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Michael Jetter University of Western Australia and IZA

Rafat Mahmood University of Western Australia and Pakistan Institute of Development Economics

David Stadelmann Universität Bayreuth

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IZA – Institute of Labor Economics							
Schaumburg-Lippe-Straße 5–9	Phone: +49-228-3894-0						
53113 Bonn, Germany	Email: publications@iza.org	www.iza.org					

ABSTRACT

Income and Terrorism: Insights from Subnational Data

To better understand potential relationships between income and terrorism, we study data for 1,527 subnational regions in 75 countries between 1970 and 2014. Results consistently imply an inverted U-shape that remains robust to accounting for a comprehensive set of region-level covariates, region- and time-fixed effects, as well as estimating an array of alternative specifications. The threat of terrorism systematically rises as low-income polities become richer, peaking at an income level of about US\$12,800 per capita (in constant 2005 PPP US\$), but then falls consistently above that level. This pattern emerges for domestic and transnational terrorism alike. Peaks in the income-terrorism relationship differ by perpetrator ideology. Thus, alleviating poverty per se may first *exacerbate* terrorism, contrary to much of the proposed recipes advocated since 9/11.

JEL Classification:	D74, O11
Keywords:	subnational income, subnational terrorism, domestic terrorism,
	transnational terrorism, terror group ideology

Corresponding author: Michael Jetter University of Western Australia

8716 Hackett Drive Crawley 6009, WA Australia E-mail: mjetter7@gmail.com "We won't win the war against terror without addressing the problem of poverty." (Wolfensohn, then-President of the World Bank, 2002).

1 Introduction

In the aftermath of the 9/11 attacks twenty years ago, US President George W. Bush, US Secretary of State John Kerry, British Prime Minister Tony Blair, along with other prominent politicians, policymakers, and commentators explicitly linked terrorism to poverty (Bush, 2002; Krueger, 2007; Sterman, 2015; Easterly, 2016).

However, cross-country research has produced ambiguous and sometimes contradictory evidence for a potential relationship between income and terrorism. Table 1 summarizes the corresponding quantitative literature, illustrating the substantial uncertainty of whether and, if so, how income connects with terrorism. In that branch of research, aggregating variables at the national level to then explore systematic relationships with indicators of terrorism has been common, largely because of data availability and convention.

In the following pages, we propose that our understanding of the income-terrorism nexus sharpens substantially once we zoom in to the subnational level, i.e., studying Balochistan, California, Catalonia, and Île-de-France instead of Pakistan, the United States, Spain, and France. Two basic observations motivate this refocus. First, terror attacks often cluster regionally within a country, rather than being spread out uniformly. For example, in the United Kingdom from 1970 to 2014, we identify striking differences between Northern Ireland (1,544 attacks) and the North (four attacks). Similarly, while the Chilean O'Higgins region was completely spared of terror attacks over that entire time period, the metropolitan region of Santiago suffered 1,612 attacks, ranking the region fourth worldwide. And second, income levels across regions within a country often differ more than incomes across countries. For example, the average income of Moscow exceeds the average income of Sicily, even though Italy is on average approximately three times richer than Russia. Such substantial within-country heterogeneities are lost when studying country-level aggregates.

Our approach matches subnational (regional) data on GDP/capita (from Gennaioli et al., 2014) with subnational data on terror attacks (from START, 2017) for 1,527 regions across 75

countries between 1970 and 2014. These sample countries are statistically representative of the global relationship between income and terrorism. Our unit of analysis constitutes the second-largest administrative unit in the respective nation, i.e., a federal state, county, or province, depending on the country. Our main estimation results and interpretations hold constant potential confounders associated with (i) population size, (ii) regions hosting a country's capital city, (iii) oil production, (iv) period-fixed, and (v) region-fixed effects. Region-fixed effects prove particularly powerful as they account for unobservable time-invariant differences across regions, such as geographical attributes that often correlate with terrorist activity (e.g., mountainous terrain or ruggedness) and unique histories of ethnic and religious conflict or colonization experiences. These fixed effects also reasonably control for certain societal and environmental aspects that only change slowly over time within a given region, such as fractionalization and polarization along ethnic or religious dimensions.

Our empirical results lend firm support to a nonlinear relationship between income and terrorism that follows an inverted U-shape. This is consistent with the cross-country findings by Enders and Hoover (2012) and Enders et al. (2016) who posit that low-income polities lack the resources terrorist organizations need, while high-income polities can afford effective counterterrorism measures. Our findings suggest that, as incomes in poor regions increase, terrorism becomes substantially more likely until an estimated peak of approximately US\$12,800 (in constant 2005 PPP US\$). For perspective, 63% of all observations in our sample would fall under that threshold. After that, economic growth is associated with a decline in terrorism. Importantly, we find this nonlinear pattern for domestic and international terrorism alike. Our analysis helps reconciling the different findings of Table 1.

We also look into the ideologies of perpetrators to explore whether different types of terrorism follow different income-related patterns. Illustrating the generality of our main findings, the inverted U-shape independently emerges for all identifiable ideologies with (i) Islamist, (ii) leftwing, (iii) right-wing, (iv) separatist, and (v) other religious groups. Interestingly, religious terrorism peaks at income levels that are lower than those for left- or right-wing terrorism – a relationship that was proposed by Enders et al. (2016) but, to our knowledge, remained untested since. The consistency with which this pattern emerges across regions around the world for over 45 years suggests a systematic inverted U-shape link between income and terrorism that

Statistically insignificant	Statistically significant negative	Statistically significant positive
Abadie (2006)	Azam and Delacroix (2006)	Blomberg and Hess $(2008b,a)^a$
Basuchoudhary and Shughart (2010)	Azam and Thelen (2008)	Blomberg and Rosendorff (2006)
Berman and Laitin (2008)	Blomberg and Hess $(2008b)^a$	Burgoon $(2006)^b$
Campos and Gassebner (2013)	Braithwaite and Li (2007)	Eyerman (1998)
Crenshaw et al. (2007)	Bravo and Dias $(2006)^b$	Koch and Cranmer (2007)
Dreher and Fischer (2010, 2011)	Li (2005)	Kurrild-Klitgaard et al. (2006)
Gassebner and Luechinger (2011)	Li and Schaub (2004)	Neumayer and Plümper (2009)
Goldstein $(2005)^b$	Testas (2004)	Piazza (2007, 2008a, 2011) ^{c,b}
Krueger and Laitin (2008)		Plümper and Neumayer (2010)
Krueger and Malečková (2003)		Walsh and Piazza (2010)
Piazza $(2006, 2008b)^b$		Tavares (2004)
Sambanis (2008)		

Table 1: Overview of the quantitative literature linking GDP/capita to terrorism (based on
Gosling, 2017).

Notes: ^aBlomberg and Hess (2008b) find a negative (positive) association with 'low (lower) income' countries. ^bGDP/capita constitutes one component of a composite indicator, such as the Human Development Index or the Government Capability Index. transcends time, ideology, and space.

Overall, our study contributes to a wider understanding of terrorism determinants, while particularly informing the debate on the link between income and terrorism. We combine existing data sources at subnational levels to introduce an integrated database that allows us to gain more refined insights into the problem. Beyond terrorism, this paper also informs the literature on the impact of economic growth on non-economic variables, as well as the benefits and costs associated with that development process (e.g., see Bloom and Canning, 2000, Friedman, 2010, and Gürlük, 2009).

Section 2 begins by positioning the theoretical backgrounds on income and terrorism. Section 3 introduces our data and sources, followed by our methodology in Section 4. Section 5 details our empirical findings, and Section 6 concludes.

