Are Economic Development and Education Improvement Associated with Participation in Transnational Terrorism?

L. Elbakidze [a] and Y.H. Jin [b]

[a] University of Idaho, 875 Perimeter Drive, University of Idaho, Mail Stop 2334, Moscow, Idaho, USA, 83844-2334
E-mail:lelbakidze@uidaho.edu

[b] Rutgers University, 55 Dudley Road, New Brunswick, NJ 08901

Acknowledgements: We are grateful for helpful comments and suggestions of the reviewers and editors of *Risk Analysis*.

Are Economic Development and Education Improvement Associated with Participation in Transnational Terrorism?

ABSTRACT

Using transnational terrorism data from 1980 to 2000, this study empirically examines the relationships between frequency of participation in transnational terrorism acts and economic development and education improvement. We find an inverse-U shaped association between the frequency of various nationals acting as perpetrators in transnational terrorism acts and per capita income in their respective home countries. As per capita incomes increase from relatively low levels, frequencies of participation in transnational terrorism increase. However, at sufficiently higher levels of per capita income, further increase in per capita income is negatively associated with the rate of participation in transnational terrorism. Education improvement from elementary to secondary is positively correlated with frequency of participation in transnational terrorism events, while further improvement from secondary to tertiary level is negatively correlated with participation in transnational terrorism. We also find that citizens of countries with greater openness to international trade, lower degree of income inequality, greater economic freedom, larger proportion of population with tertiary education, and less religious prevalence participate in transnational terrorism events less frequently.

Key words: Transnational terrorism, per capita income, education.

Are Economic Development and Education Improvement Associated with Participation in Transnational Terrorism?

1. INTRODUCTION

Academic debates pertaining to socio-economic roots of transnational terrorism have been ongoing, but no consensus has been reached. This paper contributes to this debate with an empirical investigation focusing on per capita income and education as correlates of participation in transnational terrorism. The objective is to investigate how socioeconomic conditions, especially per capita income and education, in perpetrators' countries of origin are associated with frequencies of participation in transnational terrorism. In doing so, we provide a positive, descriptive (rather than normative or prescriptive) characterization of probabilistic frequencies of participation in transnational terrorism acts consistent with basic conditions for intelligent adversary models for terrorism risk analysis outlined by Guikema.(1) Although the analysis of direct management and mitigation of the risks of terrorism attacks is beyond the scope of this study, we address a critically important component of terrorism risk analysis and management – how the patterns of participation in transnational terrorism are associated with country-level socio-economic conditions. We specifically focus on per capita income and education. Other socioeconomic factors like unemployment, religion, income inequality, economic freedom, and openness to trade are also used. Understanding such patterns plays a critical role in ARDA (anti-terrorism risk-based decision aid),(2) PRA (probabilistic risk analysis)(3) and similar types of risk assessment models as well as in more sophisticated frameworks of terrorism risk analysis which incorporate rationality of the adversary. (1,4) This study is not meant to establish causal relationships and instead examines statistical correlation between some of the socioeconomic factors and participation in transnational terrorism. A better understanding of probabilities and frequencies of participation in transnational terrorism may facilitate allocation of limited resources across prevention and preparedness measures.

As is common for studies based on statistical analysis, we focus on quantitative and descriptive modeling of adversary behavior based on observational data, without explicit normative axioms underlying utility maximization.[(1)] Implicit assumptions underlying our theoretical framework pertain to plausibility of the role of socio-economic factors in adversaries' behavior with regards to participation in transnational terrorism acts. We empirically examine statistical significance of such linkages and provide associated uncertainty bounds. In particular, we empirically examine the non-linear association between participation in transnational terrorism and income as well as education. To do so, we rely on count data analysis techniques and use data which includes frequencies of participation in transnational terrorism by nationals of various countries and corresponding country level socio-economic measures. We use a variety of econometric models, including panel and pooled specifications, and find that Zero-Inflated Negative Binomial (ZINB) and Panel Fixed Effects Negative Binomial (PFENB) specifications perform better than other count data models.

Determinants of and threats posed by domestic and transnational terrorism events may differ. [(5,6,7)] Therefore, separate investigations of these two phenomena may be warranted. We specifically focus on transnational terrorism and leave investigations of domestic terrorism [(8)] and the comparison of domestic and transnational terrorism to future studies. [(7)] In this regard, this study complements the work by Elbakidze and Jin [(9)] where similar data and empirical techniques are used to examine socioeconomic characteristics of countries victimized in transnational terrorism events. In contrast, this study focuses on characteristics of countries from which adversaries originate.

The rest of the paper is structured as follows. Section 2 provides a brief literature review, followed by data discussion in Section 3. In section 4 we review the empirical methodology. Section 5 discusses model selection results and estimates of association between participation in transnational terrorism and per capita income, education, and other variables. We close with a concluding discussion.

2. BACKGROUND LITERATURE

Becker's seminal paper [10] on rationality of crime suggests that crime decreases as market wages increase relative to the rewards of committing a crime. This reasoning is consistent with the findings of numerous studies pertaining to association between political violence and socioeconomic conditions.[5, 11-16] However, several empirical studies have challenged this view in the context of participation in terrorism acts.[17-22] For example, based on cross country analyses, several studies find no evidence of statistically significant relationships between participation in transnational terrorism and education or per capita income.[19-26] Some studies even argue that Palestinian suicide bombers actually tend to come from more educated and more economically prosperous segments of Palestinian population.[17,18,19] On the other hand, numerous studies have empirically demonstrated negative associations between participation in terrorism and country level socioeconomic conditions. [5, 11, 27-30] We believe that contradictions in previous studies merit further research on the association between participation in terrorism and socio-economic factors. This paper is intended to respond to this need.

With the exception of Enders and Hoover[32] and Lai [33], prior empirical studies have only examined linear associations between per capita income and participation in transnational terrorism events, which may be one of the reasons for statistical insignificance in some studies and for conflicting results across studies. Supporting the results of Enders and Hoover as well as

Lai, we provide an additional examination of the non-linear association between participation in transnational terrorism and per capita income.

Some of the disagreement in the literature pertaining to the association between economic conditions and terrorism is rationalized by Bueno de Mesquita, who analytically shows that, because of selective recruitment, terrorist operatives do not appear to be economically deprived or uneducated, even though lack of economic opportunity and recessionary economies may encourage voluntarism in terrorist organizations.[(31)] Kruger and Laitin also discuss a potential "robin hood" effect where individuals who themselves are not necessarily poor or uneducated might become terrorists because of impoverished conditions of their fellow citizens.[(23)] Hence, even though actual perpetrators themselves may not appear to be deprived, poverty in their countries may positively affect their propensity to participate in transnational terrorism.

The literature also includes studies which investigate the roles of education, religion, and political measures. Stern attributes involvement in terrorist acts to lack of adequate education.[(35)] She reports that religious schools in Pakistan encourage their graduates, who lack practical education, to fulfill their "spiritual obligations" by fighting against Hindus in Kashmir and other adversaries. On the other hand, Krueger and Maleckova argue that occupation, poverty and lack of education do not seem to affect attitudes toward terrorism activities.[(19)] Enders and Sandler [(36)] attribute the increase in violence of transnational terrorism events to the growth in religious terrorism in the post-cold war period. Similarly, Ivanova and Sandler show that the greatest threat of chemical, biological, radiological, and nuclear attacks comes from religious cults and groups with transnational orientations. [(37)] It has also been suggested that some developing countries might be supporting transnational terrorism due to ideological differences, past operations and policies of the developed countries, and unfavorable socioeconomic conditions. Wulf et al. argue that hatred for the developed countries may subside through efforts to improve quality of life for individuals in the developing countries.[38] Therefore, in the empirical analyses we include religion and other socio-demographic factors as explanatory variables, although we primarily focus on the association between participation in transnational terrorism and per capita income and education.

3. DATA

ITERATE (International Terrorism: Attributes of Terrorist Events) is the only dataset that can accommodate the type of investigation carried out in this study.[1] The ITERATE dataset includes records of transnational terrorism incidents including date, the incident's country of origin, location of incidents, up to three nationalities of victims, and up to three nationalities of perpetrators for each incident.[39] This dataset has been extensively used in transnational terrorism literature.[5,9,20,25,27, 28,29,30, 40, and many others] Detailed descriptions of ITERATE can be found elsewhere.[41,42,43]

Consistent with the dataset used in this study, we assume that transnational terrorism is a "premeditated threatened or actual use of force or violence to attain a political goal through fear,

---

[1] In GTD-I and Rand/MIPT datasets the nationalities of perpetrators are not readily available. Only for some of the documented incidents it may be possible to infer the nationalities of perpetrators based on perpetrator group name in GTD-I and Rand/MIPT datasets. On the other hand, the ITERATE dataset provides up to three nationalities of perpetrators for each documented event. Direct comparison of results obtained using ITERATE dataset and results that would be obtained using other datasets would be questionable at best. Therefore, this study focuses on the ITERATE dataset. As suggested by the reviewers, we have also attempted to obtain transnational terrorism data from the Worldwide Incident Tracking System previously maintained by the National Counterterrorism Center (www.nctc.gov). Unfortunately, the data was no longer available from the NCTC during revision of this paper.

coercion, or intimidation" and when its ramifications transcend national boundaries through the nationality of the perpetrators and/or human or institutional victims, location of the incident, or mechanics of its resolution.[(44)]

Using the chronological data on transnational terrorism incidents, we construct the dependent variable as an annual count of terrorism events in which citizens of various countries are documented as perpetrators. For example, the annual count of participation in transnational terrorism events for Philippines in the year 2000 is seven. [(39)] This means that Philippine nationals were documented as perpetrators in seven different transnational terrorism incidents in the year 2000. The original chronological data documents up to three nationalities of perpetrators for each transnational terrorism incident. For example, on March 15, 1982 three Salvadorans, two Nicaraguans, one Chilean, and others were arrested for intending to kidnap an unidentified American diplomat.[(39)] This single incident increases the annual count of participation in transnational terrorism events for Salvador, Nicaragua, and Chile in 1982 by one for each of the countries. We use the terms "incidents" and "counts" to refer to terrorism events and to participation by various nationals, respectively.

