Journal of Conflict Resolution
http://jcr.sagepub.com/

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Journal of Conflict Resolution published online 26 May 2014
DOI: 10.1177/0022002714535252

The online version of this article can be found at:
http://jcr.sagepub.com/content/early/2014/05/26/0022002714535252

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Peace Science Society (International)

Article

Journal of Conflict Resolution
1-31

DOI: 10.1177/0022002714535252
jcr.sagepub.com

The Changing Nonlinear Relationship between Income and Terrorism

Walter Enders[1], Gary A. Hoover[1], and Todd Sandler[2]

Abstract

This article reinvestigates the relationship between real per capita gross domestic product (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. For transnational terrorist attacks, this shift characterized not only the attack venue but also the perpetrators' nationality. The article 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 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

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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 gross domestic product (GDP) or low development (see, e.g., Piazza 2006).[1] Other public figures made similar allegations. The empirical literature, surveyed in the next section, 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 to 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 around the early 1990s (Rapoport 2004; Hoffman 2006), 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 article 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 article differs from Enders and Hoover (2012) in a number of essential ways. First, the current article examines a much longer 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 to 1992 and 1994 to 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, 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. Third, the current article develops a modified Lorenz curve to display visually the dispersion between terrorist attacks and per capita GDP percentiles for various subsamples. Enders and Hoover (2012) relied, instead, on hard-to-read scatter plots with income per capita on the horizontal axis. Fourth, the current article establishes that the nonlinear relationship between per capita GDP and terrorism cannot be adequately captured by a quadratic representation for any of the eight terrorism series examined. This finding raises questions about earlier works 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. Fifth, the current article provides a much greater in-depth econometric analysis with more controls. Finally, unlike Enders and Hoover, we provide a theoretical foundation for our anticipated findings.

Our analysis strongly suggests that the myriad findings in the literature stem from the different 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.

Preliminaries

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. Consistent with the literature, this definition views the perpetrators as below the state level in order to rule out state terrorism. Two distinct categories of terrorism are relevant. 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]

Terrorist Event Data

Two terrorist event data sets 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 to 2011 and, like other terrorist event databases, relies on the news media for its variables.

A second event data set 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 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 to 2007, which was later updated to 2008 to 2010.[5] ESG calibrated GTD transnational terrorist attacks to those in ITERATE to address periods of under- and overreporting 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.

On 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 (Rapoport 2004; Hoffman 2006). 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—for example, Direct Action in France—that specialized in domestic terrorism. With the decline of communism in Eastern Europe, many European leftist terrorist groups—for example, Red Army Faction, Italian Red Brigades, 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 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.

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., Krueger and Maleckova 2003; Abadie 2006; 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, Berrebi, and Klor 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 GTD. Fourth, these earlier studies analyzed varied samples of countries for alternative periods. For example, Blomberg, Hess, and Weerapana (2004a) examined 127 countries for 1968 to 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., Li and Schaub 2004; Piazza 2006), with the exception of Krueger and Laitin (2008) and Gassebner and Luechinger (2011). Krueger and Laitin distinguished between venue and perpetrators' countries, whereas Gassebner and Luechinger 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 only investigated transnational terrorist attacks, while Gassebner and Luechinger 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 to 1997, which was primarily before the prevalence of the fundamentalist terrorists. Subsequently, Li (2005) also found a negative relationship between per capita GDP and transnational terrorism when additional control variables were introduced.

Except for Li and Schaub (2004) and Li (2005), 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 Bueno de Mesquita 2005; Benmelech, Berrebi, and Klor 2012), 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 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.

Theoretical Discussion

We draw from the literature and our own insights to hypothesize a nonlinear, nonsymmetric relationship between per capita GDP and terrorism. In particular, we identify a number of considerations that give rise to this nonlinear relationship from the venue or perpetrators' countries' viewpoints. 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 (Lai 2007; Freytag et al. 2011; de la Calle and Sánchez-Cuenca 2012).

Since countries with very low levels of per capita GDP correlate with failed states (Piazza 2008), there might be a negative relationship between terrorism and income starting with the poorest countries. These lawless states provide an opportunity for terrorist groups to operate with impunity. In many cases, these states serve as safe havens for launching attacks abroad. Such failed states possess little counterterrorism capability or law enforcement assets, because of limited tax revenue (Fearon and Laitin 2003; Lai 2007). Another contributing factor to a clustering of terrorism at the lowest income levels may arise from opportunity cost considerations, since terrorists have few market opportunities to sacrifice by becoming terrorists (Freytag et al. 2011). As income levels grow in real terms in these failed states, counterterrorism capabilities and opportunity costs improve, thereby potentially curbing terrorism.

A peak is anticipated at some intermediate income level, whose location depends on the period, type of terrorism, and country viewpoint (see the following).[8] This peak is pronounced because there are many nonfailed states that experience terrorism or are home to perpetrators. 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 (Freytag et al. 2011). However, a threshold per capita GDP will eventually be reached where still higher per capita 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.[9] Also, potential 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, Berrebi, and Klor 2012). 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' countries, our theoretical discussion implies not only the possibility of an intermediate income peak but also the *nonsymmetrical rises and falls* on either side of this peak. For example, if a targeted government relies on defensive measures, then the reduction of terrorism beyond some 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 multiple underlying considerations, which need not be in sync as per capita GDP rises or falls. There is, thus, no reason to expect a 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 to 2010. These security measures should keep the peak level 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 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 note 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 to 2010.