2 Theoretical Background

The political and scholarly debate that followed 9/11 inextricably linked poverty to terrorism (Pilgrim, 2015; Odede, 2015; Haggar, 2021). The underlying hypothesis is grounded in existing work on civil conflict (Abadie, 2006), civil war (Collier and Hoeffler, 2004; Miguel et al., 2004), and political coups (Alesina et al., 1996). As another form of political violence, terrorism has been suggested to follow a similar logic: Poverty brings grievances that may motivate terrorism (Piazza, 2007).

Nevertheless, two decades after 9/11, the corresponding empirical evidence remains inconclusive. Cross-country studies have produced negative, positive, and null results – an artefact we illustrate in Table 1. Similarly, individual-level studies have failed to establish a systematic correlation between poverty and terrorism (Hassan, 2002; Krueger and Malečková, 2003; Sageman, 2004; Berrebi, 2007; and Benmelech et al., 2012).

Theoretically, the inconclusive link between income and terrorism may be owed to an incomplete functional form that conceals nonlinearities (Enders and Hoover, 2012; Enders et al., 2016). While very low-income polities do not offer sufficient human and monetary resources to support terrorism, high-income societies may be able to employ effective counterterrorism strategies (Lai, 2007; Enders et al., 2016). From a sociological perspective, Maslow's (1943) hierarchy of needs implies political and societal prospects only gain relevance once basic physiological needs are met. Thus, ideological and political considerations may not constitute primary objectives in impoverished societies, i.e., political violence in the form of terrorism could play less of a role. Also, economic grievances are less likely to arise in richer countries where governments can leverage more substantial funds to address concerns of their citizenry (Lai, 2007).

Consequently, ceteris paribus, terrorism, whether domestic or transnational, may peak at medium incomes. A handful of cross-country studies support this perspective (Lai, 2007; Freytag et al., 2011; De la Calle and Sánchez-Cuenca, 2012). Further, Enders et al. (2016) suggest the peak of terrorism may have changed over time, owing to the shift from left-wing ideologies that were concentrated in relatively wealthy countries to religious fundamentalists that predominantly live in the developing world. We will also explore this hypothesis and provide evidence for it using our regional data.

3 Data

3.1 Subnational Income Levels

We derive data on region-level income from Gennaioli et al. (2014) who record real GDP/capita (in constant 2005 PPP US\$) in five-year intervals for subnational units in a global sample.¹ As comprehensive data on terrorism start in 1970, we consider observations from 1970 to 2010, producing a maximum of nine observations per region and an average of six observations per region. Table 2 documents summary statistics of all variables in our main analysis, while Table A1 summarizes the variables used in additional analyses. Table A2 shows full data coverage for each country and year.

Consistent with the literature, we employ the natural logarithm of GDP/capita (e.g., see Freytag et al., 2011, Enders and Hoover, 2012, Enders et al., 2016, and Krieger and Meierrieks, 2019). Using GDP/capita levels (sans logarithm) instead, produces consistent results (see Table A5). To allow for nonlinearities, we follow Enders and Hoover (2012) and Enders et al. (2016) to incorporate a squared term of that variable.

¹Gennaioli et al. (2014) collect data on subnational population and income levels primarily from national statistics agencies. Data are scaled such that the population-weighted sum of subnational GDP equates to national GDP recorded in the Penn World Tables or, when unreported there, in the World Development Indicators.

Variable	Mean (Std. Dev.)	Min. (Max.)	Description
Panel A: Independent variables			
$Ln(GDP/capita)_{i,t}$	12,429 (12,334)	$189 \\ (166,007)$	GDP/capita in 2005 PPP US\$ (we apply the natural logarithm)
Population size (in thousands) _{i,t}	2,823 (8,367)	10 (196,243)	Population (we apply the natural logarithm)
$\operatorname{Capital}_i$	$0.05 \\ (0.22)$	$\begin{array}{c} 0 \\ (1) \end{array}$	=1 if hosts country's capital
$\operatorname{Oil}_{i,t}$	10.26 (20.56)	$\begin{matrix} 0 \\ (89.38) \end{matrix}$	Cumulative oil and gas production (per capita; we apply the natural logarithm)
Panel B: Dependent variables			
Terror attacks $_{i,t,\dots,t+4}$	$7.40 \\ (46.50)$	$0 \\ (1,479)$	# of terror attacks in $t,,t+4$
Domestic attacks _{$i,t,,t+4$}	6.27 (43.15)	$0 \\ (1,461)$	# of non-transnational terror attacks in $t,, t + 4$
Transnational attacks $_{i,t,\ldots,t+4}$	1.13 (10.90)	0 (705)	# of transnational terror attacks in $t,, t + 4$
Islamist attacks $i, t, \dots, t+4$	$0.46 \\ (13.73)$	$\begin{array}{c} 0 \\ (1,136) \end{array}$	# of terror attacks by Islamist groups in $t,, t + 4$
Leftist attacks $i, t, \dots, t+4$	2.73 (22.74)	0 (987)	# of terror attacks by Leftist groups in $t,, t + 4$
Rightist attacks _{$i,t,,t+4$}	0.13 (1.21)	$ \begin{array}{c} 0 \\ (44) \end{array} $	# of terror attacks by right-wing groups in $t,, t + 4$
Separatist attacks $_{i,t,,t+4}$	$1.59 \\ (19.29)$	$ \begin{array}{c} 0 \\ (1,230) \end{array} $	# of terror attacks by separatist groups in $t,, t + 4$
Religious non-Islamist attacks_{i,t,,t+4}	$0.40 \\ (8.74)$	0 (674)	# of terror attacks by religious, non-Islamist groups in $t,, t + 4$

regions (n=8,383 for all variables). Variables in Panel A come from Gennaioli et al. (2014), while variables in Panel B come from START (2017).

Table 2: Summary Statistics for main variables at the subnational (regional) level for 1,527

Figure 1 visualizes the global coverage of our sample. African regions remain under-represented with notable omissions including Iraq and Afghanistan – two of the countries most affected by terrorism. As such selection issues may threaten the generalizability of our findings, we carefully compare global country-level results for all years with those from studying our sample countries and years. These estimations produce consistent coefficients, which suggests that our interpretation is unlikely to suffer from misrepresentation issues (see Table A3).



Figure 1: Regional Sample Coverage.

3.2 Subnational Terrorism

For data on terrorism, we employ the well-known *Global Terrorism Database (GTD)*. Accessing information on the location of each terror attack allows us to assign each attack to a particular within-country region. Appendix B explains this procedure in detail. We then aggregate attacks over five-year intervals and merge the data with Gennaioli et al.'s (2014) data. For example, GDP/capita for Catalonia in 1970 is matched with terror attacks in Catalonia between 1970 and 1974.

Our main dependent variable measures the number of terror attacks, which constitutes the

most commonly employed measure in the literature. Additional estimations distinguish between domestic and transnational attacks.² Figure 2 plots GDP/capita against the number of terror attacks. Panel A considers all terrorism, while Panels B and C distinguish between domestic and transnational terrorism. Although these graphs do not incorporate potentially confounding factors yet, they do imply a nonlinear relationship between regional income and terrorism in the form of an inverted U-shape.

3.3 Further Covariates

Our estimations include a list of region-level covariates that may independently be associated with terrorism. Following the literature, we incorporate population size, oil production (to control for resource-curse-related dynamics; see Tavares, 2004, and Sambanis, 2008), and a binary indicator for hosting the nation's capital (because of a potential concentration of cultural, political, and religious targets).³ As the data on educational attainment feature several missing values in our sample period, we do not include that in our main regressions. Including that variable produces consistent results though for a smaller sample (see Table A5). Further, accounting for lagged terror attacks also leaves our main conclusions unchanged (see Table A5).

