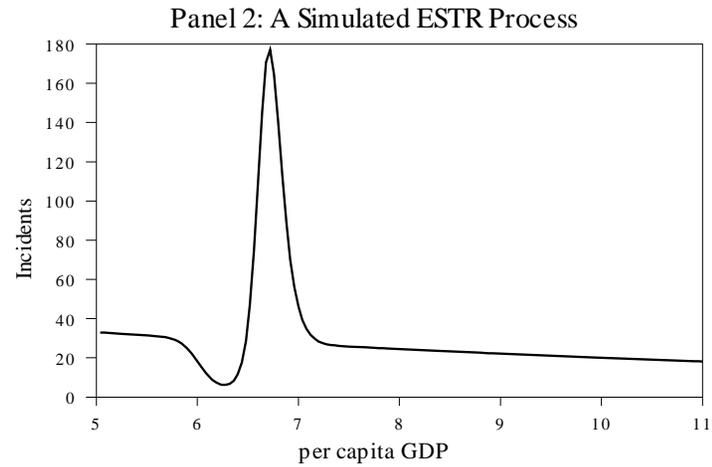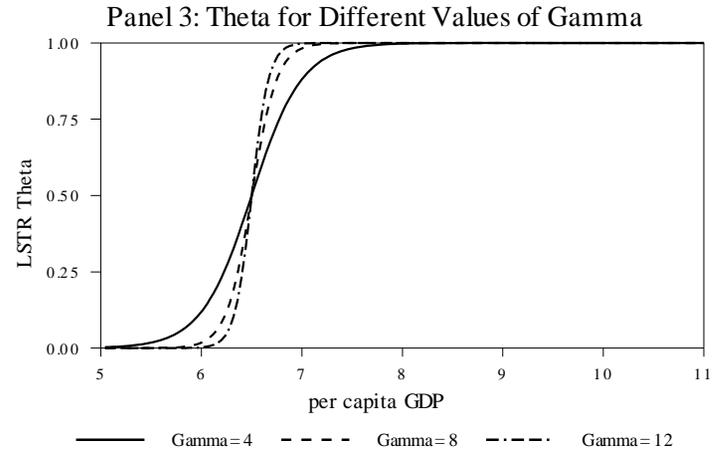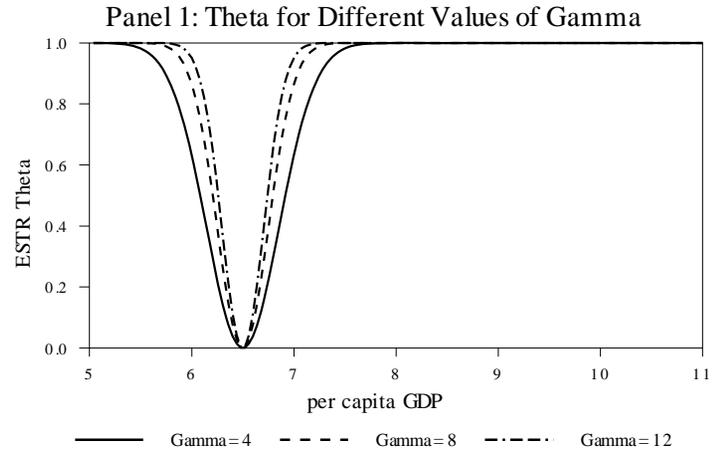
Figure 4: Effects of Income on ITERATE Casualty Incidents