Examining the Terrorism Series

Throughout the analysis, our terrorist series involve at least one casualty. 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]

The usual normality assumption is inappropriate because many countries experienced no terrorism and most countries experienced no more than a single incident. In the pre-1993 period, 53 of the 166 usable sample countries experienced no domestic casualty incidents, while 54 experienced no transnational casualty incidents (summary table available upon request). There was a slight increase in the number of incidents over time. Notably, the standard error of each series is at least twice its mean, and all series fail the Jarque–Bera test for normality. As is standard, 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 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 per capita income, while the vertical axis shows the cumulative percentage of world domestic terrorism 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 US$366 (Nigeria), US$1,028 (Honduras), US$2,410 (Chile), and US$7,947 (Slovenia).

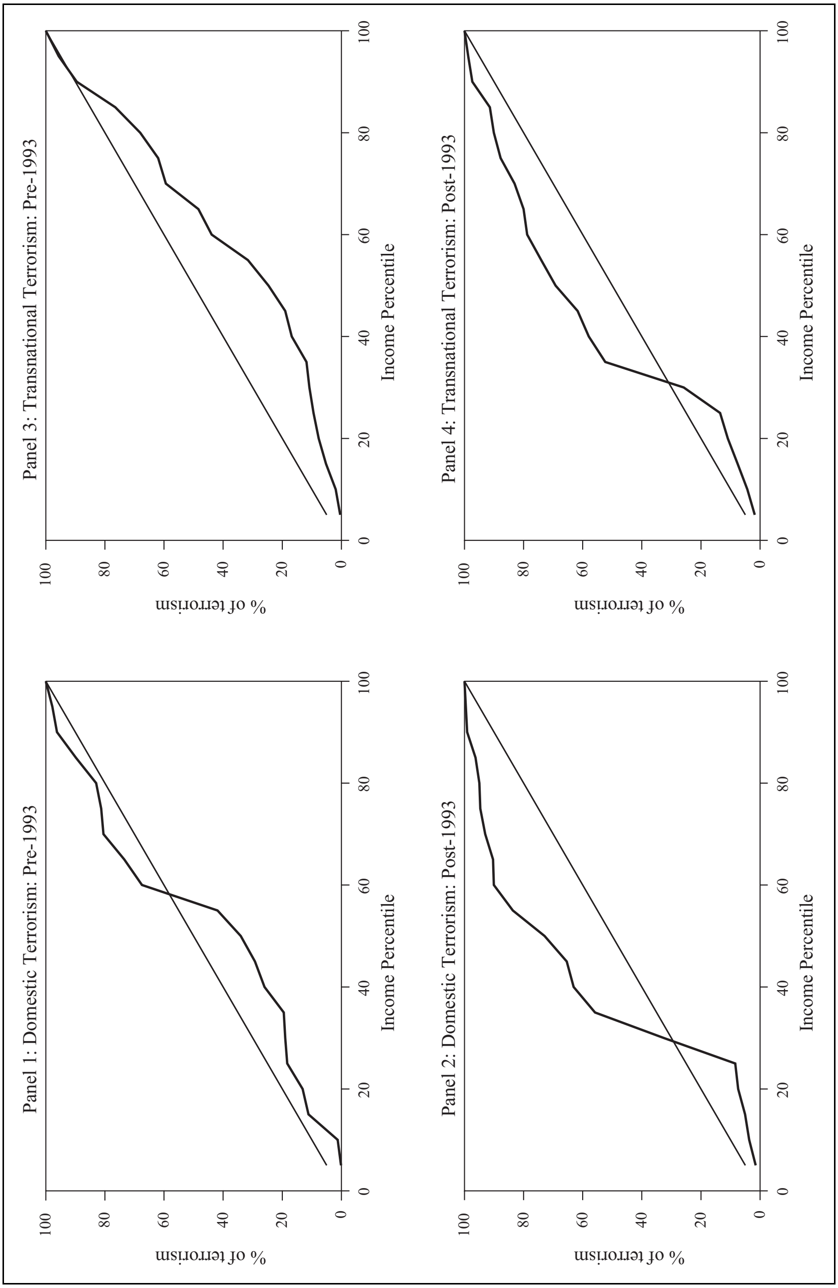

Figure 1. Lorenz curve of GTD casualty incidents.
Note: GTD = Global Terrorism Database.

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 percent of states accounted for about 18 percent of total domestic casualty incidents and the next 25 percent accounted for about 16 percent of these incidents, so that the lowest 50 percent accounted for 34 percent of these incidents. However, there are sharp increases in the amount of terrorism in the next 20 percent of the states; the countries in the 51st through 70th percentiles of the income distribution experienced 38 percent of domestic terrorism. Hence, during the pre-1993 period, domestic terrorism seems to be clustered in the states with income levels that are slightly to well above the 51st percentile. 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, and West Germany).