A major advantage of our subnational data structure comes from combining the withincountry variation for each period with the panel dimension of repeated information for each region. Our data allows us to account for region-fixed effects to hold time-invariant, region-specific particularities constant. This accounts for prevalent correlates of terrorism, such as geography and terrain, unique historical features pertaining to civil conflict, civil war, colonization, and others, as well as other long-term cultural, economic, and political artefacts. Year-fixed effects absorb any time-specific global developments that may independently correlate with terrorism.

Nevertheless, it is important to note which factors our analyses are unable to account for. In particular, unobservable aspects that inform terrorism and *do* change within a region over

²We code international attacks using the *GTD* classification which closely matches that of Enders et al. (2011). Specifically, we code transnational attacks as $INT_ANY = 1$ in the *GTD* i.e., either the attack is logistically or ideologically transnational, or the nationality of the targets or victims differs from the location of the attack. All other attacks $(INT_ANY = 0$ in the *GTD*) are coded as domestic in our main specifications. Employing alternative definitions of domestic attacks produces consistent results (available upon request). Considering a binary indicator for experiencing *any* attacks (to alleviate concerns about under-reporting in particularly low-income regions) or predicting attacks/capita (to explicitly acknowledge the role of population size; Jetter and Stadelmann, 2019) produces consistent findings (see Table A4).

³We multiply oil production by international oil prices following Brückner et al. (2012).



Panel A: GDP/capita and terror attacks

Figure 2: Subnational GDP/capita and terror attacks, displayed by kernel-weighted local polynomial smoothing along with 95% confidence intervals.

time can influence our derived coefficients associated with income levels. For example, changes in regional governance, changes in regional ethnic polities, or changes in within region inequality are only incorporated to the extent that they are correlated with our observables of population size, oil production, hosting the country's capital, educational attainment, and lagged terror attacks.

4 Empirical Methodology

4.1 Main Specification

Our main empirical strategy employs a negative binomial regression model in line with the literature (Walsh and Piazza, 2010; Young and Dugan, 2011; Young and Findley, 2011; Piazza, 2013; Gaibulloev et al., 2017) because the dependent variable constitutes a non-negative count variable and exhibits overdispersion. For region i and year t, we estimate:

$$Attacks_{i;(t,\dots,t+4)} = \beta_0 + \beta_1 Ln(GDP/capita)_{i;t} + \beta_2 Ln(GDP/capita)_{i;t}^2 + \mathbf{X}_{i;t}\beta_3 + \lambda_i + \gamma_t + \delta_{i;t}, \quad (1)$$

where β_1 and β_2 represent our main coefficients of interest. Note that observations do not overlap, as for each region we employ an observation for, say, 1970-1974, another for 1975-1979, and so on. We begin with a linear form assuming $\beta_2 = 0$ and then relax this assumption allowing for nonlinearity in accordance with Figure 2 and Enders and Hoover (2012), as well as Enders et al. (2016). $X_{i,t}$ constitutes the matrix of control variables introduced in Section 3.3; λ_i and γ_t capture region- and year-fixed effects; and $\delta_{i;t}$ represents an error term.

4.2 Potential Sources of Endogeneity

Endogeneity pertaining to reverse causality and omitted variables remains a threat to identifying causal relationship in the associated literature. First, reverse causality implies regions (or countries) may become poorer *because of* terrorism. Aggregating the dependent variable over years t to t + 4, while measuring independent variables in year t alleviates such concerns. Predicting terrorism in t + 1 until t + 4, thereby not leaving any overlap between the dependent and independent variables, produces consistent results (see Table A5). To further acknowledge potential path dependency, additional specifications account for terror attacks in the previous five years, producing consistent results (see Table A5). In sum, reverse causality is unlikely to pose a systematic threat to the interpretation of our results.

Second, omitted variables, i.e., unobservable factors could influence both regional income levels and terrorism. We control for a list of notable confounders in our main estimations and additional robustness tests incorporate educational attainment levels leading to consistent results (see Table A5). As discussed, region-fixed effects account for any statistical variation in terrorism owed to time-invariant regional cultural, ethnic, language, or religious heterogeneity. For example, cultural heritage, religious denominations or language may differ geographically within a country (e.g., across regions in the United Kingdom, Switzerland, or Tanzania) – something that country-fixed effects are not able to absorb, while region-fixed effects are better positioned to do so.

Similarly, geographical characteristics within a country often vary, and any potential association between poverty and terrorism may differ along such dimensions. For instance, Colombia's more hospitable regions happen to be wealthier (e.g., Bogotá or Medellín) than the difficult-toaccess rainforest regions. Region-fixed effects capture substantially more unobservable, terrorismrelevant variation than country-fixed effects in the traditional cross-country literature are able to. For instance, if a region differs systematically from the country average in terms of terrain or climate, but also in the de facto implementation of law and order, region-fixed effects capture such heterogeneity. Importantly, region-fixed effects also implicitly account for *country*fixed effects, i.e., any country-level heterogeneity relevant for terrorism is accounted for, such as historical events or colonial ties.

5 Regional Income and Terrorism

5.1 Main Results

Table 3 reports our main regression results. Column (1) considers a univariate regression that only employs a linear term of GDP/capita to predict terror attacks. The respective coefficient is negative and statistically significant at the 1% level (p-value of 0.000). Conclusions from this specification would support many politicians' (e.g., George Bush's) responses to 9/11 in the association between income levels and terrorism.

However, upon allowing for nonlinearity in column (2), that conclusion changes, suggesting an inverted U-shape: GDP/capita becomes a positive predictor, while its squared term emerges as a negative predictor (p-values of 0.016 and 0.006). The fourth row from the bottom reports the GDP/capita level at which the income-terrorism relationship is suggested to peak, corresponding to US\$2,826.

	(1)	(2)	(3)	(4)	(5) Domestic terrorism	(6) International terrorism
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}$	-0.351^{***} (0.094)	3.131^{**} (1.294)	4.690^{***} (1.287)	3.517^{***} (0.379)	3.677^{***} (0.416)	5.472^{***} (0.638)
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}^2$		-0.197^{***} (0.072)	-0.282^{***} (0.072)	-0.186^{***} (0.021)	-0.202^{***} (0.024)	-0.298^{***} (0.036)
Control variables ^{a} and time-period-fixed effects			\checkmark	\checkmark	\checkmark	\checkmark
Region-fixed effects				\checkmark	\checkmark	\checkmark
GDP/capita at maximum		2,826	4,087	12,763	8,969	9,713
N^b	8,383	8,383	8,383	5,351	5,055	$3,\!357$
# of regions ^b	1,527	1,527	1,526	863	802	517
# of time periods	9	9	9	9	9	9

Table 3: Main results, predicting terror attacks for region i in years t, ..., t + 4 in a negative binomial regression framework.

Notes: Standard errors clustered at the regional level are displayed in parentheses for columns (1) - (3) while columns (4) - (6) report standard errors based on the observed information matrix, using the option vce(oim) in STATA. * p < 0.10, ** p < 0.05, *** p < 0.01. ^aControl variables include the logarithm of population size, a binary indicator for the location of the capital city, and the natural logarithm of oil produced. ^bThe decline in the number of observations in columns (4)-(6) stems from the introduction of region-fixed effects, where regions with no terror attacks are dropped automatically.