Panel 1: By Location: Pre-1993

per capita GDP

Panel 3: By Nationality: Pre-1993

per capita GDP

Panel 2: By Location: Post-1993

per capita GDP

Panel 4: By Nationality: Post-1993

per capita GDP
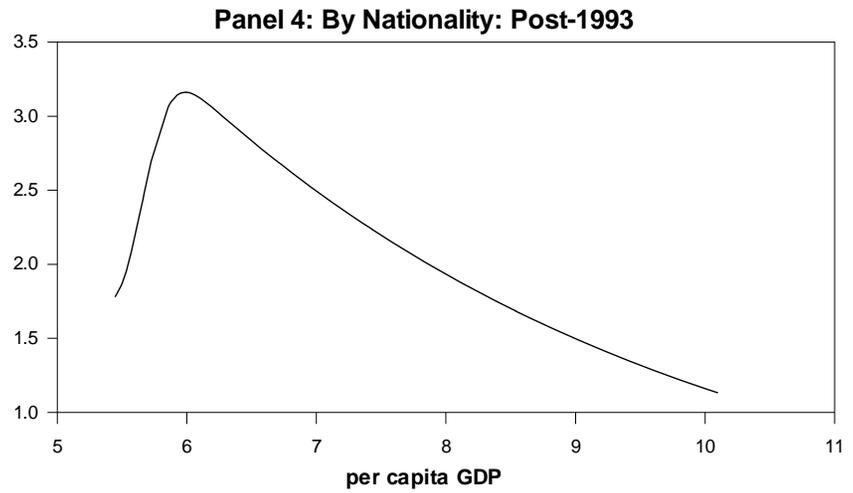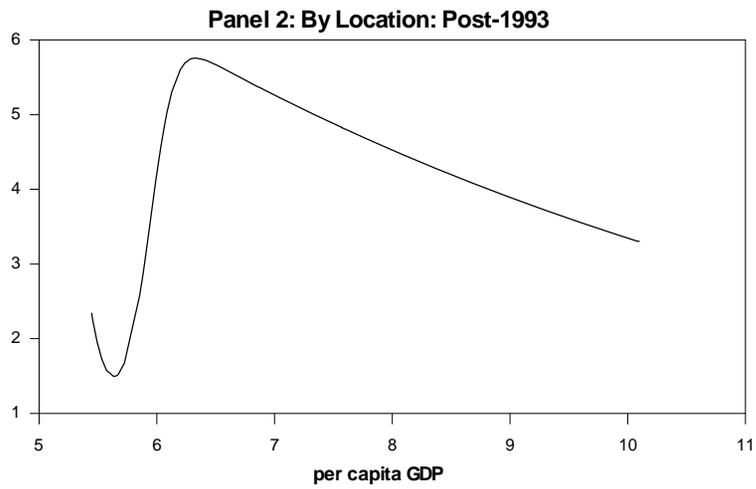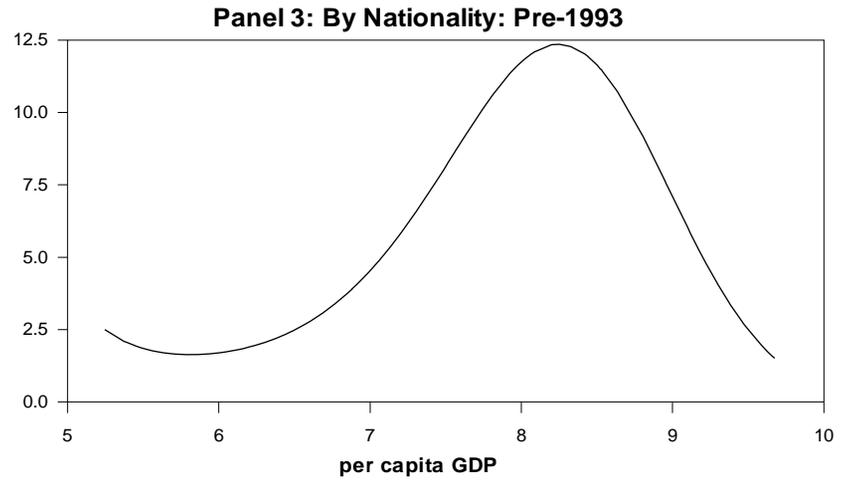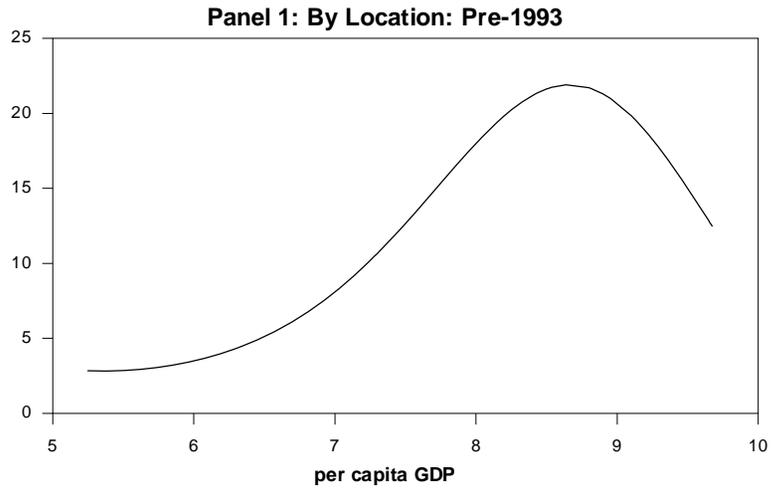
Figure 5: Effects of Income on GTD Casualty Incidents