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 percent of countries ranked by per capita GDP levels only sustained about 7 percent of the domestic terrorism incidents with casualties, whereas the next 30 percent accounted for about 65 percent of these incidents. Because the next 10 percent of countries suffered about 18 percent of the domestic terrorism, the richest 40 percent experienced only 10 percent of these incidents. For the post-1993 data set, the 20th, 40th, 60th, and 80th percentiles correspond to real per capita GDP levels of US$287 (Ghana), US$1,431 (Paraguay), US$4,133 (Lithuania), and US$14,531 (Spain). Terrorism was clustered in the 30th to 60th income percentiles although the point at which the rapid increases in terrorism occurred shifted toward the lower end of this 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 (Enders and Sandler 2006). This era was also marred with many internal conflicts in these 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 percent of states had only 24 percent of transnational terrorism with casualties, whereas the next richer 40 percent of states sustained 66 percent 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 percent of countries accounted for about 11 percent of transnational terrorism; however, the next richer 30 percent of countries accounted for 50 percent 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 (Enders and Sandler 2012, 328-33) would also reinforce the Lorenz pattern in panel 4, where countries in the 25th to 35th percentiles sustained a disproportionately large percentage of transnational terrorist attacks and rich countries suffered a disproportionately small percentage of transnational terrorist attacks.

In Figure 2, we use ITERATE data to show the 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.

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 high-income and upper end of the middle-income countries; countries in the 55th to 70th percentiles had 25 percent of transnational terrorism and countries in the upper 10 percentiles had 30 percent of these attacks. In contrast, the perpetrators tended to hail from the upper middle-income countries; countries in the 55th to 70th percentiles had 44 percent of the terrorism. 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 patterns agree with our priors. Terrorist attacks became more concentrated in lower income countries, 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).

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 equation (1), what measure of terrorism or sample period is selected, or whether equation (1) is estimated with ordinary least squares or with maximum likelihood estimation using a Poisson or negative binomial distribution. The key point is that the specification in equation (1) does not allow for the type of clustering described in the previous section. In equation (1), if gdp_i increases by one unit, terrorism increases by α_1 units, and if gdp_i increases by two units, terrorism increases by $2\alpha_1$ units. However, this is not the pattern observed in Figures 1 and 2, where per