Columns (3) and (4) first add the covariates introduced in equation (1) and time-periodfixed effects, before also accounting for region-fixed effects. The inverted U-shape persists, while the suggested peak rises to US\$12,763. This value roughly corresponds to regions such as Quintana Roo (Mexico) in 1980 or Kaliningrad (Russia) in 2010. It is important to recall that the specification in column (4) exploits within-region variation only, i.e., we only compare the same region to itself at different income levels. Thus, the derived coefficients do not rely on any cross-regional differences, not even within the same country. A corollary of that statistical artefact is that a low-income region is suggested to experience rising likelihoods of terrorism as its GDP/capita levels increase; but as soon as GDP/capita levels surpass the peak for that same region, terrorism diminishes, everything else equal.

Columns (5) and (6) delineate between domestic and transnational terrorism, acknowledging the often-proposed distinction between these types of terrorism and their underlying dynamics (Enders and Hoover, 2012; Enders et al., 2016). Our results are consistent: In both cases, we derive statistical significance at the one percent level for both coefficients of interest, as well as the signs suggested by our benchmark estimation from column (4). Domestic terrorism peaks at a level of GDP/capita that is lower than that for transnational terrorism, but the corresponding difference remains small (a conclusion that also emerges from Figure 3).⁴

Figure 3 visualizes the suggested relationships from columns (4)-(6). The peaks of the inverted-U shape are comparable for domestic and transnational terrorism, which implies a universal nonlinearity of the relationship between income and terrorism. Interestingly, the slope of the relationship differs to some degree, as transnational terrorism appears to be more responsive to GDP/capita in quantitative terms.

5.2 Robustness Checks

We conduct a large series of alternative specifications to test the validity of these results.

In particular, we implement alternative estimation techniques and measures of terrorism by (i) calculating bootstrapped standard errors, (ii) applying Poisson and Ordinary Least Square (OLS) methods, (iii) considering alternative measures of terrorism with attacks per *year*, terror per capita, a binary indicator for experiencing *any* terrorism, and deaths from terrorism. Across all these specifications, the inverted U-shaped relationship prevails with remarkable consistency (see Table A4).

Table A5 documents regression results from (i) considering levels of GDP/capita (i.e., not applying the natural logarithm), (ii) controlling for years of educational attainment at the regional level, (iii) controlling for terror attacks in the past five years, (iv) using an alternative time frame for our outcome variable (from t+1 to t+4), and (v) considering annual GDP/capita

⁴This result is also consistent with a narrative of strict security measures across borders encouraging perpetrators to target foreign entities at home (Enders et al., 2016).



Figure 3: Visualizing regression results from columns (4)-(6) of Table 3.

data as reported in Gennaioli et al. (2014) without adjusting observations to conform with our five-year panel structure. Again, results remain consistent.

5.3 Terror Group Ideologies

Finally, we explore the link between poverty and terrorism for different group ideologies. Prior cross-country research has suggested the role of income levels may vary depending on a group's ideological background (Enders et al., 2016). Consistent with the common distinctions, we delineate between Islamist, left-wing, right-wing, ethnic/separatist, and religious non-Islamist groups (e.g., see Kis-Katos et al., 2014). Table 4 provides further support for a universal nonlinearity when distinguishing between these categories, as the inverted U-shaped pattern emerges across all five group ideologies.⁵ These results prevail when delineating between domestic and transnational terrorism (Tables A7 and A8).

Notably, the corresponding peaks differ in terms of magnitude, although moderately. This finding supports the theoretical proposition that peaks in terrorism differ with perpetrator ideology (e.g., Enders et al., 2016): The peak of terrorism associated with Islamist and other religious ideologies occur at income levels that are lower than those for left-wing or right-wing ideologies.

6 Conclusion

This paper analyzes the relationship between income and terrorism at the subnational (regional) level. Using data for 1,527 subnational entities from 1970 to 2014, all results provide firm support for an inverted U-shape in how regional income levels link to regional terror attacks. This result prevails once we account for a comprehensive set of covariates, as well as region- and year-fixed effects; when delineating between domestic and transnational terrorism; and even when distinguishing between terror group ideology. Contrary to the post-9/11 claims of poverty being a monotonically positive predictor of terrorism, these results suggest poverty alleviation can

⁵We extend Kis-Katos et al.'s (2014) code beyond 2008 to include newer terrorist organizations that conducted ten or more attacks. Nevertheless, limiting our analysis to 2008 produces consistent results (available on request). Table A6 reports results for a stricter definition of group identity in which a group is considered Islamist if their main identity is religious and their religious identity is Islam.

Group identity:	(1) Islamist	(2) Left-wing	(3) Right-wing	(4) Ethnic/ separatist	(5) Religious non-Islamist
${\rm Ln}({ m GDP}/{ m capita})_{i,t}$	7.075^{***} (1.378)	$\begin{array}{c} 4.829^{***} \\ (0.661) \end{array}$	$\begin{array}{c} 10.399^{***} \\ (1.760) \end{array}$	5.519^{***} (0.782)	10.039^{***} (1.687)
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}^2$	-0.408^{***} (0.081)	-0.269^{***} (0.037)	-0.569^{***} (0.098)	-0.308^{***} (0.044)	-0.584^{***} (0.095)
Control variables ^{a}	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Time-period- and region-fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
GDP/capita at maximum	5,827	7,910	9,302	7,781	$5,\!405$
Ν	841	3,060	1,456	2,036	806
# of regions ^b # of time periods	145 9	$ 441 \\ 9 $	$\begin{array}{c} 191 \\ 9 \end{array}$	3069	$ \begin{array}{c} 107 \\ 9 \end{array} $

Table 4: Distinguishing by group ideology, predicting the number of terror attacks for subnational region i in years t, ..., t + 4 in a negative binomial regression framework.

Notes: Standard errors based on the observed information matrix, using the option vce(oim) in STATA), are displayed in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. ^aControl variables include the logarithm of population size, a binary indicator for the location of the capital city, and the natural logarithm of oil produced.

potentially lead to *more* terrorism for countries that are currently to the left of the average peaks we derive.

Naturally, we advise caution in the interpretation of these findings since, similar to most of the cross-country literature, our analysis is not able to *fully* resolve all empirical challenges. For example, unobservable factors that change within a subnational region over time may still be able to bias the coefficients we derive. Nevertheless, the subnational data structure allows us to substantially alleviate these endogeneity concerns, especially when compared to the crosscountry literature. Our most complete estimations exploit within-region variation only, i.e., any time-invariant differences across regions (even within the same country) are filtered out. Carefully structuring corresponding time sequencing by using contemporaneous GDP/capita levels to predict subsequent terrorism further addresses threats from reverse causality. Results also remain consistent when accounting for lagged terror levels.

In sum, the fact that the inverted U-shape emerges in virtually all settings provides what we believe to be the strongest empirical evidence to date for a systematic, universal link between income levels and terrorism. We hope these insights can inform national and regional policymakers, as well as inspire further research into a topic that has informed substantial political and societal decisions since 9/11.