Some of the documented transnational incidents are excluded from the analysis either because of unknown perpetrators and/or their nationalities or because of missing corresponding socio-economic data for the perpetrators' country of origin. Table I shows that our sample of countries accounts for 33% (2,677/8162) of total documented incidents and 49% (2,677/5,504) of the documented incidents for which at least one nationality of the perpetrators is known.[2]

[2] To address the representativeness of the incidents included in this study, we compare characteristics and outcomes of incidents between three incident groups -- those included in this study (group 1); those with unknown perpetrators or their nationalities (group 2); and those with at least one known nationality of perpetrators but are excluded from the study due to lack of corresponding socio-economic data (group 3).

Furthermore, our sample covers 48% (2748/5731) of total terrorism participation counts with known perpetrator nationalities only, and 18% (2748/15461) of total participation counts with either known or unknown perpetrator nationalities. Seventy one out of the 2,748 terrorism counts correspond to terrorism incidents with confirmed perpetrators from more than one country.

The economic variables include GDP per capita (measured in terms of thousands of 2000 US dollars), the percent of population living on less than one dollar per day, the percent of population living on one to two dollars per day[3], the GINI index that measures income equity among households on a scale of zero (perfect equality) to one (absolute inequality), unemployment rate, openness to trade (the share of total imports and exports relative to GDP), and an index of economic freedom. The index of economic freedom is obtained from the

---

The study sample in group 1 is qualitatively similar to the samples in groups 2 and 3. In particular, incidents in the three groups are similarly distributed over time -- 59% of the incidents in group 1 occurred in 1990s compared with 64% and 61% in groups 2 and 3 respectively. For the incidents with known nationality of at least one perpetrator in 1980-2000, countries which are included in the analysis (group 1) on average have 1.83 annual counts of participation in transnational terrorism compared to 1.73 for the counties excluded from the study due to lack of corresponding socioeconomic data (group 3). The Shapiro-Wilk test result suggests that the terrorism count does not follow a normal distribution as its test statistic (10.41) exceeds the critical value at the 1% significance level. Therefore, we use the nonparametric Kruskal-Wallis test to evaluate the difference between the mean annual terrorism counts of the two groups. The Kruskal-Wallis χ^2 test statistic is 3.83 with the degree of freedom of two and the corresponding p-value 0.15, which suggests that the average terrorism count by country for those included in the analysis is not statistically different from those excluded from the analysis at the 15% significance level.

[3] We are aware that the World Bank's estimates of percent of population living on less than one or two dollars per day have been criticized for consistency and appropriateness as descriptors of international poverty.[46] However, we use these estimates as the best available indicators.

Heritage Foundation.[45] It is measured on a scale of one to five, where one denotes an economic environment and policies that are most conducive to economic freedom, and a score of five denotes a set of policies that are least conducive to economic freedom. Education variables are represented by the share of population, ages 15 and older, who can read and write, and the share of labor force with the highest achieved education levels being primary, secondary, and tertiary. The shares of population practicing Christianity, Islam, Hinduism, Buddhism, other religions, and no religion at all are also included to control for the religion effects. Table II shows summary statistics of the independent variables.

Socioeconomic data, except for the index of economic freedom (obtained from the Heritage Foundation) and religious measures (obtained from CIA's World Factbook), are collected from the World Bank database. We also rely on countries' national statistics services to obtain some of the missing values for socioeconomic variables. In cases were some of the values are not available we use the historically closest available data estimates to fill in the missing observations where appropriate. For example, the earliest available economic freedom index from 1990s is used as a proxy for the economic freedom index for the 1980s and early 1990s except for countries like those of the former Soviet Union where significant political and socioeconomic changes of that time don't allow for such extrapolation. For most countries, the estimates of the population share living on less than one or two dollars per day are available for one particular year. These estimates are used as best available approximations for the remaining years. The GINI index, education variables, and religion variables are also filled in a similar manner. Table II presents the summary statistics of socioeconomic variables.

The dataset used in this study consists of 1403 observations by country and year from 1980 to 2000.[4] From 77 countries in our dataset, citizens of 67 countries have participated in at least one transnational terrorism event during the study period. Table III presents the average annual counts of participation per country in the sample. The distribution of participation counts, shown in the second column of Table IV, reveals that the country-year observations with at most five counts of participation account for 91% of all observations. Table IV also shows that 60% of observations have zero counts of participation in transnational terrorism attacks. The phenomenon of excessive number of zero values in the data (zero inflation) for the dependent variable may be problematic if the full sample of observations with zero values in the dependent variable consists of subsamples which differ in terms of data generating processes [5] and distributional properties.(37, 47) This issue is addressed in the methodology section.

---

[4] Out of 1540 possible country-year combinations (77*20), our sample consists of 1403 observations due to the reduced time horizon for some of the countries. Each country-year observation can represent several transnational terrorism participation counts shown in Table I. Reduced time horizons were used for the countries affected by the end of the Cold War and the breakup of the Soviet Union because unstable political and economic conditions did not allow for extrapolation of available estimates. For example, the economic data for the Republic of Georgia in the World Bank database became available only in 1994. Due to the highly unstable sociopolitical situation in Georgia in the 80s and the beginning of the 90s, extrapolation of data from 1994 to previous years is not appropriate. Therefore, the observations for the Republic of Georgia in our dataset start from 1994.

[5] For example, countries may have zero counts of documented participation either because no attempts have been made to participate in transnational terrorism by their nationals, or because successful counterterrorism policies and prevention activities deterred participation. As a result, the full sample can have an "excessive" number of observations with zero values in the dependent variable, and analysis using singular data generation mechanism may not be appropriate. Some of the zero values may be due to favorable socioeconomic conditions, and others may be due to successful deterrence policies. Hence,

4. EMPIRICAL METHODOLOGY

Poisson regression models are widely used and are a customary starting point for count data analyses.[34] A key property of a Poisson distribution is that its variance is equal to its mean. However, this assumption is frequently violated in count data analysis. This condition is commonly referred to as over-dispersion [34, 48] and can be caused by unobserved heterogeneity among individuals and/or by an excessive number of observations with zero values in the dependent variable. When heterogeneity is present, the estimates based on a Poisson regression will be inefficient.[34] Negative binomial (NB) regression models have been used to deal with the issue of possible heterogeneity due to mean and variance inequality.

The second possible source of over-dispersion can be an excessive number of observations with zero values in the dependent variable, which is a concern in this study because almost 60% of the observations in the sample have zero counts of participation (see Table IV). The number of observations with zero values in the dependent variable can, and often does, exceed the number of such observations that can be generated by the Poisson or Negative Binomial distributions. Traditional Poisson and NB models do not account for an excessive number of zeroes which may appear in the dependent variable due to different data generating processes, and thus can produce biased estimates. These models assume that all observations in the data are generated by the same data generating process/distribution (Poisson or NB). On the other hand, Zero-inflated regression models, such as zero-inflated Poisson (ZIP) or zero-inflated NB (ZINB), explicitly take into account the possibility that there may be some observations with zero values in the dependent variable, which are generated by a different process as compared to the rest of the observations (see footnote 6). Zero-inflated count data models have been used

---

the two subsamples of observations with zero values in the dependent variable may not be generated by the same data generating process (like Poisson or Negative Binomial distributions).

extensively in the literature [37,49-54] and are designed to explicitly distinguish frequencies of observing zeroes as part of Poisson or negative binomial distributions from frequencies of observing zeroes which do not fall within these distributions. The extra zeroes which do not fit Poisson or negative binomial distributions are typically modeled using the logit specification within a zero-inflated Poisson or negative binomial specification. See appendix for a more detailed discussion of these models.