Panel 1: Domestic Terrorism: Pre-1993

per capita GDP

**Panel 3: Transnational Terrorism: Pre-1993**

per capita GDP

Panel 2: Domestic Terrorism: Post-1993

per capita GDP

Panel 4: Transnational Terrorism: Post-1993

per capita GDP
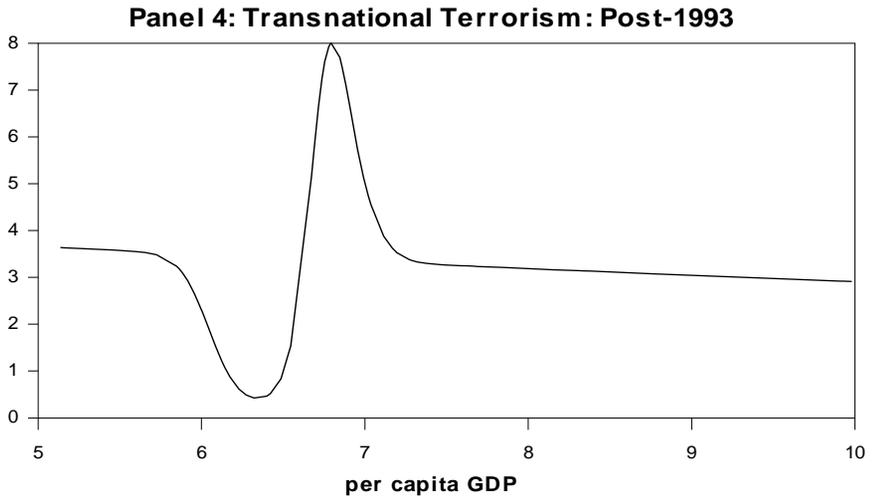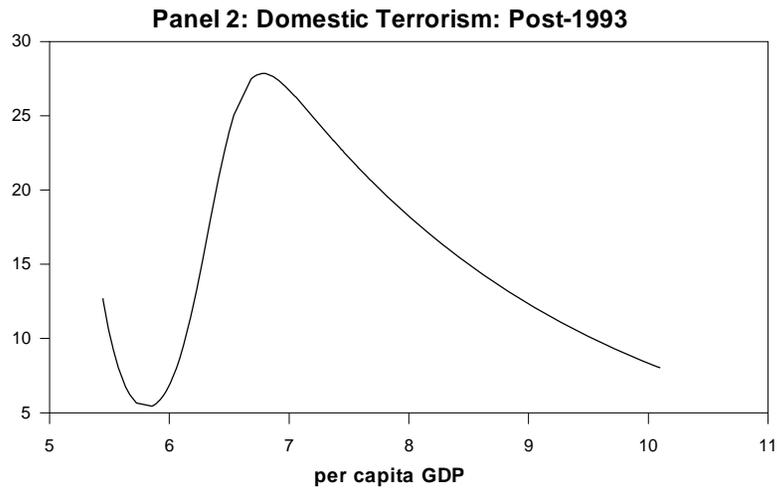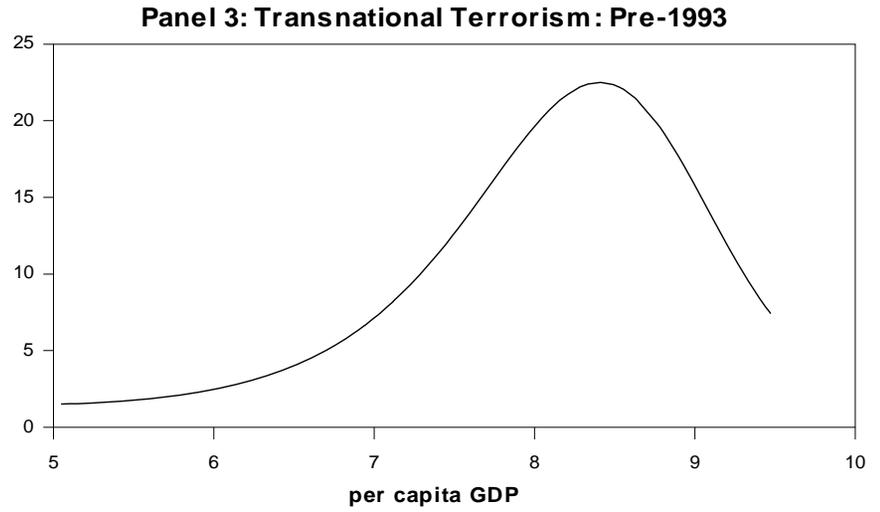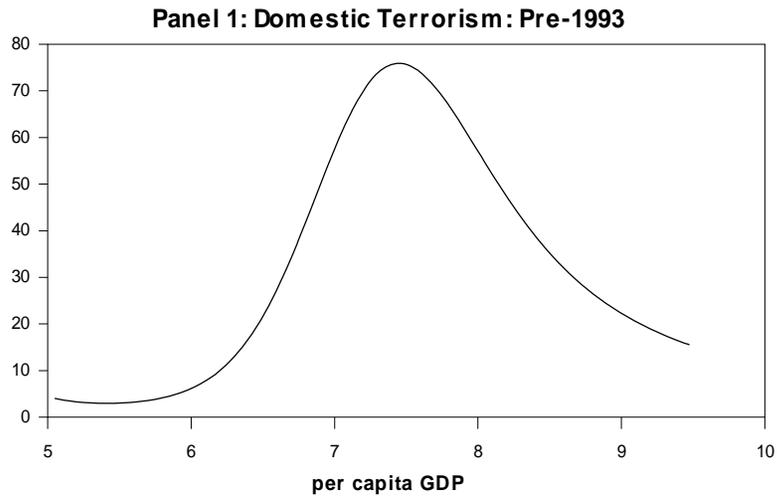
**Table 1: Summary Statistics of the Terrorism Incident Series
(per year country averages)**