References

- Abadie, A. (2006). Poverty, political freedom, and the roots of terrorism. *American Economic Review*, 96(2):50–56.
- Alesina, A., Özler, S., Roubini, N., and Swagel, P. (1996). Political instability and economic growth. *Journal of Economic Growth*, 1(2):189–211.
- Azam, J.-P. and Delacroix, A. (2006). Aid and the delegated fight against terrorism. Review of Development Economics, 10(2):330–344.
- Azam, J.-P. and Thelen, V. (2008). The roles of foreign aid and education in the war on terror. *Public Choice*, 135(3-4):375–397.
- Basuchoudhary, A. and Shughart, W. F. (2010). On ethnic conflict and the origins of transnational terrorism. Defence and Peace Economics, 21(1):65–87.
- Benmelech, E., Berrebi, C., and Klor, E. F. (2012). Economic conditions and the quality of suicide terrorism. *The Journal of Politics*, 74(1):113–128.
- Berman, E. and Laitin, D. D. (2008). Religion, terrorism and public goods: Testing the club model. *Journal of Public Economics*, 92(10-11):1942–1967.
- Berrebi, C. (2007). Evidence about the Link Between Education, Poverty and Terrorism among Palestinians. *Peace Economics, Peace Science, and Public Policy*, 13(1):1–38.
- Blomberg, S. B. and Hess, G. D. (2008a). The Lexus and the olive branch: Globalization, democratization and terrorism. *Terrorism, Economic Development, and Political Openness*.
- Blomberg, S. B. and Hess, G. D. (2008b). From (no) butter to guns? Understanding the economic role in transnational terrorism. *Terrorism, Economic Development, and Political Openness.*
- Blomberg, S. B. and Rosendorff, B. P. (2006). A gravity model of globalization, democracy and transnational terrorism. USC CLEO Research Paper, (C06-6).
- Bloom, D. E. and Canning, D. (2000). The health and wealth of nations. *Science*, 287(5456):1207–1209.
- Braithwaite, A. and Li, Q. (2007). Transnational terrorism hot spots: Identification and impact evaluation. *Conflict Management and Peace Science*, 24(4):281–296.
- Bravo, A. B. S. and Dias, C. M. M. (2006). An empirical analysis of terrorism: Deprivation, Islamism and geopolitical factors. *Defence and Peace Economics*, 17(4):329–341.
- Brückner, M., Ciccone, A., and Tesei, A. (2012). Oil price shocks, income, and democracy. *Review of Economics and Statistics*, 94(2):389–399.
- Burgoon, B. (2006). On welfare and terror: Social welfare policies and political-economic roots of terrorism. *Journal of Conflict Resolution*, 50(2):176–203.

- Bush, G. W. (2002). United States of America: Remarks by Mr. George W. Bush President at the International Conference on Financing for Development. March 22, 2002.
- Campos, N. F. and Gassebner, M. (2013). International terrorism, domestic political instability, and the escalation effect. *Economics & Politics*, 25(1):27–47.
- Collier, P. and Hoeffler, A. (2004). Greed and grievance in civil war. Oxford Economic Papers, 56(4):563–595.
- Crenshaw, E., Robison, K., and Jenkins, J. C. (2007). The "roots" of transnational terrorism: A replication and extension of Burgoon. In Annual Meetings of the American Sociological Association, New York City, NY (August 2007).
- De la Calle, L. and Sánchez-Cuenca, I. (2012). Rebels without a territory: An analysis of nonterritorial conflicts in the world, 1970–1997. *Journal of Conflict Resolution*, 56(4):580–603.
- Dreher, A. and Fischer, J. A. (2010). Government decentralization as a disincentive for transnational terror? An empirical analysis. *International Economic Review*, 51(4):981–1002.
- Dreher, A. and Fischer, J. A. (2011). Does government decentralization reduce domestic terror? An empirical test. *Economics Letters*, 111(3):223–225.
- Easterly, W. (2016). The war on terror vs. the war on poverty. The New York Review of Books.
- Enders, W. and Hoover, G. A. (2012). The nonlinear relationship between terrorism and poverty. *American Economic Review*, 102(3):267–72.
- Enders, W., Hoover, G. A., and Sandler, T. (2016). The changing nonlinear relationship between income and terrorism. *Journal of Conflict Resolution*, 60(2):195–225.
- Enders, W., Sandler, T., and Gaibulloev, K. (2011). Domestic versus transnational terrorism: Data, decomposition, and dynamics. *Journal of Peace Research*, 48(3):319–337.
- Eyerman, J. (1998). Terrorism and democratic states: Soft targets or accessible systems. International Interactions, 24(2):151–170.
- Freytag, A., Krüger, J. J., Meierrieks, D., and Schneider, F. (2011). The origins of terrorism: Cross-country estimates of socio-economic determinants of terrorism. *European Journal of Political Economy*, 27:S5–S16.
- Friedman, B. M. (2010). The moral consequences of economic growth. Vintage.
- Gaibulloev, K., Piazza, J. A., and Sandler, T. (2017). Regime types and terrorism. *International Organization*, pages 1–32.
- Gassebner, M. and Luechinger, S. (2011). Lock, stock, and barrel: A comprehensive assessment of the determinants of terror. *Public Choice*, 149(3-4):235.
- Gennaioli, N., La Porta, R., De Silanes, F. L., and Shleifer, A. (2014). Growth in regions. Journal of Economic Growth, 19(3):259–309.

- Goldstein, K. B. (2005). Unemployment, inequality and terrorism: Another look at the relationship between economics and terrorism. Undergraduate Economic Review, 1(1):6.
- Gosling, T. L. (2017). States of terror: Regional income and terrorism. Unpublished manuscript.
- Gürlük, S. (2009). Economic growth, industrial pollution and human development in the Mediterranean region. *Ecological Economics*, 68(8-9):2327–2335.
- Haggar, K. E. (2021). President Al-Sisi Fights Terrorism by Eliminating Informal Settlements. *Daily News Egypt.*
- Hassan, N. (2002). An arsenal of believers. Le Débat, (3):134–143.
- Jetter, M. and Stadelmann, D. (2019). Terror per capita. Southern Economic Journal, 86(1):286–304.
- Kis-Katos, K., Liebert, H., and Schulze, G. G. (2014). On the heterogeneity of terror. European Economic Review, 68:116–136.
- Koch, M. T. and Cranmer, S. (2007). Testing the "Dick Cheney" hypothesis: Do governments of the left attract more terrorism than governments of the right? *Conflict Management and Peace Science*, 24(4):311–326.
- Krieger, T. and Meierrieks, D. (2019). Income inequality, redistribution and domestic terrorism. World Development, 116:125–136.
- Krueger, A. (2007). What makes a terrorist? It's not poverty and lack of education, according to economic research by Princeton's Alan Krueger Look elsewhere. The American (Washington, DC), 1(7):16–22.
- Krueger, A. B. and Laitin, D. D. (2008). Kto kogo?: A cross-country study of the origins and targets of terrorism. Terrorism, economic development, and political openness, pages 148–173.
- Krueger, A. B. and Malečková, J. (2003). Education, poverty and terrorism: Is there a causal connection? *Journal of Economic Perspectives*, 17(4):119–144.
- Kurrild-Klitgaard, P., Justesen, M. K., and Klemmensen, R. (2006). The political economy of freedom, democracy and transnational terrorism. *Public Choice*, 128(1-2):289–315.
- Lai, B. (2007). "Draining the swamp": An empirical examination of the production of international terrorism, 1968 - 1998. Conflict Management and Peace Science, 24(4):297–310.
- Li, Q. (2005). Does democracy promote or reduce transnational terrorist incidents? Journal of Conflict Resolution, 49(2):278–297.
- Li, Q. and Schaub, D. (2004). Economic globalization and transnational terrorism: A pooled time-series analysis. Journal of Conflict Resolution, 48(2):230–258.
- Maslow, A. H. (1943). A theory of human motivation. Psychological Review, 50(4):370.
- Miguel, E., Satyanath, S., and Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of political Economy*, 112(4):725–753.