Using appropriate statistical tests, we are able to evaluate and compare Poisson, NB, ZIP, and ZINB models. For nested models (Poisson vs. NB; and ZINB vs. ZIP), we test for over-dispersion (inequality of mean and variance of the distributions as assumed by Poisson specifications) using the null hypothesis that the dispersion parameter is statistically not different from zero ($\alpha = 0$). For non-nested models (ZINB vs NB; and ZIP vs. Poisson), we use Voung tests (see appendix for further details) to test for zero inflation (the presence of excessive number of observations with zero values in the dependent variable which do not follow Poisson or negative binomial distributions). As shown in Figure 1, if the Vuong test favors the ZINB model over the NB model, then a statistical test on H_o: $\alpha = 0$ is used to contrast ZINB versus ZIP. If H_o: $\alpha = 0$ is rejected, then ZINB is considered to be the most appropriate specification, and individual heterogeneity as well as excessive number of observations with zero values in the dependent variable contribute to over-dispersion. If we fail to reject H_o: $\alpha = 0$, then the ZIP model is compared to the Poisson model using the Vuong test. If ZIP is the most appropriate specification, then only the presence of an excessive number of observations with zero values in the dependent variable is responsible for over-dispersion. Otherwise, no over-dispersion is present and a Poisson model is favored. On the other hand, if the initial Vuong test favors the NB model, then we test if the heterogeneity parameter α is significantly different from zero to contrast NB vs. Poisson. A rejection of $H_o: \alpha = 0$ at this stage suggests that the NB model is the most appropriate specification and individual heterogeneity (inequality of mean and variance of the distribution as assumed by the Poisson specification) is responsible for over-dispersion. Otherwise, a Poisson and ZIP are compared.

Poisson, NB, ZIP, and ZINB models all treat data as pooled. We extend the empirical analysis by employing a panel fixed effects negative binomial specification (PFENB) that takes advantage of the panel structure of the data. However, this specification does not explicitly account for the possibility of over-dispersion for the dependent variable which may be due to some of the observations with zero values in the dependent variable being generated via non-Poisson and non-negative binomial distributions.

5. ESTIMATION RESULTS

5.1 Model Selection and Specification

As shown in Table V, the Vuong test (*Vuong*-statistic = 4.70 and *p*-value = 0.00) suggests that the ZINB model fits the data better than the NB model, and the likelihood-ratio test of $\alpha = 0$ indicates that the ZINB model outperforms the ZIP model (LR-statistic=187 and p-value = 0.00). Furthermore, the ZIP model fits the data better than the Poisson model based on the likelihood ratio test (LR-statistic = 6.19 and p-value = 0.00). We therefore conclude that the ZINB model is a more appropriate specification than Poisson, ZIP, or NB models. This conclusion is also reinforced by the finding that, relative to the other pooled models, ZINB has the smallest values of the AIC (Akaike's Information Criterion) and the highest ratio of correct predictions[6,7]. Table

[6] The ratio of correct prediction is the percentage of observations for which the predicted number of participation counts equals their actual counts.

IV shows predicted counts from ZINB and PFENB models. Panel specification of negative binomial performs better than ZINB in terms of predicting zero and two participation counts. However, it does not do a good job in predicting events with 1 or 4 and larger number of participation counts relative to the ZINB model. We present the results from both ZINB and PFENB specifications.

5.2 Income and Poverty

Table V shows the results of the ZINB and PFENB models. Column 1 presents coefficients (with associated standard errors in Column 2) from the inflation module of the ZINB model. These estimates show the association between the independent variables and probability of observing zero participation which falls outside of the negative binomial distributional specification. Columns 3 and 4 show the coefficients and associated standard errors from the negative binomial module of the ZINB model – the association between the independent variables and frequency of participation given that the participation is distributed according to the negative binomial specification. Columns 5 and 6 show coefficients and corresponding standard errors from the PFENB estimation. In the rest of this paper we focus on discussing the implications for the frequencies of participation rather than the implications for observing non-NB distributed zero values in the dependent variable (inflation). Therefore, discussion of the results revolves around the coefficients in Column 4 of table V.

Unlike most of the previous studies of transnational terrorism, we include GDP per capita and its square term in the estimation and detect a statistically significant, although small in

---

[7] In addition to the pooled models discussed above, we also used a two part model [55,56] and a selection model, as part of the pooled data analysis. [57,58] These specifications provide poorer fits than the models we present. The results from these models, as well as Poisson, Zero Inflated Poisson, and Negative Binomial, are available upon request. Here we present only the results from ZINB and PFENB.

magnitude, non-linear correlation between GDP per capita and frequencies of participation in transnational terrorism. The coefficients of GDP per capita suggests that an increase of GDP per capita is positively (negatively) associated with frequencies of participation in terrorism when a country has a relatively low (high) level of per capita income. ZINB and PFENB specifications produce similar inflection points for the non-linear relationship between per capita income and participation: $19,766 for the ZINB and $20,521 for the PEFNB for both decades combined. Using ZINB as an example for illustration, an increase in income per capita is positively correlated with participation in transnational terrorism events in 1232 country-year observations where the GDP per capita is lower than $19,766 and negatively correlated with participation in 171 country-year observation where the GDP per capita is higher than $19,766. This result is qualitatively consistent with Enders and Hoover and Lai [(32,33)], but the inflection point tends to be at a higher per capita income in our results than in Enders and Hoover. This difference can be caused by differences in respective samples in terms of country composition.

Figures 2a-2d illustrate the relationship between per capita GDP and counts of participation in transnational terrorism, with corresponding uncertainty bounds, for ZINB and PFENB specifications in 1980s and 1990s. The X-axis is the average per capita GDP for each country in the 80s and the 90s respectively. The Y-axis is the predicted participation counts evaluated at the mean values of all independent variables except per capita GDP and the decade dummy. The ZINB results (figures 2a and 2b) show a small but stronger inverse U shaped association[8] relative to the PFENB results (figures 2c and 2d). This is not surprising given that

[8] The expected values on these figures are not showing strictly quadratic relationship because in ZINB and PFENB specifications the expected values are not quadratic functions of GDP per capita. For example, ZINB specification for the expected value in equation (9-1), provided in the appendix, combines equations (1) and (7) in multiplicative forms. Equations (1) and (7) are individually monotonic

the PFENB specification does a poorer job in predicting higher participation counts than does ZINB, as evident from table IV. Hence, although PFENB has a higher ratio of overall correct predictions, the ZINB results can be more informative, particularly for higher participation counts.

Table V also shows that according to the ZINB results, the proportion of population living on less than one dollar per day (pv1) and the proportion of population living on between one and two dollars per day (pv12) are positively correlated with frequency of participation in transnational terrorism. However, the PFENB results show that an increase in the proportion of population living on less than one dollar per day is negatively associated with frequency of participation in transnational terrorism. On the other hand, both models show that an increase in the proportion of population living on between one and two dollars per day is positively associated with participation frequency.

5.3 Education

Primary, secondary, and tertiary education measures have mixed associations with participation in transnational terrorism in terms of signs as well as statistical significance (Table V). The coefficients are not statistically significant in the PFENB regression. On the other hand, in the ZINB specification, the coefficients for secondary and tertiary education levels are statistically significant.

The individual coefficients for elementary, secondary, and tertiary education cannot be used to examine how participation in transnational terrorism might be correlated with a potential redistribution of population from one group of education attainment level to another. Therefore,

---

transformations of quadratic functions. However, (9-1) is no longer quadratic. Nevertheless, overall the inverse U shaped trend is still evident from figures 2 a-d.

we perform the following exercise. Let β_j denote the coefficients of the variables representing the percentage of labor force with the highest achieved education being primary ($j=p$), secondary ($j=s$), and tertiary levels ($j=t$). Based on the ZINB model, the improvement of education, corresponding to moving 1% of labor force from the primary education level, as highest achieved, to the secondary education level, is associated with conditional frequency by $(-\beta_p+\beta_s)\exp(x\mathbf{\beta})(1-\pi_i)$. Similarly, the association between moving 1% of labor force from the secondary education level to the tertiary level and frequency of participation in transnational terrorism can be expressed as $(-\beta_s+\beta_t)\exp(x\mathbf{\beta})(1-\pi_i)$. Although the coefficient of primary education in the ZINB model is not statistically significant, the Wald test shows that we fail to reject the hypotheses that $-\beta_p+\beta_s$ is greater than zero and $-\beta_s+\beta_t$ is less than zero. In the PFENB specification, $-\beta_p+\beta_s$ is greater than zero at the 5% significance level, but the hypothesis that β_s is greater than β_t is rejected (see Table V). These results imply that improving education levels of labor force from the primary level to the secondary level is positively correlated with the frequency of participation in transnational terrorism events. On the other hand, improving education levels of labor force from secondary to tertiary level is negatively correlated with the frequency of participation in transnational terrorism based on the ZINB estimation.

5.4 Other variables

The signs of the other statistically significant variables are consistent with expectations. For example, despite opposing views in the literature [11, 17-20, 26-30] about the role of economic factors in terrorism, one might expect that persistent unemployment, income inequality, and lack of economic freedom may contribute to accumulation of hatred towards more prosperous and free societies which may be deemed responsible for inferior living conditions in perpetrators' countries of origin.[38] Our results show that the unemployment rate is positively associated with frequencies of participation in transnational terrorism events. The economic freedom index displays a positive association with participation in terrorism acts, implying that the decrease in economic freedom has a positive association with involvement in transnational terrorism acts. Income inequality, measured by the GINI index, has a positive sign, although statistically insignificant in the PFENB estimation. Based on the ZINB results, income inequality is positively correlated with participation in transnational terrorism attacks. The coefficient associated with literacy is statistically significant and positive in the ZINB estimation but negative and statistically insignificant in the PFENB model. Openness to trade has a negative and statistically significant correlation with frequency of participation in terrorism acts in both models, which suggests that as a country becomes more internationally integrated participation in transnational terrorism by its citizens decreases. This result differs from Li and Schaub who find no direct statistically significant relationship between trade and transnational terrorism acts within the countries' borders.(28) However, they do propose a possible indirect effect of trade through its positive effect on economic development, which is shown to have a negative effect on terrorism.