	Sample	Mean	Std. Err.	Max	Zeros
The GTD Data					
Domestic Casualty	Pre-1993	3.20	9.78	67.41	53
Domestic Casualty	Post-1993	3.78	13.22	119.90	24
Transnational Casualty	Pre-1993	0.59	1.28	8.56	54
Transnational Casualty	Post-1993	0.45	1.38	14.66	43
The ITERATE Data					
Casualty (by Location)	Pre-1993	0.63	1.38	10.68	53
Casualty (by Location)	Post-1993	0.41	0.99	8.94	63
Casualty (by Nationality)	Pre-1993	0.33	0.69	4.73	72
Casualty (by Nationality)	Post-1993	0.23	0.53	3.44	91

Table 2: Diagnostics with Squared Logarithm of GDP

Series	Intercept	*lgdp*	*lgdp²*	*lpop*	*eta*	*Chi_sq*	*AIC*	*AIC(lin)*
Location_pre (IT)	−12.247	2.897	−0.165	0.601	1.600	7297.911	**−86.29**	−86.27
	(−31.88)	(74.78)	(−76.78)	(1043.20)	(15.80)	(0.00)		
Location_post (IT)	−1.926	0.299	−0.023	0.578	1.654	0.524	−24.26	**−24.27**
	(−0.93)	(0.54)	(−0.61)	(6.59)	(15.75)	(0.77)		
Nationality_pre (IT)	−12.760	3.187	−0.208	0.640	1.821	11.880	**−32.87**	−32.83
	(−3.54)	(3.33)	(−3.40)	(7.92)	(13.04)	(0.00)		
Nationality_post (IT)	−4.957	1.026	−0.078	0.603	1.811	10.365	−8.40	**−8.41**
	(−1.89)	(1.51)	(−1.81)	(8.19)	(11.79)	(0.01)		
Domestic_pre (GTD)	−24.273	6.187	−0.391	0.999	2.052	42.317	**823.55**	−823.40
	(−6.63)	(6.44)	(−6.30)	(11.86)	(17.84)	(0.00)		
Domestic_post (GTD)	−6.166	1.382	−0.100	1.047	1.573	1.425	**−614.00**	−613.99
	(−1.36)	(1.07)	(−1.12)	(11.30)	(14.67)	(0.49)		
Transnational_pre (GTD)	−16.196	3.826	−0.224	0.655	1.583	30.458	**−80.63**	−80.55
	(−4.03)	(3.62)	(−3.32)	(10.23)	(13.93)	(0.00)		
Transnational_post (GTD)	−7.590	1.676	−0.114	0.691	1.327	4.345	**−29.46**	−29.43
	(−2.65)	(2.08)	(−2.08)	(8.90)	(9.40)	(0.11)		

Notes: Boldfaced entries in the AIC column indicate that the model containing the quadratic *lgdp* term is selected. t-statistics are in parentheses, except for the *prob*-values in parentheses beneath the Chi-square statistic.

Table 3: ESTR and LSTR Estimates of the Terrorism Incident Series (Negative Binomial)

Series	α_0	lgdp	lgdp^2	lpop	β_0	lgdp	lgdp^2	lpop	γ	c	AIC
Location_pre (IT)	21.55	–5.69		0.38	92.36	–3.42		0.65	0.02	2.72	–86.40
	(10.40)	(–3.55)		(1.75)	(2.03)	(–0.68)		(1.03)	(4.08)	(2.29)	
Location_post (IT)	–0.82	–0.18		0.53	1.12	0.03		0.04	10.00	5.63	–24.34
	(–0.36)	(–0.51)		(0.60)	(0.44)	(0.09)		(0.04)		(49.60)	
Nationality_pre (IT)	30.05	–6.42		0.41	69.12	–3.00		0.78	0.04	4.09	–33.04
	(30.80)	(–45.65)		(3.18)	(19.84)	(–19.35)		(2.42)	(7.20)	(15.91)	
Nationality_post (IT)	7.22	–0.07		–1.47	–7.22	–0.18		2.11	10.00	5.40	–8.48
	(1.78)	(–0.87)		(–1.50)	(–1.76)	(–2.26)		(2.13)		(64.92)	
Domestic_pre (GTD)	–15.41	2.03		1.30	20.82	–2.69		–0.36	0.40	5.88	–823.65
	(–2.51)	(2.02)		(7.86)	(7.52)	(–4.43)		(–1.38)	(1.99)	(13.03)	
Domestic_post (GTD)	–0.70	–0.27		0.92	2.18	–0.12		0.15	3.69	5.79	–614.13
	(–0.62)	(–2.33)		(2.87)	(1.39)	(–1.44)		(0.41)	(1.74)	(54.47)	
Transnational_pre (GTD)	–6.85	3.53	–0.13	7.77	–17.04	2.15	–0.20	–7.14	1.86	3.30	–80.71
	(–0.76)	(12.06)	(–1.68)	(0.97)	(–7.61)	(1.60)	(–12.34)	(–0.89)	(1.24)	(2.78)	
Transnational_post (GTD)	–76.55	10.47		1.96	75.50	–10.52		–1.37	10.00	6.53	–29.66
	(–18.42)	(15.27)		(4.67)	(17.15)	(–15.32)		(–3.00)		(120.85)	

Note: *t*-statistics are indicated in parentheses.