- Neumayer, E. and Plümper, T. (2009). International Terrorism and the Clash of Civilizations. British Journal of Political Science, 39(4):711.
- Odede, K. (2015). If you really want to fight terrorism, start by fighting child poverty. *The Guardian*. Published on August 21, 2015.
- Piazza, J. A. (2006). Rooted in poverty?: Terrorism, poor economic development, and social cleavages. *Terrorism and Political Violence*, 18(1):159–177.
- Piazza, J. A. (2007). Draining the swamp: Democracy promotion, state failure, and terrorism in 19 Middle Eastern countries. *Studies in Conflict & Terrorism*, 30(6):521–539.
- Piazza, J. A. (2008a). Incubators of terror: Do failed and failing states promote transnational terrorism? International Studies Quarterly, 52(3):469–488.
- Piazza, J. A. (2008b). Do democracy and free markets protect us from terrorism? International Politics, 45(1):72–91.
- Piazza, J. A. (2011). Poverty, minority economic discrimination, and domestic terrorism. Journal of Peace Research, 48(3):339–353.
- Piazza, J. A. (2013). Regime Age and Terrorism: Are New Democracies Prone to Terrorism? International Interactions, 39(2):246–263.
- Pilgrim, S. (2015). Poverty and injustice feeding terrorism, French minister says. France 24 News. Published on February 10, 2015.
- Plümper, T. and Neumayer, E. (2010). The friend of my enemy is my enemy: International alliances and international terrorism. *European Journal of Political Research*, 49(1):75–96.
- Sageman, M. (2004). Understanding terror networks. University of Pennsylvania Press.
- Sambanis, N. (2008). Terrorism and civil war. Terrorism, Economic Development, and Political Openness, pages 174–206.
- START (2017). Global Terrorism Database. National Consortium for the Study of Terrorism and Responses to Terrorism (START). Retrieved from http://www.start.umd.edu/gtd.
- Sterman, D. (2015). Don't Dismiss Poverty's Role in Terrorism Yet. Time, 4.
- Tavares, J. (2004). The open society assesses its enemies: Shocks, disasters and terrorist attacks. Journal of Monetary Economics, 51(5):1039–1070.
- Testas, A. (2004). Determinants of terrorism in the Muslim world: An empirical cross-sectional analysis. *Terrorism and Political Violence*, 16(2):253–273.
- Walsh, J. I. and Piazza, J. A. (2010). Why respecting physical integrity rights reduces terrorism. Comparative Political Studies, 43(5):551–577.
- Wolfensohn, J. D. (2002). Fight terrorism by ending poverty. New Perspectives Quarterly, 19(2):42–44.

- Young, J. K. and Dugan, L. (2011). Veto players and terror. *Journal of Peace Research*, 48(1):19–33.
- Young, J. K. and Findley, M. G. (2011). Promise and pitfalls of terrorism research. *International Studies Review*, 13(3):411–431.

Appendix A

Variable	Ν	Mean (Std. Dev.)	Min. (Max.)	Description
Panel A: Dependent variables Terror $\operatorname{attacks}_{t1,\ldots,t+4}$	8,353	5.91	0 (1160)	# of terror attacks in $t1,, t+4$
Terror attacks per year $_{t,,t+4}$	8383	(36.84) 1.48 (9.30)	(1160) 0 (295.80)	# of terror attacks per year in $t,, t + 4$
Terror attacks per capita _{t,t+4}	8383	4.06 (29.14)	0 (1021.87)	# of terror attacks per million of population in $t,, t + 4$
Terror attacks $(Y/N)_{t,,t+4}$	8383	0.34 (0.47)	0 (1)	Any terror attack (Y/N) in $t,, t + 4$
Killed in terror $attacks_{t,,t+4}$	8,383	12.15 (138.49)	0 (10,335)	# of people killed in terror attacks in $t,, t + 4$
Islamists_alt attacks_{t,,t+4}	8,383	$0.35 \\ (13.01)$	$\begin{array}{c} 0 \\ (1135) \end{array}$	# of terror attacks by groups with prime identity Islam in $t,, t + 4$
Left_alt attacks _{$t,,t+4$}	8,383	$1.96 \\ (19.56)$	$\begin{pmatrix} 0\\(986) \end{pmatrix}$	# of terror attacks by groups with prime identity Left in $t,, t + 4$
Right_alt attacks_{t,,t+4}	8,383	$0.11 \\ (1)$	$\begin{pmatrix} 0\\(36) \end{pmatrix}$	# of terror attacks by groups with prime identity Right in $t,, t + 4$
Ethnic/sep_alt attacks_{t,,t+4}	8,383	1.37 (13.62)	0 (674)	# of terror attacks by groups with prime identity Ethnic/separatists in $t,, t + 4$
Religious Non-Islamist_alt attacks_{t,,t+4}	8,383	$ \begin{array}{c} 0.02 \\ (0.47) \end{array} $	$\begin{pmatrix} 0 \\ (25) \end{pmatrix}$	# of terror attacks by groups with prime identity Religious but not Islam in $t,, t + 4$
Islamists domestic attacks $t, \dots, t+4$	8383	0.37 (13.27)	$0 \\ (1123)$	# of domestic terror attacks by Islamist groups in $t,, t + 4$
Islamists transnational attacks $t, \dots, t+4$	8383	$0.09 \\ (1.95)$	$\begin{matrix} 0 \\ (120) \end{matrix}$	# of transnational terror attacks by Islamist groups in $t,, t + 4$
Left domestic $attacks_{t,,t+4}$	8383	2.29 (21.20)	0 (877)	# of domestic terror attacks by Left-wing groups in $t,, t + 4$
Left transnational $attacks_{t,,t+4}$	8383	0.44 (4.15)	0 (171)	# of transnational terror attacks by Left-wing groups in $t,, t + 4$
Right domestic $attacks_{t,,t+4}$	8383	$0.10 \\ (0.88)$	$\begin{array}{c} 0 \\ (34) \end{array}$	# of domestic terror attacks by Right-wing groups in $t,, t + 4$
Right transnational $attacks_{t,,t+4}$	8383	$0.04 \\ (0.60)$	$\begin{array}{c} 0 \\ (35) \end{array}$	# of transnational terror attacks by Right-wing groups in $t,, t + 4$
Ethnic/Sep domestic attacks _{$t,,t+4$}	8383	$1.09 \\ (16.85)$	$0 \\ (1218)$	# of domestic terror attacks by ethnic or separatist groups in $t,, t + 4$
Ethnic/Sep transnational attacks _t ,, $t+4$	8383	0.5 (8.6)	0 (673)	# of transnational terror attacks by ethnic or separatist groups in $t,, t + 4$
Religious Non-Islamists domestic attacks $t, \dots, t+4$	8383	$0.24 \\ (4.23)$	$ \begin{array}{c} 0 \\ (242) \end{array} $	# of domestic terror attacks by religious (non-Islamist) groups in $t,,t+4$
Religious Non-Islamists transnational attacks $t, \dots, t+4$	8383	$0.16 \\ (7.58)$	$\begin{pmatrix} 0 \\ (673) \end{pmatrix}$	# of transnational terror attacks by religious (non-Islamist) groups in $t,,t+4$
GDP/capita	8,383	12,429.07 (12,334.17)	$188.97 \\ (166,007.3)$	GDP per capita in 2005 PPP US\$
Education	6,940	7.34 (3.23)	0.67 (13.76)	Years of educational attainment

 Table A1:
 Summary Statistics for additional variables.