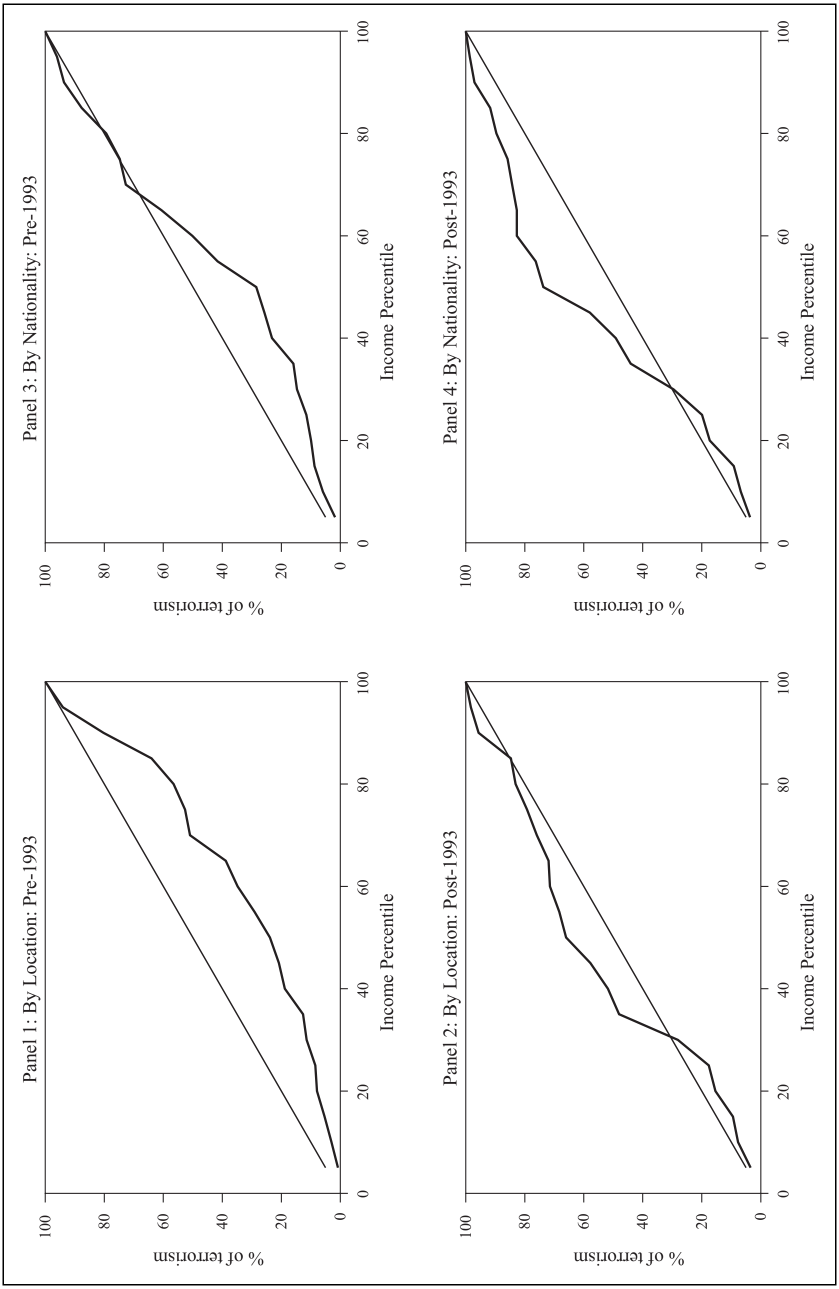

Figure 2. Lorenz curve of ITERATE casualty incidents.
Note: ITERATE = International Terrorism: Attributes of Terrorist Events.

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]

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

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 heteroscedasticity) are in parentheses.[12]

Hence, pooling the ITERATE data over the entire 1970 to 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 GDP 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 1 are instructive, where the first four series use GTD data, while the last four series use ITERATE (IT) 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, thereafter further per capita income increases reduce terrorism. In six of the eight cases, the overall fit of the model with the $(lgdp_i)^2$ term is selected by the Akaike Information Criterion (AIC) over the linear specification. Finally, a χ^2 test indicates that the null hypothesis that both the $lgdp$ and $(lgdp)^2$ coefficients jointly equal zero cannot be maintained in five of the eight cases.

Exponential STR (ESTR) and Logistic Variant of the STR (LSTR) Models

As we show in ensuing sections, the relationship between terrorism and per capita income is often more complicated than adding a quadratic per capita income term.

Table 1. Diagnostics with Squared Logarithm of GDP.

Series	Intercept	*lgdp*	*lgdp*^{2}	*lpop*	η	χ^2	AIC	AIC(lin)
Domestic_pre (GTD)	–24.273 (–6.63)	6.187 (6.44)	–0.391 (–6.30)	0.999 (11.86)	2.052 (17.84)	42.317 (.00)	**823.55**	–823.40
Domestic_post (GTD)	–6.166 (–1.36)	1.382 (1.07)	–0.100 (–1.12)	1.047 (11.30)	1.573 (14.67)	1.425 (.49)	−**614.00**	–613.99
Transnational_pre (GTD)	–16.196 (–4.03)	3.826 (3.62)	–0.224 (–3.32)	0.655 (10.23)	1.583 (13.93)	30.458 (.00)	**–80.63**	–80.55
Transnational_post (GTD)	–7.590 (–2.65)	1.676 (2.08)	–0.114 (–2.08)	0.691 (8.90)	1.327 (9.40)	4.345 (.11)	**–29.46**	–29.43
Location_pre (IT)	–12.247 (–31.88)	2.897 (74.78)	–0.165 (–76.78)	0.601 (1,043.20)	1.600 (15.80)	7,297.911 (.00)	**–86.29**	–86.27
Location_post (IT)	–1.926 (–0.93)	0.299 (0.54)	–0.023 (–0.61)	0.578 (6.59)	1.654 (15.75)	0.524 (.77)	–24.26	**–24.27**
Nationality_pre (IT)	–12.760 (–3.54)	3.187 (3.33)	–0.208 (–3.40)	0.640 (7.92)	1.821 (13.04)	11.880 (.00)	**–32.87**	−32.83
Nationality_post (IT)	–4.957 (–1.89)	1.026 (1.51)	–0.078 (–1.81)	0.603 (8.19)	1.811 (11.79)	10.365 (.01)	–8.40	**–8.41**

Note: AIC = Akaike Information Criterion; GDP = gross domestic product; IT = ITERATE; lin = linear; GTD = Global Terrorism Database.
Boldface entries in the AIC column indicate that the model containing the quadratic *lgdp* term is selected. *t*-statistics are in parentheses, except for the *p* values in parentheses beneath the chi-square statistic.

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:

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

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

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

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 equation (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 equation (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 toward 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.