The results also demonstrate that increases in the proportions of the population who practice any of the considered religions, relative to the proportion of population practicing no religion at all, are positively associated with frequency of participation in terrorism attacks based on the ZINB model. In the PFENB model, the results are similar, except that the proportions of population practicing Christianity and Buddhism do not have statistically significant coefficients. These results provide an important context for Enders and Sandler who attribute the increase in severity of terrorist attacks in the post-cold war period mainly to the growth of religious terrorism.(36) Similarly, Ivanova and Sandler find that religious cults and groups with transnational orientations pose the largest threat to society in terms of chemical, biological, radiological, and nuclear terrorism.[59] Further studies are needed to examine these linkages in greater detail.

5.5 Robustness check

As acknowledged in the data section, 51% of terrorism incidents with a known nationality of at least one perpetrator are left out of the analysis due to a lack of appropriate socio-economic data. The excluded observations primarily correspond to low income countries for which socio-economic data could not be obtained. Matching countries with the World Bank's 2007 classification of low, lower middle, upper middle, and high income groups, we find that the percentage of low income countries in the group of countries which are left out from the analysis is three times greater than the percentage of low income countries in the study sample (40.79% versus 11.76%). However, the percentages of high income countries in the subsamples are statistically similar (30.26% versus 27.94%). To include some of the omitted countries we expand the sample from 77 to 97 countries by including only GDP per capita and its square term, education variables, total population, and the decade dummy, which increases our sample size from 1403 to 1902 country-year observations. The results in Table VI suggest a similar inverse U-shaped association between GDP per capita and participation in transnational terrorism. However, in this case the corresponding coefficients in the PFENB estimation are not statistically significant. The t-tests on education measures show that $-\beta_p + \beta_s$ is greater than zero and $-\beta_s + \beta_t$ is less than zero at the 1% significance level in the ZINB model (see Table VI). These hypotheses are rejected in the PFENB model.

6. CONCLUDING DISCUSSION

Despite a significant number of empirical studies addressing the linkages between socio-demographic variables and participation in terrorism, only two published studies have examined the non-linearity in the relationship between participation in transnational terrorism and per capita income[32,33], and no published study has examined such nonlinear relationship between participation in transnational terrorism and education. This study addresses these gaps in the literature using count data analysis techniques and data including the ITERATE dataset on participation in transnational terrorism events and country-level socio-economic data about perpetrators' countries of origin. We find an inverse U-shaped relationship between country level economic affluence, measured by per capita GDP, and frequency of respective nationals acting as perpetrators in transnational terrorism events. At low per capita income levels, an increase in income is positively correlated with participation in transnational terrorism. However, at higher levels of per capita income, a further increase in per capita income is negatively correlated with participation in transnational terrorism. These patterns are small in magnitude but are more pronounced in the ZINB results than in the PFENB results. Our results confirm the findings of Enders and Hoover [32], using a different dataset and a different empirical strategy. Our results are also consistent with Lai[33] who relies on the same terrorism data source but covers a different time period.

We find strong evidence against Lai's conclusion that all observations in the dataset are generated by the same data generating process (distributional assumption) and that no zero inflation in the dependent variable [34] is present. In contrast, we explicitly account for the possibility that some of the country-year observations with zero participation in terrorism acts could be generated by a different data generating processes than other observations with zero participation. This study relies on econometric specifications which account for the possibility of excessive number of observations with zero values in the dependent variable. In our specification, the excessive number of observations with zero values in the dependent variable refers to the observations which fall outside of the assumed distributions for frequencies of participation like Poisson or negative binomial.

A possible interpretation for the non-linear association between participation in transnational terrorism and per capita income may be that extreme poverty may preclude opportunities to participate in terrorism acts, while relative alleviation of poverty may provide marginal resources to participate in terrorism acts and materialize accumulated hatred.[38, 60] Clearly, such interpretation is subject to further scrutiny and verification considering complexity of linkages between culture, broadly defined and including but not limited to factors examined in this paper, and participation in terrorism. Future studies ought to consider the two directional relationships between culture, as a cultivator of participation in terrorism, and its components including but not limited to those examined in this paper. Nevertheless, if confirmed, the above interpretation would be consistent with Peter Bernholz's argument of increases in "supreme value" based terrorism as a result of increased resource availability. [60] In other words, a marginal increase in resource availability, which may be viewed as insufficient to make a meaningful difference for individual welfare and future prospects, may allow potential perpetrators to materialize their hatred for the societies which may be deemed to be responsible for their impoverished living conditions, and/or are viewed as cultural threats.

One of the implications of our results may be that a heightened diligence is warranted for development initiatives in the short run partly because of the possible unintended risk of increased opportunities for participation in transnational terrorism as economic conditions improve. However, potential increase in the propensity to participate in transnational terrorism, perhaps in part due to marginal increase in resource availability, should not be interpreted as a deterring factor for economic aid, but rather as a potential obstacle which should be recognized as part of international development efforts. A wrong interpretation of the results in this study would be to conclude that poverty reduction efforts, including foreign aid, in developing countries ought to be curtailed as part of the overall fight against terrorism.[61] Wulf *et al*. propose that possible reasons why some developing countries might be supporting terrorism include ideological differences, past operations and policies of the developed countries, and unfavorable socioeconomic conditions. [38] They argue that through efforts to improve quality of life for individuals in developing countries, the hatred for developed countries may subside. Indeed, others have also argued that economic development and education improvement could in the long run deter participation in terrorism activities [29,31,62] perhaps due to increased opportunity and the costs of participation[10]. Furthermore, according to Bird *et al*., if participation in terrorism is caused by feelings of relative deprivation, then suppression of terrorism, at least to some degree, depends on poverty reduction.[40] Joseph Stiglitz writes that international development efforts, like financial assistance programs, aimed at alleviating poverty in developing countries ought to be designed and implemented in the ways which take into account local cultural specificities and incorporate the development of institutional mechanisms for ensuring that the aid funds are used as intended and that potential negative side effects are minimized.[63]

This study is the first of its kind to suggest a non-linear relationship between education and participation in transnational terrorism. The results show that limited education is positively correlated with frequency of participation in transnational terrorism events, while advanced education is negatively correlated with participation in transnational terrorism. Marginally better educated individuals who may be exposed to particular and narrow political views may be better informed about relative quality of life in and foreign policies of rich countries. The resulting sense of relative deprivation and limited, possibly distorted views of political reality may encourage engagement in international terrorism as the last and simplest resort to self-fulfillment. Advanced education, on the other hand, may provide more comprehensive and broader viewpoints, which may discourage engagement in international terrorism. Our result contradicts the argument of Krueger and Maleckova that lack of education has no association with terrorism.[19] According to Stern, lack of practical education can contribute to inclination to participate in terrorism activities as part of one's "spiritual obligation".[35] The appropriateness of local educational categories as indicators of general education level is questionable because some schools may be deliberately teaching their students to become supporters of extremist movements.[18,35] This argument suggests that the implicit definition of "education" used in various studies[17,18,19] may not be consistent. Future studies in this direction should include efforts to develop and employ more consistent measures of education attainment.

It should be noted that the data used in this study were assembled using best available information and some extrapolation was necessary to fill the missing data. Therefore, caution is warranted for the interpretation of the results. The additional limitation of this study is a relatively poor fit of the estimated models as evidenced by the log-likelihood values, Wald Chi Square values, and ratios of correct predictions. Additional studies are needed to examine the non-linear relationship between economic development and participation in transnational terrorism and to examine the nonlinear role of education. Our intent in this study is to stimulate further work in this direction. We do not claim to have provided conclusive evidence, but instead aim to encourage further work in this direction. Further studies based on either more complete records or on alternative approaches, which would avoid reliance on observational data, are necessary to fully understand the potentially nonlinear linkages between country level socio-economic factors and participation in transnational terrorism acts. Our findings should be interpreted as no more than a preliminary support of the idea that socio-economic factors may be non-linearly associated with participation in transnational terrorism acts. We do not claim to have uncovered causal relationships in this study. Instead, we present evidence of possible correlation between some of the important socio-economic variables and participation in transnational terrorism without establishing directional causalities or specific mechanisms underlying such correlations.

REFERENCES

1. Guikema, S. Modeling Intelligent Adversaries for Terrorism Risk Assessment: Some Necessary Conditions for Adversary Models, Risk Analysis, 2012, 32(7):1117-1121

2. Dillon RL, Liebe RM, Bestafka T. Risk-Based Decision Making for Terrorism Applications Risk Analysis, 2009, 29(3):321-335

3. Ezell BC, Bennett SP, von Winterfeldt D, Sokolowski J, Collins AJ. Probabilistic Risk Analysis and Terrorism Risk, Risk Analysis, 2010, 30(4):575-589

4. Brown GC, Cox LA Jr. How Probabilistic Risk Assessment Can Mislead Terrorism, Risk Analysts, 2011, 31(2):196-204

5.. Derin-Gure P. Does Terrorism Have Economic Roots? Boston University, Working Paper Series. 2009Available at http://www.bu.edu/econ/workingpapers/papers/terrorism_BUworkingpaper.pdf. Accessed August 19, 2009.