	1970	1975	1980	1985	1990	1995	2000	2005	2010	Tota
Albania					\checkmark		\checkmark		\checkmark	3
Argentina	\checkmark		\checkmark			\checkmark	~	\checkmark		5
Australia		\checkmark			\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	6
Austria	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	9
Bangladesh			\checkmark			\checkmark	\checkmark	\checkmark		4
Belgium	\checkmark					\checkmark	\checkmark	\checkmark	\checkmark	5
Benin					\checkmark		\checkmark	\checkmark		3
Bolivia			\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	7
Bosnia and Herzegovina									\checkmark	1
Brazil	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	9
Bulgaria					\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	5
Canada	√	√.	√.	√.	√.	√	√	\checkmark	√.	9
Chile	√.	√	√.	√	√	√	√		v	8
China	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	9
Colombia	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	√	√.	√.	9
Croatia							√.	√	v	3
Zzech Republic	,	,	,	,	,	V	V,	V	V,	4
Denmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	Ý	~	V	\checkmark	9
Ecuador					,	\checkmark	 	~		3
Egypt, Arab Rep.					\checkmark	,	~	\checkmark	,	3
El Salvador						V	~	,	V	3
Estonia	,			,	,	V	V,	Ý	~	4
Finland	V	,	,	~	V	~	v _	~	√ √	7
France	\checkmark	\checkmark	\checkmark	\checkmark	V	~	V,	~	V,	9
Germany, East	/	/	/	/	~	\checkmark	V,	~	1	5
Germany, West	~	<i>√</i>	v		v		v	~	~	9
Greece	\checkmark	√	√	√	~	~	√	~	\checkmark	9
Guatemala					/	\checkmark	/	~	√	3
Honduras		/			\checkmark	√	v	~	/	4
Hungary		\checkmark	/	/	/	/	~	1	Ý	4
ndia ndonesia	/		\checkmark	v	\checkmark	×,	√	~	1	7
	\checkmark			√		\checkmark	/	\checkmark	\checkmark	5
ran, Islamic Rep.			,		/	,	v		v	3 6
reland		,	V	,	V	Ý	v,	~	V	
taly		\checkmark	~		V	~	V	\checkmark	\checkmark	8
Japan		V	V	V	~	~	v	V	× ✓	8
Jordan					/	~	<i>\</i>	/	√ √	3
Kazakhstan					\checkmark	\checkmark	~	~	V	5
Kenya Zenya				/	/	,	/	~	/	1
Korea, Rep.				\checkmark	\checkmark	\checkmark	~	\checkmark	\checkmark	6 3
Kyrgyz Republic Latvia							•	× ✓		3
Lesotho				/		\checkmark	~	V		3
Lithuania				v		× √	*	\checkmark	\checkmark	4
Macedonia					\checkmark	v	*	× ✓	↓	4
Malaysia	\checkmark	./	./		× ✓	\checkmark	•	¥ ✓	× ✓	8
Me√ico		\checkmark	\checkmark		v	`	•	v	~	7
Mongolia	v	v	v		\checkmark	v	•	~	~	5
Morocco						•			~	4
Mozambique					•	\checkmark	`	~	`	4
Nepal						•	~	`	•	2
Netherlands						\checkmark			\checkmark	4
Nicaragua		\checkmark				•			•	3
Nigeria					\checkmark				\checkmark	2
Norway		\checkmark	\checkmark			\checkmark	\checkmark	\checkmark		6
Pakistan	\checkmark	¥	~	\checkmark	\checkmark	~	~	¥		8
Panama						1	1	1	\checkmark	4
Paraguay					\checkmark		\checkmark		√	3
Peru	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	9
Philippines		\checkmark	1	\checkmark	\checkmark	\checkmark		\checkmark	\checkmark	7
Poland					\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	5
Portugal		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	8
Romania						\checkmark	\checkmark	\checkmark	\checkmark	4
Russian Federation						\checkmark	\checkmark	\checkmark	\checkmark	4
Serbia							\checkmark			1
Slovak Republic						\checkmark	\checkmark	\checkmark	\checkmark	4
Slovenia						\checkmark	\checkmark	\checkmark	\checkmark	4
South Africa	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	9
Spain			\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	7
Sri Lanka					$ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ $	$\langle \cdot \rangle$	\checkmark	\checkmark	\checkmark	5
Sweden				\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	6
Switzerland	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	9
Fanzania			\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	7
Fhailand			\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	7
Furkey		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark			6
Jkraine					\checkmark			\checkmark	\checkmark	3
United Arab Emirates			\checkmark		\checkmark		\checkmark	\checkmark	\checkmark	5
United Kingdom	\checkmark					\checkmark	\checkmark	\checkmark	\checkmark	5
United States	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	9
Jruguay					\checkmark	\checkmark	\checkmark			3
Jzbekistan						1	\checkmark	\checkmark		3
Venezuela	\checkmark		\checkmark		\checkmark					3
Vietnam					~	\checkmark	\checkmark	\checkmark	\checkmark	$\tilde{5}$
			33	30	50	65	75	71	65	438

 Table A2:
 Country-years that appear in the regional data set.

	All country-years	Sample countries	Sample country-years	All country-years	Sample countries	Sample country-years
Panel A: Dependent variable	e - Terror attacks					
Ln(country $GDP/capita)_{i,t}$	23.989	90.724	123.770	501.310**	1016.198^{**}	1242.816^*
	(17.017)	(71.510)	(102.559)	(199.062)	(476.781)	(674.529)
$Ln(country GDP/capita)_{i,t}^2$				-30.266**	-61.777**	-71.963*
				(11.929)	(29.856)	(36.388)
Panel B: Dependent variable	- Domestic terr	or attacks				
$Ln(country GDP/capita)_{i,t}$	26.003	84.391	125.255	405.002**	886.987^{*}	1046.545^{*}
	(15.974)	(68.627)	(99.771)	(181.363)	(447.070)	(625.057)
$Ln(country GDP/capita)_{i,t}^2$				-24.032**	-53.575*	-59.246*
· · · · · · · · · · · · · · · · · · ·				(10.849)	(28.050)	(33.376)
Panel C: Dependent variable	e - Transnational	terror attac	ks			
$Ln(country GDP/capita)_{i,t}$	-2.015	6.333	-1.485	96.308**	129.210***	196.271^{**}
	(2.625)	(6.148)	(13.021)	(37.302)	(45.979)	(78.383)
$Ln(country GDP/capita)_{i,t}^2$				-6.234**	-8.202***	-12.717**
, , . , . , . , .				(2.402)	(2.938)	(5.065)
Ν	1,624	581	419	1,624	581	419

Table A3: Comparison between our sample and global database.

Notes: Country GDP per capita is in constant 2010 US dollars and is obtained from United Nations Statistical Database. All regressions control for Country-FE and Year-FE. Standard errors clustered at country level are displayed in parentheses.^{*} p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01.

Table A4: Robustne	ss checks using the	ne main specification	of Column 6 in Table 3.
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	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation Method:	NBREG ^a	Poisson	OLS	OLS .	OLS	Logit	NBREG
Dependent Variable:	Subnational $\operatorname{terror}_{t,\ldots,t+4}$			Subnational terror per $year_{t,,t+4}$	Subnational terror per capita $_{t,,t+4}$	Subnational terror $(Y/N)_{t,,t+4}$	Subnational killed in terror $_{t,,t+4}$
$Ln(GDP/capita)_{i,t}$	3.517^{***} (0.480)	15.651^{***} (2.593)	72.161^{***} (14.090)	14.432^{***} (2.818)	21.552^{*} (11.092)	7.604^{***} (1.023)	4.454^{***} (0.489)
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})^2_{i,t}$	-0.186^{***} (0.027)	-0.963^{***} (0.153)	-4.434^{***} (0.841)	-0.887^{***} (0.168)	-1.264^{**} (0.616)	-0.439^{***} (0.060)	-0.261^{***} (0.028)
Control variables ^{b}	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Time period- and region- fixed effects	~	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Ν	$5,\!351$	5,351	8,383	8,383	8,383	4,644	3,808

Notes: Standard errors are displayed in parentheses. Column (1) reports bootstrapped standard errors, columns (2) - (4) report robust standard errors clustered at the regional level, and columns (5) and (6) report standard errors based on the observed information matrix, using the option vce(oim) in STATA. * p < 0.10, ** p < 0.05, *** p < 0.01. ^aSpecification (1) reports bootstrapped standard errors (10) reports bootstrapped standard errors (11) and (12) consider subnational GPD/capita and controls for the years reported in the Gennaioli et al. (2014) dataset without any adjustment. ^bControls include logged subnational population, logged value of oil production, and a binary indicator for location of capital in the region.