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

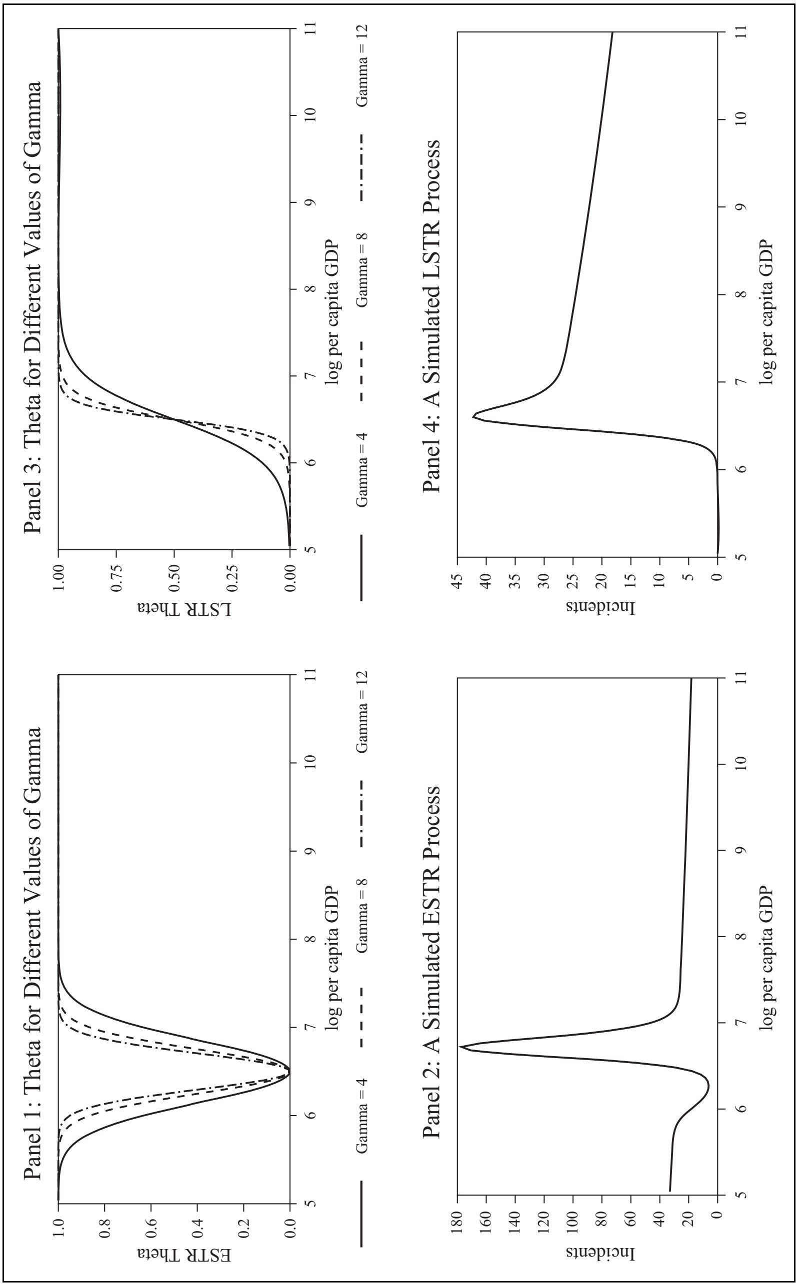

Figure 3. ESTR and LSTR processes.
Note: ESTR = exponential smooth transition regression; LSTR = logistic variant of the smooth transition regression model.

captured by large values of γ. The type of quadratic specification reported in Table 1 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 subsequently, 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 cannot capture such extreme clustering.

In the LSTR model, θ_i has the form

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

Unlike the U shape of the ESTR specification, equation (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

$$\begin{aligned}\hat{T}_i = \exp\big[&\big(\alpha_0 + \alpha_1 lgdp_i + \alpha_2 lpop_i + \alpha_3 lgdp_i^2\big)\\ &+\theta_i\big(\beta_0 + \beta_1 lgdp_i + \beta_2 lpop_i + \beta_3 lgdp_i^2\big)\big].\end{aligned} \tag{6}$$

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.[15] Given the well-known difficulties in estimating γ, we constrained the upper bound for γ to be no greater than 10.00.[16] The results for each series are shown in Table 2. 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 1. 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 fifth line of Table 2, the estimated equation is given by

$$\begin{aligned} \hat{T}_i &= \underset{(10.40)}{\exp[(21.55} - \underset{(-3.55)}{5.69}lgdp_i + \underset{(1.75)}{0.38}lpop_i) + \theta_i(\underset{(2.03)}{92.36} - \underset{(-0.68)}{3.42}lgdp_i + \underset{(1.03)}{0.65}lpop_i)], \\ \theta_i &= 1 - \exp[-\underset{(2.29)}{0.02}(lgdp_i - 2.72)^2], \quad \eta = 1.57. \end{aligned} \tag{7}$$

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

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 an ESTR model, the interpretation of the coefficients in Table 2 can be difficult since the model is highly nonlinear in its parameters.

We rely on Figures 4 and 5 to display the nonlinear relationship between terrorism and the log of real per capita GDP for GTD and ITERATE terrorism samples, respectively. In panel 1 of Figure 4, we display this relationship for Domestic_pre (GTD) when evaluated at the sample mean for $lpop_i$. Panel 1 shows that increases in $lgdp_i$ act to augment domestic casualty incidents until real per capita GDP reaches US$1,762 (i.e., exp(7.47) = 1,762) with a maximum of almost seventy-nine incidents. Further increases in real GDP reduce terrorism. In panel 2, post-1993 domestic attacks initially fall, then rise to a maximum of almost twenty-eight 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 toward the lower income countries. Panel 3 of Figure 4 has the largest number of incidents at a per capita income of US$4,316, consistent with the dominant leftist and nationalist/separatist terrorists favoring richer venues for pre-1993 transnational terrorist attacks. Panel 4, however, shows a substantial clustering of terrorism in countries with per capita GDP levels in the range of US$800 to US$1,000 (i.e., exp(6.68) ≅ 800 and exp(6.91) ≅ 1,000). Thus, over time there has been a substantial movement of terrorism toward the low-income countries. For panels 2 and 4 of Figure 4, the post-1993 shifts of the greatest concentration of terrorist attacks to lower per capita GDP levels agree with our priors. Also, consistent with our priors, domestic terrorism peaks at a smaller per capita GDP level than