Table 4: Pre-Testing for Nonlinearity in the Presence of the Covariates

Covariates	Obs.	Prob(F)	e_0	t-Stat.	Prob(F)	e_0	t-Stat.
				Pre-1993 data			
		Transnational Terrorism (by Nationality)			Domestic Terrorism		
Freedom House	153	0.000	−1.533	−3.782	0.000	−1.866	−2.904
POLITY	139	0.000	−0.152	−0.252	0.000	−0.150	−0.225
Rule of Law	112	0.000	−0.681	−5.260	0.000	−1.013	−8.536
Ethnic Tension	112	0.000	−0.228	−2.628	0.000	−0.272	−2.832
Religious Tension	112	0.000	−0.288	−3.158	0.000	−0.372	−2.492
log(Education/Pop)	146	0.000	−0.785	−3.127	0.000	−0.358	−0.945
Log(Area)	153	0.000	−0.154	−1.444	0.000	−0.176	−1.598
Gini Coefficient	71	0.000	0.100	4.959	0.000	0.149	4.449
Unemployment	104	0.000	0.035	1.415	0.000	−0.025	−0.880
				Post-1993 data			
		Transnational Terrorism (by Nationality)			Domestic Terrorism		
Freedom House	162	0.000	−1.590	−3.958	0.000	−1.980	−3.804
POLITY	148	0.000	−1.949	−6.004	0.000	−1.051	−2.058
Rule of Law	131	0.000	−0.392	−3.185	0.000	−0.797	−2.669
Ethnic Tension	128	0.000	−0.120	−1.115	0.000	−0.511	−3.433
Religious Tension	128	0.000	−0.649	−7.239	0.000	−0.618	−4.358
log(Education/Pop)	162	0.000	0.547	1.618	0.000	0.356	0.677
Log(Area)	162	0.000	−0.173	−1.484	0.000	−0.375	−3.442
Gini Coefficient	139	0.000	−0.027	−1.479	0.000	−0.026	−1.031
Unemployment	143	0.000	0.027	1.078	0.000	0.063	2.116

Data Appendix to "The Changing Nonlinear Relationship between Income and Terrorism"

Walter Enders, Gary A. Hoover, and Todd Sandler

Table A1: Alphabetical List of Countries Used in the Study

Albania	Cyprus	Kenya	Puerto Rico
Algeria	Czech Republic	Korea, Rep.	Qatar
Andorra	Denmark	Kuwait	Romania
Angola	Djibouti	Kyrgyz Republic	Russian Federation
Antigua and Barbuda	Dominica	Lao PDR	Rwanda
Argentina	Dominican Republic	Latvia	Saudi Arabia
Armenia	Ecuador	Lebanon	Senegal
Australia	Egypt, Arab Rep.	Lesotho	Serbia
Austria	El Salvador	Liberia	Sierra Leone
Azerbaijan	Equatorial Guinea	Libya	Singapore
Bahamas, The	Eritrea	Lithuania	Slovak Republic
Bahrain	Estonia	Luxembourg	Slovenia
Bangladesh	Ethiopia	Macao SAR, China	Somalia
Barbados	Fiji	Macedonia, FYR	South Africa
Belarus	Finland	Madagascar	Spain
Belgium	France	Malawi	Sri Lanka
Belize	Gabon	Malaysia	Sudan
Benin	Gambia, The	Maldives	Suriname
Bermuda	Georgia	Mali	Swaziland
Bhutan	Germany	Malta	Sweden
Bolivia	Ghana	Mauritania	Switzerland
Bosnia and Herzegovina	Greece	Mauritius	Syrian Arab Republic
Botswana	Grenada	Mexico	Tajikistan
Brazil	Guatemala	Moldova	Tanzania
Brunei Darussalam	Guinea	Morocco	Thailand
Bulgaria	Guinea-Bissau	Mozambique	Togo
Burkina Faso	Guyana	Myanmar	Trinidad and Tobago
Burundi	Haiti	Namibia	Tunisia
Cambodia	Honduras	Nepal	Turkey
Cameroon	Hong Kong, China	Netherlands	Uganda
Canada	Hungary	New Zealand	Ukraine
Cayman Islands	Iceland	Nicaragua	United Arab Emirates
Cen. African Republic	India	Niger	United Kingdom
Chad	Indonesia	Nigeria	United States
Chile	Iran, Islamic Rep.	Norway	Uruguay
China	Iraq	Pakistan	Uzbekistan
Colombia	Ireland	Panama	Venezuela, RB
Comoros	Israel	Papua New Guinea	Vietnam
Congo, Rep.	Italy	Paraguay	Virgin Islands (U.S.)
Costa Rica	Jamaica	Peru	Yemen, Rep.
Cote d'Ivoire	Japan	Philippines	Zambia
Croatia	Jordan	Poland	Zimbabwe
Cuba	Kazakhstan	Portugal	

Variables Used in Analysis

Many variables are not available for all countries over the entire sample period. As such, in all instances, each variable used in the study is the sample average over the available dates.