Estimation Method:	(1) NBREG	(2) NBREG	(3) NBREG	(4) NBREG	(5) NBREG ^b	(6) NBREG ^b
Dependent Variable:		Subnational terror _{$t,,t+4$}		Subnational terror $_{t1,,t+4}$	Subnational $terror_{t,,t+4}$	Subnational terror $_{t1,,t+4}$
$\mathrm{Ln}(\mathrm{GDP}/\mathrm{capita})_{i,t}$		3.708^{***} (0.479)	3.520^{***} (0.481)	3.647^{***} (0.396)	3.555^{***} (0.425)	3.456^{***} (0.439)
$\mathrm{Ln}(\mathrm{GDP}/\mathrm{capita})_{i,t}^2$		-0.212^{***} (0.027)	-0.181^{***} (0.027)	-0.194^{***} (0.022)	-0.187^{***} (0.024)	-0.180^{***} (0.025)
Control variables ^{c}	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
$\text{GDP}/\text{capita}_{i,t}$	0.020^{***} (0.005)					
$\mathrm{GDP}/\mathrm{capita}_{i,t}^2$	-0.000^{***} (0.000)					
Education		\checkmark				
Terror attacks $t=5,,t=1$			\checkmark			
Time period- and region- fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Ν	5,351	4,280	3,882	5,084	4,624	4,411

Table A5: Further robustness checks using the main specification of Column 6 in Table 3.

Notes: Standard errors based on the observed information matrix, using the option vce(oim) in STATA, are displayed in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. ^aSpecification (1) reports bootstrapped standard errors (100 reps). ^bSpecifications (5) and (6) consider subnational GDP/capita and controls for the years reported in the Gennaioli et al. (2014) dataset without any adjustment. ^cControls include logged subnational population, logged value of oil production, and a binary indicator for location of capital in the region.

Table A6:	Predicting terror attacks in period $t,, t + 4$ perpetrated by groups with various
	identities considering only prime identity of the group, building on the specification
	in column(6) Table $\frac{3}{2}$.

	(1) Islamists _{alt}	$(2) \\ Left_{alt}$	$(3) \\ Right_{alt}$	$(4) \\ Ethnic/Sep_{alt}$	(5) Religious Non-Islamists _{alt}
Dependent variable: Subno	ational terror	t,,t+4			
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}$	7.993^{***} (1.676)	8.201^{***} (0.875)	9.708^{***} (1.926)	5.455^{***} (0.816)	11.591^{***} (3.825)
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}^2$	-0.461^{***} (0.099)	-0.487^{***} (0.050)	-0.526^{***} (0.106)	-0.304^{***} (0.046)	-0.649^{***} (0.215)
Control variables ^{a}	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Time period- and region- fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
GDP/capita at the maximum	5,820.83	4,489.36	9902.67	7,932.22	7,554.45
Ν	648	2,393	1,349	1,897	291

Notes: Standard errors based on the observed information matrix, using the option vce(oim) in STATA, are displayed in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. ^aControls include logged subnational population and a binary indicator for location of capital in the region.

	(1) Islamists	(2) Left	(3) Right	(4) Ethnic/Sep	(5) Religious Non-Islamists
Dependent variable: Subnation	al domestic	$terror_{t,,t+}$	-4		
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}$	5.678^{***} (1.886)	8.890^{***} (0.837)	$\begin{array}{c} 11.952^{***} \\ (1.996) \end{array}$	6.800^{***} (1.100)	$7.816^{***} \\ (2.025)$
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}^2$	-0.349^{***} (0.115)	-0.525^{***} (0.048)	-0.665^{***} (0.111)	-0.408^{***} (0.064)	-0.478^{***} (0.115)
Control variable ^{a}	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Time period- and region- fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
GDP/capita at the maximum	3,410.69	4,753.64	7994.16	4,160.26	3,553.66
Ν	548	2,459	1,308	1,321	614

Table A7: Displaying results for domestic terror attacks in period t, ..., t + 4 perpetrated by groups with various identities, building on the specification in column(6) Table 3.

Notes: Standard errors based on the observed information matrix, using the option vce(oim) in STATA, are displayed in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. ^aControls include logged subnational population, value of oil production, educational attainment, and a binary indicator for location of capital in the region.

Table A8: Displaying results for transnational terror attacks in period t, ..., t + 4 perpetrated
by groups with various identities, building on the specification in column(6) Table
3.

	(1) Islamists	(2) Left	(3) Right	(4) Ethnic/Sep	(5) Religious Non-Islamists
Dependent variable: Subnation	al transnat	ional terror	<i>t</i> ,, <i>t</i> +4		
$Ln(GDP/capita)_{i,t}$	$11.148^{***} \\ (2.349)$	5.139^{***} (1.166)	10.879^{**} (4.585)	$\begin{array}{c} 10.217^{***} \\ (1.289) \end{array}$	23.163^{***} (3.982)
$\operatorname{Ln}(\operatorname{GDP}/\operatorname{capita})_{i,t}^2$	-0.616^{***} (0.135)	-0.278^{***} (0.064)	-0.515^{**} (0.243)	-0.576^{***} (0.073)	-1.298^{***} (0.222)
Control variables ^{a}	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Time period- and region- fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
GDP/capita at the maximum	8,507.48	10,329.98	38,643.58	7,107.63	7,499.36
Ν	571	2,044	509	1,396	453

Notes: Standard errors based on the observed information matrix, using the option vce(oim) in STATA, are displayed in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. ^aControls include logged subnational population, value of oil production, and a binary indicator for location of capital in the region.

Appendix B: Data Preparation for Regional Income Levels and Terror Attacks

The original data on GDP/capita constitute an unbalanced panel in which intervals between observations for each entity varies. We adjust the data to construct a panel containing five-yearly data by matching the observation on a subnational entity for a year to the closest year in the five-yearly panel. For example, the Albanian Berat region reports GDP/capita for 1990, 2001, and 2009. We assign these observations to the years 1990, 2000, and 2010. Keeping reported years in their original format produces consistent findings (see Table A5).

To match regional GDP/capita data with terror attacks, we follow a three-step matching process: First, we match the subnational entity listed in the GTD with the corresponding entity in the Gennaioli et al. (2014) database. This data-merging mechanism itself remains imperfect because subnational entities listed in the GTD are not standardized in terms of spellings or changes in the boundaries of the entities over time. Second, for those observations, we match the respective information from the GTD by hand to the regional level identified by Gennaioli et al. (2014). Some terror attacks lack information on the subnational entity but feature more disaggregated geographical identifiers (e.g., city-level). Third, we exploit the geographical coordinates of the remaining attacks to match them to a subnational region. The terror incidents that remained unmatched after the three steps were discarded. Overall, these steps allow us to match 92% of all 107,221 attacks listed in our sample period.