Table 2. 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
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)	
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)	

Note: GTD = Global Terrorism Database; IT = ITERATE; ESTR = exponential smooth transition regression; LSTR = logistic variant of the smooth transition regression model; AIC = Akaike Information Criterion. *t*-statistics are indicated in parentheses.

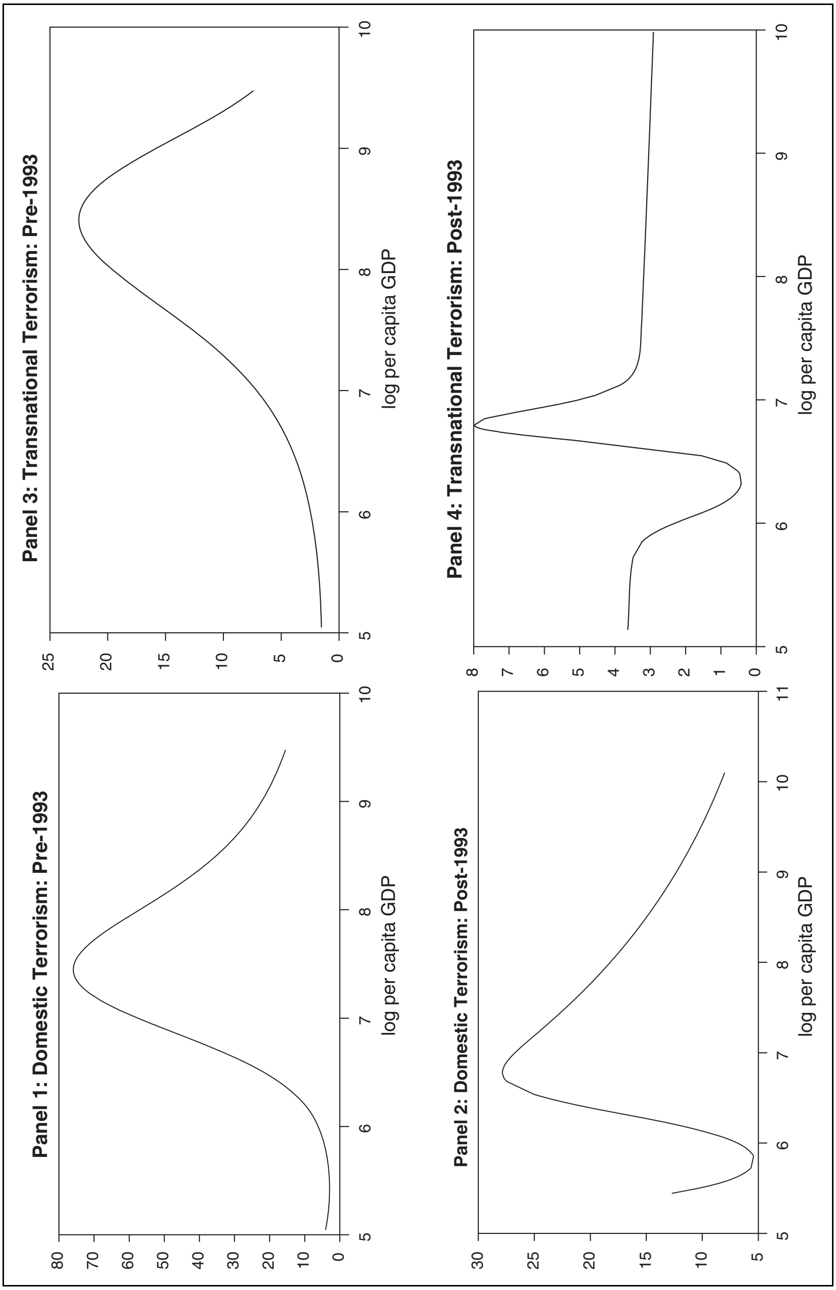

Figure 4. Effects of income on GTD casualty incidents.
Note: GTD = Global Terrorism Database.