6. Bandyopadhyay S, Younas J. Does Democracy Reduce Terrorism in Developing Countries? Federal Reserve Bank of St. Louis, Working Paper, 2009: 023A. Available online: http://211.253.40.86/mille/service/ers/20000/IMG/000000016807/2009-023.pdf Last accessed 01/23, 2013

7. Enders W, Sandler T, Gaibulloev K. Domestic Versus Transnational Terrorism: Data, Decomposition, and Dynamics, Journal of Peace Research, 2011; 48(3):319–337

8. Piazza JA. Poverty, minority economic discrimination, and domestic terrorism, Journal of Peace Research, 2011; 48(3):339–353

9. Elbakidze L, Jin Y. Victim Countries of Transnational Terrorism: An Empirical Characteristics Analysis, Risk Analysis, 2012; 32(12):2015-2165.

10. Becker GS. Crime and Punishment: and Economic Approach. Journal of Political Economy, 1968; 76:169-217.

11. Blomberg BS, Hess GD.. "The Lexus and the Olive Branch: Globalization, Democratization, and Terrorism." In Keefer and Loayza (ed) Terrorism, Economic Development, and Political Openness. 116-147. Cambridge and New York: Cambridge University Press, 2008.

12. Hess GD, Orphanides A. Economic Conditions, Elections and the Magnitude of Foreign Conflicts. Journal of Public Economics, 2001; 80:121-140.

13. Fearon JD, Laitin DD. Ethnicity, Insurgency and Civil War. The American Political Science Review, 2003; 97(1):75-90

14. Muller EN, Seligson MA. Inequality and Insurgency. The American Political Science Review, 1987; 81(2):425-452

15. London B, Robinson TD. The Effects of International Dependence on Income Inequality and Political Violence. American Sociological Review, 1989; 54(2):305-308

16. Blomberg BS, Hess GD. The temporal links between conflict and economic activity. Journal of Conflict Resolution, 2002; 46(1):74-90.

17. Benmelech E, Berrebi C. Human Capital and the Productivity of Suicide Bombers. Journal of Economic Perspectives, 2007; 21(3):223-238.

18. Berrebi C. Evidence about the Link between Education, Poverty and Terrorism Among Palestinians, Peace Economics. Peace Science and Public Policy, 2007; 13(1), Article 2.

19. Krueger AB, Maleckova J. Education, Poverty and Terrorism: Is There a Causal Connection? Journal of Economic Perspectives*,* 2003; 17(1): 119-144.

20. Kurrild-Klitgaard P, Kustesen K M, Klemmensen R. The Political Economy of Freedom, Democracy and Transnational Terrorism. Public Choice, 2006; 128:289-315

21. Abadie A. Poverty, Political Freedom, and the Roots of Terrorism. American Economic Review, 2006; 96(2): 50-57.

22. Piazza JA. Rooted in Poverty?: Terrorism, Poor Economic Development, and Social Cleavages. Terrorism and Political Violence, 2006; 18:159-177.

23. Krueger AB, Laitin DD. Kto-Kogo?: A Cross-Country Study of the Origins and Targets of Terrorism. In Keefer P, Loayza N. Eds. Terrorism, Economic Development, and Political Openness eds. (Cambridge: Cambridge University Press), 2008; pp. 148-73.

24. Piazza JA. Do Democracy and Free Markets Protect Us From Terrorism? International Politics, 2008; 45:72–91

25. Testas A. Determinants of terrorism in the Muslim world: an empirical cross-sectional analysis. Terrorism and Political Violence, 2004; 16(2):253–273.

26. Gassebner M, Luechinger S. Lock, stock, and barrel: A comprehensive assessment of the determinants of terror. Public Choice, 2011; 149(3-4):235-261

27. Basuchoudhary A, Shughart WF II. On Ethnic Conflict and Origins of Transnational Terrorism. Defense and Peace Economics, 2010; 21(1):65-87

28. Li Q, Schaub D. Economic Globalization and Transnational Terrorism: a Pooled Time Series Analysis. Journal of Conflict Resolution, 2004; 48(2):230-258

29. Li, Q. Does Democracy Promote or Reduce Transnational Terrorist Incidents? Journal of Conflict Resolution, 2005; 49(2):278-297.

30. Blomberg BS, Hess GD, Weerapana A. Economic Conditions and Terrorism. European Journal of Political Economy, 2004; 20(2):463-478

31. Bueno de Mesquita E. The Quality of Terror. American Journal of Political Science, 2005; 49(3):515–530

32. Enders W, Hoover G. The Nonlinear Relationship Between Terrorism and Poverty, American Economic Review Papers and Proceedings: American Economic Review; 2012; Available online at http://www.vanderbilt.edu/AEA/, Last Accessed 01/23, 2013

33. Lai B. Draining the Swamp: An Empirical Examination of the Production of International Terrorism, 1968-1998, Conflict Management and Peace Science, 2007; 24(4): 297-310.

34. Cameron CA, Trivedi PK. Regression Analysis of Count Data. Cambrdge: Cambridge University Press. 1998

35. Stern J. Pakistan's Jihad Culture. Foreign Affairs, 2000; 79(6):115–26.

36. Enders W, Sandler T. Is Transnational Terrorism Becoming More Threatening? A Time-Series Investigation. Journal of Conflict Resolution, 2000; 44(3):307-332.

37. Ivanova K, Sandler T. CBRN Attack Perpetrators: An Empirical Study. Foreign Policy Analysis, 2007; 3:273-294

38. Wulf WA, Haimes Y, Longstaff TA. Strategic Alternative Responses to Risks of Terrorism. Risk Analysis, 2003; 23(3):429-444

39. Mickolus E, Sandler T, Murdock JM, Flemming P. International Terrorism: Attributes of Terrorist Events (ITERATE), 1968-2004. 2005; Vinyard Software, Dunn Loring, VA

40. Bird G, Blomberg BS, Hess GD. International Terrorism: Causes, Consequences and Cures, World Economy, 2008; 31(2):255-274

41. Sandler T, Enders W. An Economic Perspective on Transnational Terrorism. European Journal of Political Economy, 2004; 20(2):301-316

42. Enders W, Sandler T. The Effectiveness of Antiterrorism Policies: A Vector-Autoregression-Intervention Analysis. The American Political Science Review, 1993; 87(4):829-844

43. Mickolus E, Sandler T, Murdock JM, Flemming P. International Terrorism: Attributes of Terrorist Events. (ITERATE 4), Vinyard Software, Dunn Loring, VA. 1993

44. Mickolus E, Sandler T, Murdock JM. *International Terrorism in the 1980s: A Chronology of Events*. 2 vols. Ames: Iowa University Press. 1989

45. Heritage Foundation, Index of Economic Freedom. 2010. http://www.heritage.org/research/features/index/ (accessed, September 4th, 2010)

46. Wade RH. Is Globalization Reducing Poverty and Inequality? World Development, 2004; 32(4):567-589

47. Burgoon B. On welfare and terror: Social welfare policies and political-economic roots of terrorism. Journal of Conflict Resolution, 2006; 50(2):176–203.

48. Winkelmann R, Zimmermann KF. Recent Developments in Count Data Modeling: Theory and Application. Journal of Economic Surveys, 1995; 9(1):1-24.

49. Heilbron D. Zero-altered and Other Regression Models for Count Data with Added Zeros. Biometrical Journal, 1994; 36(5):531-547.

50. Welsh AH, Cunningham RB, Donnelly CD, Lindenmayer DB. Modeling the Abundance of Rare Species: Statistical Models for Counts with Extra Zeros. Ecological Modeling, 1996; 88(1):297-308.

51. Bohning D, Dietz E, Schlattmann P, Mendonca L, Kirchner U. The Zero-inflated Poisson Model and the Decayed, Missing and Filled Teeth Index in Dental Epidemiology. Journal of the Royal Statistical Society, Series A (Statistics in Society), 1999; 162(2):195-209.

52. Dalrymple ML, Hudson IL, Ford RPK. Finite Mixture, Zero-inflated Poisson and Hurdle Models with Application to SIDs. Computational Statistics and Data Analysis, 2003; 41(3-4):491-504.

53. Yip KCH, Yau KKW. On Modeling Claim Frequency Data in General Insurance with Extra Zeros. Insurance: Mathematics and Economics, 2005; 36:153-163.

54. Mullahy J. Specification and Testing of Some Modified Count Data Models. Journal of Econometrics, 1986; 33(3):341-365

55. Hu TW, Sung HY, Keeler TE. Reducing Cigarette Consumption in California: Tobacco Taxes vs. an Anti-smoking Media Campaign. American Journal of Public Health, 1995; 85(9):1218-1222.

56. Wasserman J, Manning WG, Newhouse JP, Winkler JD. The Effects of Excise Taxes and Regulations on Cigarette Smoking. Journal of Health Economics, 1991; 10(1):43-64.