Domestic Terrorism: This variable corresponds to the average number of domestic terrorist incidents within a country over the 1970–1992 and 1994–2010 periods, respectively. In some places in the analysis, the terrorism variable indicates the cumulative number of attacks during the respective periods. We use the decomposition from the ESG (2011) data set. In addition, we use only incidents with at least one casualty (i.e., murdered or injured individual). For all domestic incidents, the nationalities of the perpetrators and victims match the location of the incident.

Transnational Terrorism: For the GTD and ITERATE data, this variable corresponds to the average number of transnational terrorist incidents that occur within a country during the 1970–1992 and 1994–2010 periods, respectively. In some places in the analysis, the terrorism variable indicates the cumulative number of attacks during the respective periods. We use only incidents with at least one casualty. For the GTD data, we employ the decomposition from the ESG data set. For the ITERATE data, we can measure terrorism by either the location of the incident or the nationality of the perpetrator. For all transnational incidents, the location, nationalities of the perpetrators, and nationalities of the victims are not all the same.

Freedom House and POLITY: The Freedom House (2012) and POLITY (Marshall and Jaggers 2012) variables measure political freedom. The Freedom House variable measures political rights and civil liberties on a scale from 1 to 7, with lower values indicating more freedom. If the *sum* of these two indices is less than or equal to 5, the country is deemed to have a high degree of political and civil freedom. In this case, we set the dummy variable for Freedom House equal to one; otherwise, we set the dummy variable equal to zero. Our POLITY measure is a dummy variable equal to zero if the overall POLITY score is less than 7, and equal to unity otherwise. Higher POLITY values indicate more democratic principles characterize the country.

Rule of Law: This variable indicates the strength and impartiality of the legal system along with the popular observance of the law. This is an index that varies between 0 and 6, with higher values indicating more respect for law and order. The data source is International Country Risk Guide 2012 http://www.prsgroup.com/icrg.aspx.

Ethnic Tension and Religious Tension: Each of these indices varies from 0 to 6, where smaller values indicate more tension. Ethnic Tension refers to racial, nationality, or language divisions, while Religious Tension indicates religious suppression and persecution. The data source is International Country Risk Guide 2012 http://www.prsgroup.com/icrg.aspx.

The remaining variables are from the World Bank's (2012) *World Development Indicators*. The annual values for each variable are averaged over two time periods: 1970–1992 and 1994–2010. Not all of the years are available for some countries (as shown in Table A2). In such circumstances, we averaged all of the available years.

Area$_i$: The area of country i.

Education: World Banks' (2012) measure of the number of individuals receiving secondary education. (Indicator code: SE.SEC.ENRL)

Gini Coefficient: measurement of income inequality. Larger values reflect greater income inequality.   (Indicator code: SI.POV.GINI).

lgdp$_i$: The natural logarithm of real per capita GDP in country i (in constant 2000 US dollars). Unfortunately, real per capita GDP figures are not available for Afghanistan.

lpop$_i$: The natural logarithm of population in country i.

Unemployment: The overall unemployment rate in a country as a percent of total labor force.

Table A2: Availability of the Raw Data

Variable	No. of countries
Education (1970–1992)	163
Education (1994–2010)	172
Per capita GDP (1970–1992)	158
Per capita GDP (1994–2010)	167
Ethnic Tension (1984–1992)	126
Ethnic Tension (1994–2010)	138
Gini (1970–1992)	73
Gini (1994–2010)	142
Population (1970–1992)	172
Population (1994–2010)	172
Religious Tension (1984–1992)	126
Religious Tension (1994–2010)	138
Unemployment (1970–1992)	113
Unemployment (1993–2010)	148