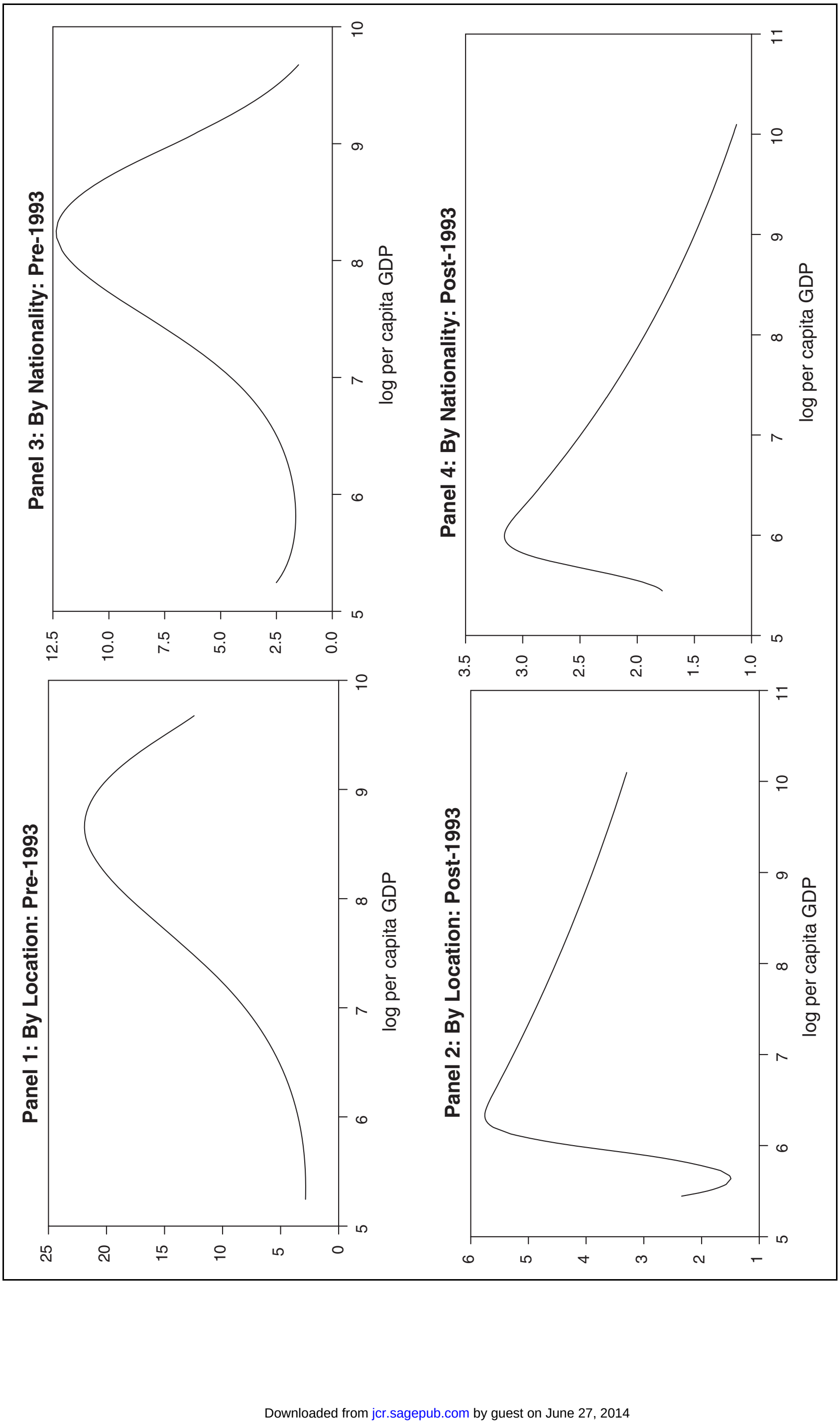

Figure 5. Effects of income on ITERATE casualty incidents.
Note: ITERATE = International Terrorism: Attributes of Terrorist Events.

transnational terrorism during 1970 to 1992. Finally, 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.

In panel 1 of Figure 5, increases in real per capita income cause the level of transnational terrorism to rise until a maximum of about twenty-two incidents when $lgdp = 8.63$, corresponding to a real per capita GDP of US$5,633. Subsequent increases in per capita GDP result in a decline in transnational terrorism. In panel 2 of Figure 5, 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 log($5.56) = $261), increases in real per capita GDP raise the level of terrorism until a per capita income level of about US$480. Thereafter, increases in per capita income levels gradually reduce 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, consistent with the greater dominance of the religious fundamentalist and nationalist/separatist terrorist groups after 1993. 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. 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.

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. This exercise also allows us to address the omitted variable concern. 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 equation (4) into equation (3) to obtain

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

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

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

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 equation (8) are identified in the null model. Although equation (8) relies on the ESTR specification, the analogous issue holds for the LSTR specification using equation (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 equation (4) as follows:

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

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

$$\theta_i = a_0 + a_1 lgdp_i + a_2 lgdp_i^2 + a_3 lgdp_i^3. \tag{11}$$

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

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

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 equation (12).

Given the large number of parameters that would be necessary to estimate in an unrestricted model, we estimate the following restricted form of equation (12):[18]

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

where z_i is one of the previously mentioned covariates. In moving from equation (12) to equation (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 equation (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 equation (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 domestic terrorism and transnational terrorism based on the perpetrators' nationality in the pre- and post-1993 eras. These four series 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 3 reports the results for the pre-1993 values for domestic terrorism and transnational terrorism by perpetrators' nationality. The lower 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 p values of the F statistic for the null hypothesis that all values of the c_js$(j = 1, \ldots, 4)$ equal zero. Since the p 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., accept the alternative hypothesis that terrorism is affected by real GDP levels). Although not reported in Table 3, it is always the case that the p values of the test for linearity (i.e., the test that $c_2 = c_3 = c_4 = 0$) are smaller than .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 $e_0 = 0$.[19]

Before discussing Table 3, 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.