57. Heckman JJ. Sample Selection Bias as a Specification Error. Econometrica, 1979; 47(1):153-161

58. Greene WH. Account for excess zeros and sample selection in Poisson and Negative Binomial Models. Working Paper no. EC-94-10, Department of Economics, Stern School of Business, New York University. 1994

59. Ivanova K, Sandler T. CBRN Incidents: Political Regimes, Perpetrators and Targets, Terrorism and Political Violence, 2006; 18(3):423-448.

60. Bernholz P. Supreme Values as the Basis for Terror. European Journal of Political Economy, 2004; 20(2):317-333

61. Azam JP, Delacroix A. Aid and the Delegated Fight Against Terrorism. Review of Development Economics, 2006; 10(2):330–344

62. Azam JP, Thelen V. The Roles of Foreign Aid and Education in the War on Terror. Public Choice, 2008; 135:375-397

63. Stiglitz J. Globalization and its Discontents, W.W. Norton and Company Inc. new York, N,Y. 2002

64. Lambert D. Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing. Technometrics, 1992; 34(1):1-14.

65. Cheung YB. Zero-inflaated models for regression analysis of count data: a study of growth and development, Statistics in Medicine, 2002; 21:1461–1469

66. Vuong QH. Likelihood Ratio Tests for Model Selection and Non-nested Hypotheses, Econometrica, 1989; 57(2):307-333.

Table I. Number of terrorism incidents and participation counts

	Terrorism incidents		Terrorism participation counts	
	With known nationalities only	Including unknown nationality	With known nationalities only	Including unknown nationalities[a]
Documented				
Total	5,504	8,162	5,731	15,461
During 80s	3,038	4,651	3,170	10,346
During 90s	2,466	3,511	2,561	5,115
Study sample				
Total	2,677		2,748	
During 80s	1,493		1,542	
During 90s	1,184		1,206	

[a] Terrorism events with unknown nationalities of perpetrators involve those incidents for which the number of participating nationalities was documented, however the identity of those nationalities was not known

Table II. Summary statistics of social-economic variables

Variable name	Variable definition	Mean	SD	Min.	Max.
Income measures					
GDP	GDP per capita ($1,000)	6.62	8.86	0.07	44.76
GINI	GINI index (0=perfectly equality; 1=perfectly inequality)	0.40	0.11	0.19	0.74
PV1	population ratio living under $1 per day	0.11	0.15	0.00	0.71
PV12	population ratio living on $1 to $2 per day	0.15	0.15	0.00	0.57
Education measures					
Literacy	population ratio who can read and write	0.82	0.20	0.29	1.00
Primary	percent of labor force with primary education as the highest achieved	0.38	0.18	0.03	0.85
Secondary	percent of labor force with secondary education as the highest achieved	0.29	0.19	0.00	0.79
Tertiary	percent of labor force with tertiary education as the highest achieved	0.15	0.11	0.00	0.54
Religion measures					
Christianity	Christian population ratio	0.63	0.37	0.00	1.00
Islam	Muslim population ratio	0.18	0.32	0.00	1.00
Hinduism	Hindu population ratio	0.02	0.10	0.00	0.81
Buddhism	Buddhist population ratio	0.05	0.19	0.00	0.95
Other religion	population ratio with other religions	0.07	0.09	0.00	0.66
No religion	population ratio with no religions at all	0.06	0.15	0.00	0.94
Other variables					
Unemployment	unemployment rate	0.09	0.06	0.00	0.36
Openness to trade	(export+import)/GDP)	0.67	0.52	0.09	4.97
Freedom	economic freedom (1=highest economic freedom; 5=lowest economic freedom)	3.01	0.64	1.80	4.78
Population (1,000 million)	Total population of a nation	0.06	0.17	0.00	1.26

Table III. Average annual participation in transnational terrorism events from 1980 to 2000

Country	Average No.	Country	Average No.
Albania	0.67	Lithuania	0.00
Algeria	3.81	Luxembourg	0.05
Argentina	1.48	Malaysia	0.05
Armenia	0.10	Mexico	0.43
Australia	0.24	Morocco	0.52
Azerbaijan	0.24	Mozambique	2.67
Belgium	0.90	Namibia	0.10
Bangladesh	0.19	Netherlands	0.24
Bolivia	0.81	Nicaragua	1.24
Brazil	0.38	Nigeria	1.10
Bulgaria	0.05	Norway	0.05
Cambodia	3.71	Pakistan	1.90
Canada	0.48	Panama	0.90
Chile	2.81	Paraguay	0.00
Czech Republic	0.00	Peru	8.00
Colombia	17.71	P.R. China	0.81
Costa Rica	0.43	Philippines	8.86
Croatia	0.05	Poland	0.52
Denmark	0.19	Portugal	2.10
Dominican Rep.	0.38	Rep. of South Africa	2.38
Ecuador	0.71	Romania	0.19
El Salvador	4.86	Rwanda	0.52
Estonia	0.00	Slovak Rep.	0.05
Ethiopia	1.76	Slovenia	0.00
Finland	0.00	Spain	8.10
France	4.10	Sri Lanka	1.52
Georgia	0.33	Sweden	0.29
Ghana	0.00	Thailand	0.38
Guatemala	2.90	Trinidad and Tobago	0.05
Honduras	2.29	Tunisia	0.67
Hungary	0.00	Turkey	10.76
India	2.67	Uganda	0.76
Indonesia	1.52	Ukraine	0.14
Ireland	0.43	United Kingdom	0.62
Japan	2.10	United States	4.48
Jordan	2.24	Uruguay	0.05
Kyrgyzstan	0.00	USSR/Russia	1.90
Latvia	0.05	Venezuela	0.57
		West Germany	10.86

Table IV. Observed and predicted frequencies of the annual counts of terrorism events

Actual counts		*Predicted counts*		
Observed counts	Frequency (percent)	Count range	ZINB	PFENB
0	832 (59.30)	[0,0.5)	368 (26.23)	502 (35.78)
1	240 (17.11)	[0.5, 1.5)	469 (33.43)	784 (55.88)
2	94 (6.70)	[1.5, 2.5)	219 (15.61)	112 (7.89)
3	52 (3.71)	[2.5, 3.5)	92 (6.65)	5 (0.36)
4	40 (2.85)	[3.5, 4.5)	105 (7.48)	0 (0.00)
5	25 (1.78)	[4.5, 5.5)	47 (3.35)	0 (0.00)
6+	120 (8.55)	[5.5, $\propto$)	103 (7.34)	0 (0.00)
Total	1403		1403	1403
Ratio of correct prediction			0.33	0.60

Note: Figures in the parenthesis are percentages and figures above the parenthesis are frequencies. The actual event counts for each observation are integers. However, the predicted event counts are not necessarily integers. To facilitate comparison between predicted and actual counts we use symmetric ranges, as shown in the third column, to round the predicted counts to corresponding integers.

Table V. Results from Zero-inflated Negative Binomial and Panel Fixed Effects Negative Binomial models

	ZINB Model					
	Inflation		NB-frequencies		PFENB Model	
	Estimate	Std.	Estimate	Std.	Estimate	Std.
	1	2	3	4	5	6
GDP per capita ($1,000)	-0.46**	(0.18)	0.24***	(0.05)	0.10*	(0.05)
Square of GDP per capita	0.005	(0.01)	-0.01***	(0.00)	-0.002*	(0.001)
Gini index	-4.31	(3.26)	8.42***	(1.14)	1.73	(1.53)
pv1	30.18***	(4.87)	3.19***	(0.92)	-2.18***	(1.00)
pv12	-15.43***	(4.19)	2.18**	(0.91)	2.68**	(1.19)
Literacy	23.42***	(6.06)	4.23***	(0.65)	-0.29	(0.96)
Primary education	-6.82***	(2.58)	0.09	(0.56)	1.35*	(0.71)
Secondary education	0.81	(2.27)	1.77***	(0.63)	0.25	(0.75)
Tertiary education	-7.62***	(2.67)	-2.28***	(0.78)	1.07	(0.94)
Christian	1.26	(3.03)	2.79***	(0.77)	1.39	(1.09)
Hindu	83.16***	(10.96)	2.51***	(0.58)	1.68***	(0.89)
Buddhist	-3.36	(4.06)	3.87***	(0.84)	1.87	(1.19)
Muslim	4.1	(3.03)	5.41***	(0.75)	0.96***	(1.02)
Other religions	14.10***	(3.29)	10.47***	(1.19)	3.44***	(1.56)
Unemployment rate	-18.94***	(5.27)	3.18***	(1.09)	3.61***	(1.33)
Openness to trade	0.37	(0.50)	-0.58***	(0.17)	-0.66***	(0.24)
Freedom index	-2.64***	(0.84)	0.91***	(0.24)	0.59***	(0.24)
Population (Billion)	-87.52***	(10.93)	1.78**	(0.71)	-0.13	(0.10)
Decade (1=1990s)	0.64	(0.41)	-0.46***	(0.11)	-0.45***	(0.09)
Constant	-7.77	(5.97)	-14.12***	(1.76)	-4.97***	(2.00)
Dispersion parameter (α)			1.80***	(0.13)		
No. of observations (countries)	1403(77)				1268(67)	
Log likelihood	-1969				-1589	
Wald chi2(19) [p-value]	177.73 [0.00]				83.36[0.00]	
H_0: $\beta_s > \beta_p$	$\chi^2(1)=12.4$[0.00]				$\chi^2(1)=2.88$[0.04]	
H_0: $\beta_s > \beta_t$	$\chi^2(1)=18.6$[0.00]				$\chi^2(1)=0.61$[0.78]	

Model selection statistics

Likelihood ratio test — NB vs. Poisson: $\bar{\chi}^2 = 4122$[0.00] — ZINB vs. ZIP: $\bar{\chi}^2 = 187$[0.00]

Vuong test — ZIP vs. Poisson: Z=6.19[0.00] — ZINB vs. NB: Z=4.70[0.00]

AIC: $AIC_{PFENB} < AIC_{ZINB} < AIC_{NB} < AIC_{ZIP} < AIC_{Poisson}$ (3218<4020 < 4226 < 6216 < 8347)

Correct prediction ratio: PFENB>ZINB>NB>Poisson>ZIP (60%>33%>24%>23%>22%)

Asterisks (*, **, ***) indicate 10%, 5%, and 1% significance levels. Numbers in brackets are p-values for different statistical tests. AIC stands for Akaike's Information Criteria, pv1 and pv12 stand for the proportion of population living on less than one dollar per day, and the proportion of population living on between one and two dollars per day respectively A reduced sample size was used in the PFENB model due to lack of variability in the dependent variable for ten countries with no documented participation.