In Table 3, all four measures of terrorism are negative and significantly related to the Freedom House (2012) measure, so that increases in civil and political rights

Table 3. Pretesting for Nonlinearity in the Presence of the Covariates.

Covariates	Obs.	*p* (*F*)	e_0	*t*-statistics	*p* (*F*)	e_0	*t*-statistics
		Pre-1993 data					
		Domestic terrorism			Transnational terrorism (by nationality)		
Freedom House	153	.000	−1.866	−2.904	.000	−1.533	−3.782
POLITY	139	.000	−0.150	−0.225	.000	−0.152	−0.252
Rule of law	112	.000	−1.013	−8.536	.000	−0.681	−5.260
Ethnic tension	112	.000	−0.272	−2.832	.000	−0.228	−2.628
Religious tension	112	.000	−0.372	−2.492	.000	−0.288	−3.158
log(Education/population)	146	.000	−0.358	−0.945	.000	−0.785	−3.127
Log(Area)	153	.000	−0.176	−1.598	.000	−0.154	−1.444
Gini coefficient	71	.000	0.149	4.449	.000	0.100	4.959
Unemployment	104	.000	−0.025	−0.880	.000	0.035	1.415
		Post-1993 data					
		Domestic terrorism			Transnational terrorism (by nationality)		
Freedom House	162	.000	−1.980	−3.804	.000	−1.590	−3.958
POLITY	148	.000	−1.051	−2.058	.000	−1.949	−6.004
Rule of law	131	.000	−0.797	−2.669	.000	−0.392	−3.185
Ethnic tension	128	.000	−0.511	−3.433	.000	−0.120	−1.115
Religious tension	128	.000	−0.618	−4.358	.000	−0.649	−7.239
log(Education/population)	162	.000	0.356	0.677	.000	0.547	1.618
Log(Area)	162	.000	−0.375	−3.442	.000	−0.173	−1.484
Gini coefficient	139	.000	−0.026	−1.031	.000	−0.027	−1.479
Unemployment	143	.000	0.063	2.116	.000	0.027	1.078

reduce terrorism. The point estimates for POLITY are always negative, but 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, for example, 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 percentage 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.

Concluding Remarks

This article establishes a robust nonlinear relationship between per capita income and various terrorist time series during 1970 to 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 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.

Authors' Note

We have profited from comments from two anonymous referees. Replication materials are available at the *Journal of Conflict Resolution* website at http://jcr.sagepub.com/.

Acknowledgment

The authors would like to thank Aidan Hathaway for his excellent research assistance.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was funded, in part, by the US Department of Homeland Security (DHS) through the Center for Risk and Economic Analysis of Terrorist Events (CREATE) at the University of Southern California, Grant 2010-ST-061-RE0001-04. However, any opinions, findings, conclusions, and recommendations are solely those of the authors and do not necessarily reflect the views of DHS or CREATE.

Notes

1. Low per capita gross domestic product (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.
2. In a different context, Meierrieks and Gries (2013) showed that the growth–terrorism relationship changed after the end of the cold war. The current article is not about economic growth.
3. We leave out 1993 because the data for this year are incomplete in the Global Terrorism Database. The diminished influence of the leftists in the late 1980s was documented in Alexander and Pluchinsky (1992).
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.
5. The interested reader should consult Enders, Sandler, and Gaibulloev (2011) for details.
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 to 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.
8. 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.
9. Our theoretical discussion follows that of the literature where per capita GDP proxies workers' opportunity cost. We recognize the imperfection of this proxy.

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, twelve of the seventeen 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.
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 (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.
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 equation (2).
13. Similar results hold when we use the GTD domestic and transnational terrorism series.
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. Given a recent article by Gaibulloev, Sandler, and Sul (2014), we are not concerned about the reversed causality between terrorism and income. After correcting for Nickell bias and cross-sectional dependence, these authors showed that terrorism had no significant impact on per capita GDP growth or other macroeconomics aggregates for myriad cross sections.
16. 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.
17. No country in this sample has an income level sufficiently large to drive θ_i to 1. In Table 2, all equations, except Transnational_pre (GTD), are best estimated in the exponential form of the smooth transition regression (STR) model.
18. Note that the coefficients in equation (13) are related in the substitution of equation (11) into equation (3) as $c = \alpha_0 + a_0\beta_0,\ c_1 = a_0\beta_1 + a_1\beta_0 + \alpha_1,\ c_2 = a_1\beta_1 + a_2\beta_0,\ c_3 = a_2\beta_1 + a_3\beta_0,\ c_2 = a_3\beta_1.$

19. Since the number of observations for each equation differs *b*y covariate, the AIC cannot be used to assess fit across the different covariates.

Supplemental Material

The online appendix is available at http://jcr.sagepub.com/

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