Table VI. Estimation results using the expanded dataset of 97 countries

	ZINB Model		
	Inflation	NB	PFENB Model
GDP per capita ($1,000 in 2000 US$)	0.21***	0.05**	0.01
	(0.07)	(0.02)	(0.02)
Square of GDP per capita	-0.005**	-0.002**	-0.004
	(0.017)	(0.015)	(0.001)
Decade (1=1990s)	1.07***	-0.29***	-0.45***
	(0.29)	(0.11)	(0.07)
Population (Billion)	-110.37***	0.23	-0.17
	(22.04)	(0.36)	(0.42)
Primary education	2.35	0.26	1.20***
	(2.58)	(0.37)	(0.43)
Secondary education	9.61***	2.59***	0.51
	(2.23)	(0.45)	(0.49)
Tertiary education	-9.27**	-3.29***	-0.68
	(4.00)	(0.65)	(0.68)
Constant	-3.59*	0.62***	-0.63
	(2.18)	(0.23)	(0.25)
Dispersion parameter		1.07***	
		(0.07)	
No. of observations	1902 (97)		1628 (82)[1]
Log likelihood	-2647		-1988
H$_0$: $\beta_s > \beta_p$	$\chi^2(1)$=27.80 [0.00]		$\chi^2(1)$=1.79[0.90]
H$_0$: $\beta_s > \beta_t$	$\chi^2(1)$=43.28[0.00]		$\chi^2(1)$=1.75[0.10]

Model selection statistics

Likelihood ratio test: NB vs. Poisson: $\bar{\chi}^2 = 7196$[0.00] ZINB vs. ZIP: $\bar{\chi}^2 = 200$[0.00]

Vuong test: ZIP vs. Poisson: Z = 7.75[0.00] ZINB vs. NB: Z = 8.00[0.00]

AIC: $AIC_{PFENBB}<AIC_{ZINB}<AIC_{NB}<AIC_{ZIP}<AIC_{Poisson}$ (3992<5328<5582<8762<12776)

Correct prediction ratios: PFENB>ZINB>NB>ZIP>Poisson (25%>24%>13%>12%>11%)

Asterisks (*, **, ***) indicate 10%, 5%, and 1% significance levels. Numbers in the parenthesis are standard deviations; and numbers in brackets are p-values for likelihood ratio and Vuong tests. AIC stands for Akaike's Information Criteria.

[1] 15 countries (274 country-year observations) are dropped from the fixed effect NB model because of all zero outcomes.

Figure 1. The Procedure to check for model specification among the Poisson, NB, ZIP and ZINB models

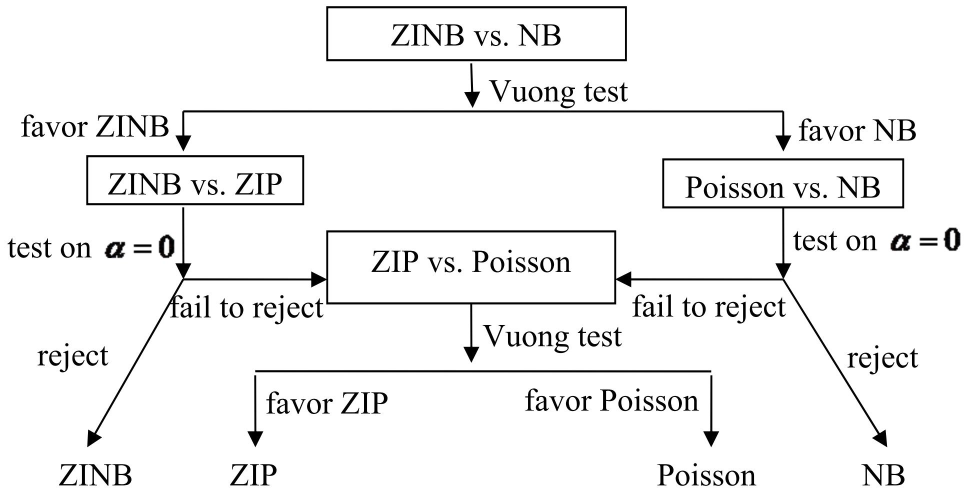
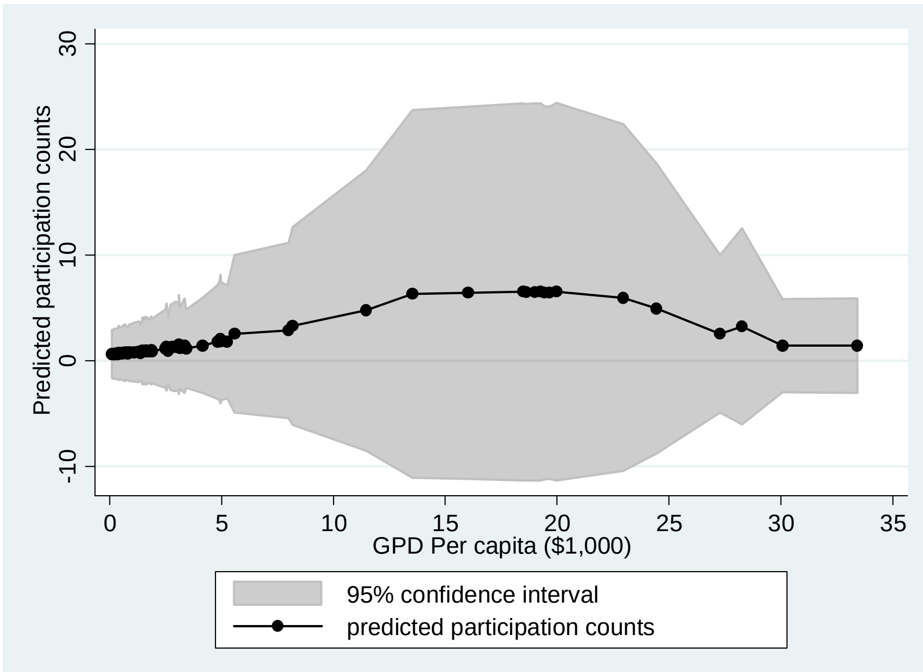
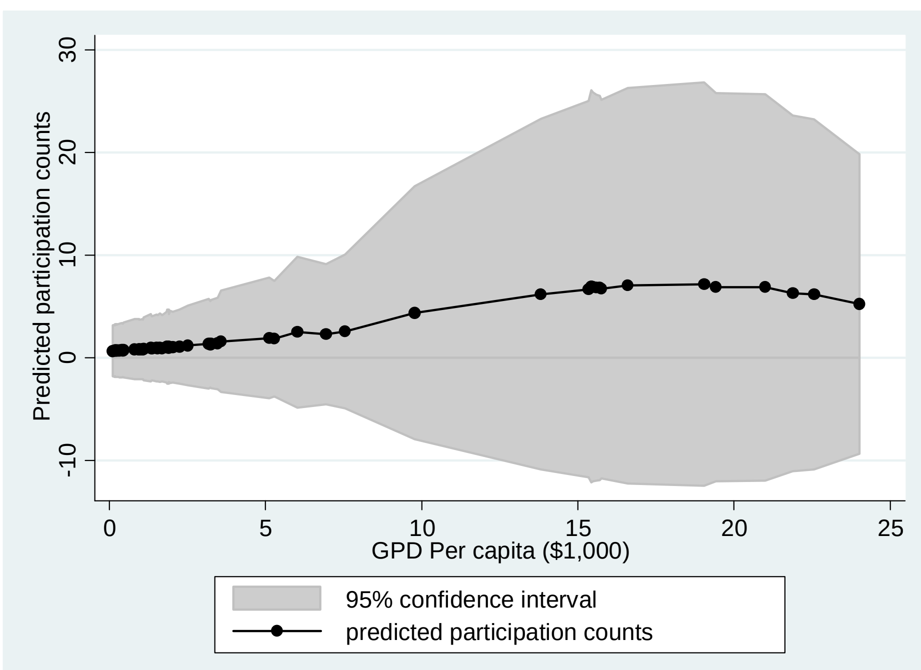


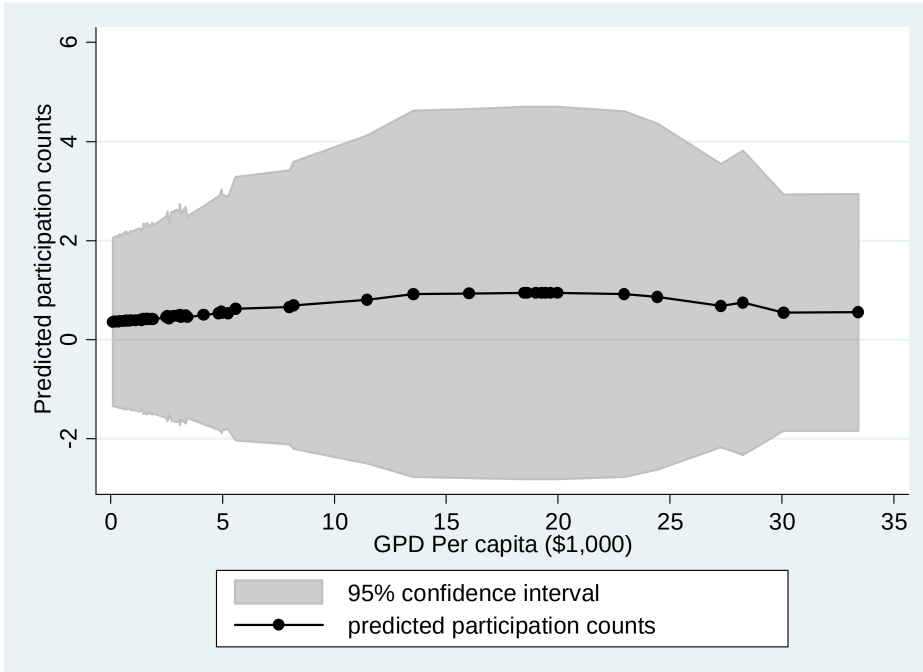
Figure 2. The association between GDP per capita and counts of participation in transnational terrorism events with associated confidence bounds at 95% significance. Results are presented for ZINB and PFENB specifications for 1980s and 1990s.



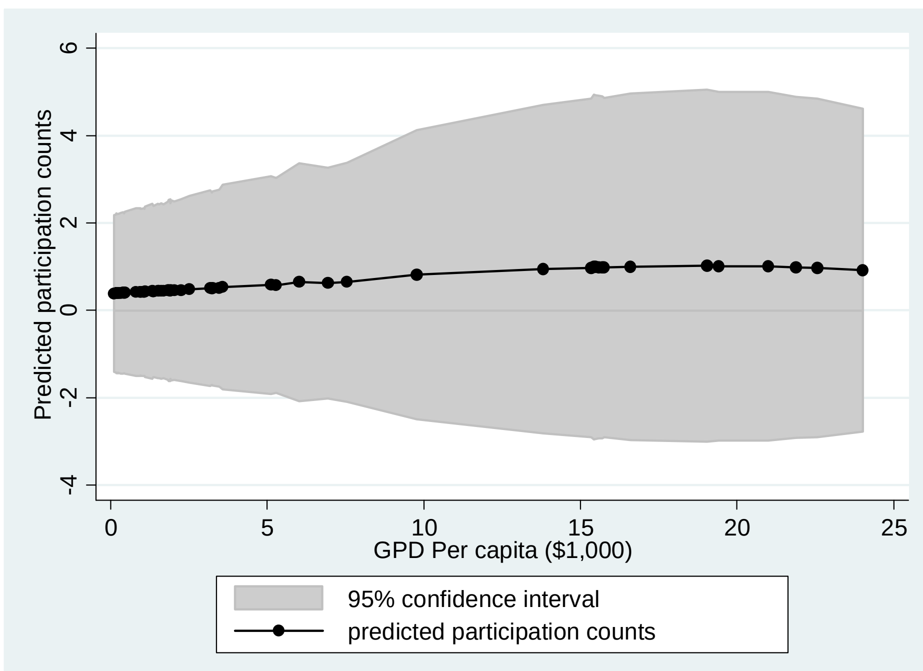
(a) Results of ZINB in 1990s



(b) Results of ZINB in 1980s



(c) Results of PFENB in 1990s



(d) Results of PFENB in 1980s

Appendix A

In a basic Poisson regression model with a logarithm link function, the number of events *y* for individual *i* has a Poisson distribution with a conditional mean λ_i depending on individual *i*'s characteristics, x_i:

(1) $\lambda_i(x_i) = E(y_i \mid x_i) = \exp(x_i \beta)$,

where β is a vector of unknown coefficients associated with the covariate vector x_i. For convenience of notation, we drop x_i in $\lambda_i(x_i)$ and use λ_i below. The probability density function of *y* given *x* is

(2) $$f(y_i \mid x_i) = \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!}.$$

The NB model adds an error term ε, to the conditional mean of the Poisson distribution to model the unobserved heterogeneity,

(3) $E(y_i \mid x_i) = \exp(x_i \beta + \varepsilon_i)$.

where $\exp(\varepsilon_i)$ is normally assumed to follow a gamma distribution with mean one and variance α. The probability density function of *y* given *x* now becomes

(4) $$f(y_i \mid x_i) = \frac{\Gamma(y_i + 1/\alpha)}{y_i!\Gamma(1/\alpha)} \left(\frac{1}{1+\alpha\lambda_i}\right)^{1/\alpha} \left(\frac{\lambda_i}{1/\alpha + \lambda_i}\right)^{y_i}.$$

The conditional mean and variance of y_i under the NB model are

(5-1) $E(y_i \mid x_i) = \lambda_i$ and

(5-2) $VAR(y_i \mid x_i) = \lambda_i(1 + \alpha\lambda_i)$.

where, α is the variance of gamma distribution and indicates the degree of over-dispersion. As α becomes larger, the distribution will be more dispersed. As α gets close to zero, the NB model converges to the Poisson model. The Poisson and NB models are nested, and a statistical rejection of the null hypothesis of $\alpha = 0$ will favor NB over Poisson specification.

Lambert [64] first introduced ZIP model as

$$(6)\quad \begin{array}{lll} y_i = 0 & \text{with probability} & \pi_i \\ y_i \sim \text{Poisson}(\lambda_i) & \text{with probability} & 1\text{-}\pi_i\ (y_i = 0,1,2,...) \end{array}$$

The probability of having an extra zero which is not subject to the Poisson distribution, π_i, is assumed to have a logit function (7). The unobserved probability π_i is generated as a logistic or probit function of observable covariates to ensure nonnegativity. The choice between logit and probit is usually unimportant since the two functions are similar and usually give very similar results.[65]

$$(7)\quad \pi_i = \frac{\exp(z_i\gamma)}{1 + \exp(z_i\gamma)},$$

where z_i is a vector of observable covariates and γ is a vector of coefficients associated with z_i. The mean and variance of y_i in the ZIP model are

$$(8\text{-}1)\quad E(y_i \mid x_i) = (1 - \pi_i)\lambda_i \text{ and}$$

$$(8\text{-}2)\quad VAR(y_i \mid x_i) = \lambda_i(1 - \pi_i)(1 + \lambda_i\pi_i).$$

Equations (8-1) and (8-2) show that $\frac{\pi_i}{1 - \pi_i}$ indicates the degree of over-dispersion. As π_i approaches zero, the ZIP model converges into the Poisson model.

Similarly, to account for individual heterogeneity and excess zeros simultaneously, ZINB model [34, 58] with a logit link function is used. The mean and variance of y_i under the ZINB model are

(9-1) $\quad E(y_i \mid x_i) = (1-\pi_i)\,\lambda_i$ and

(9-2) $\quad VAR(y_i \mid x_i) = \lambda_i(1-\pi_i)(1+\lambda_i(\pi_i+\alpha))$.

Equations (9-1) and (9-2) show that $\frac{\pi_i + \alpha}{1-\pi_i}$ reflects the degree of over-dispersion in the ZINB models, which accounts for over-dispersion from both zero inflation and unobservable heterogeneity.

The Poisson and ZIP models are not nested, and neither are the NB and ZINB models. Vuong [66] (1989) proposed a likelihood ratio test for non-nested models, and Greene [58] adapted the technique for the cases of ZIP versus Poisson, and ZINB versus NB models. The test statistic is

(10) $$Z = \frac{\sqrt{N}\,\overline{m}}{s_m},$$

where $\overline{m}$ and s_m are the mean and standard deviation of m_i and N is the number of observations. m_i is defined as $m_i = \ln\frac{\hat{p}_1(y_i \mid x_i)}{\hat{p}_2(y_i \mid x_i)}$ where $\hat{p}_1(y_i \mid x_i)$ and $\hat{p}_2(y_i \mid x_i)$ are the predicted probabilities from the competing models. Asymptotically, Z has a standard normal distribution, with large positive values (>1.96) favoring the zero-inflated model and with large negative values (<-1.96) favoring the nonzero-inflated model at a 5% significance level.