Near East Demographics and Terrorism

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Abstract This paper analyzes the probable change in the incidence of terrorist events due to demographic factors for the Near East Region. I first present the predominant literature view that poverty, income inequality, and cultural differences are not important factors impacting the number of terrorist acts. I then analyze the specific demographic characteristics of cultural fractionalization, income inequality, purchase price parity, and literacy fractions. The main contribution of this paper is statistical analysis of these demographic factors for the Near East subset of countries. The evidence of my analysis suggests that those countries with above average regional values for the female literacy fraction and the male literacy fraction are more likely to suffer from a terrorist attack. Additional findings support the general notion that cultural fractionalization, income inequality and per-capita national output appear to be unrelated to terrorism event risk.
Note: All tables are in the Appendix to this article.

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I. Introduction

Intuitively, differences between citizens and socioeconomic status may seem to be underlying motivations for an individual's willingness to participate in violent terrorism. One might first envision an individual or group with aggregated grievances that originate from dissimilarities in culture, income, and/or overall poverty levels (Kilcullen, 2004, p. 13). In order to bring attention to a specific complaint an aggrieved party may pursue increasingly more violent actions if local methods fail to redress the concerns. Then, because individuals practice selective disengagement of moral self-sanctions when they carry out activities that further their interests (Bandura, 1990, p. 161-162), the ultimate step might entail terrorism as the tactic to solicit international attention. The hypothetical case presented here is an example of terrorism motivated by situation (Blazakis, 2013).

Although it could be argued that society has the moral imperative to explore complaints that bring about resentment and resulting terrorism (Richardson, 2006, p. 220), the innate "rooted-in-poverty" hypothesis (Piazza, 2006, p. 160), which blames demographics, is often an oversimplification. The notion that poor countries are fertile grounds for terrorism due to a wide margin between the rich and poor, a low level of educated people, and high illiteracy rate (Piazza, 2006, p. 160) may appeal to policy makers because it necessitates a familiar political or regulatory mode of action; however, it is contradicted by the empirical research about the socioeconomic factor effect on the occurrence of terrorism.. There is little support for links between poverty, employment, and GDP growth to terrorism (Krueger, 2008, p. 1-2; Piazza, 2006, p. 160-161). Further, the banal conclusion that the terrorists "'hate our way of life and freedom'" (Krueger, 2008, p. 2) does not stand up to the evidence. Notably, this sentiment may be intended only to stifle additional discourse (Stritzke, 2009, p. 319).

Risk Factors

Setting explicit causation aside, the aforementioned issues are still considered "risk factors" that may lead to local support of terrorism by the increasing feelings of alienation (Richardson, 2006, p. 57). So what are the theoretical connections between demographic characteristics and terrorism? Are these connections substantiated by the evidence?

Starting with poverty: if the level of output per person (e.g., GDP per capita) and terrorism were directly related then the poorest countries in the most underprivileged of regions would experience a disproportionately high number of events relative to the richer parts of the world (Richardson, 2006, p. 56). Yet the continent of Africa is not inundated by attack (Richardson, 2006, p. 55). In fact, higher income countries are most often democracies and this form of government facilitates "dissident groups" to commit acts of violent terrorism to whatever ends they desire (Eubank and Weinberg, 2001, p. 163).

Income inequality may be seen as a measure of economic grievance (Fearon and Laitin, 2003, p. 88). Consequently, higher economic inequality should arguably translate into an increased risk of terrorism. As a result, per the previous logic, Latin America and Africa should suffer a higher proportion of terrorism due to their high rates of income inequality, but these countries do not (Richardson, 2006, p. 56). Moreover, inequality is a suboptimal indicator of risk for civil insurgency (Fearon and Laitin, 2003, p. 88), to which terrorism could be viewed as a subordinated tactic. In a conflicting study involving 85 countries for the four-year period from 1973-1977, the empirical analysis suggested that income inequality was a predictor of political violence (Muller and Seligson, 1987, p. 444).

Another demographic factor that could relate to the motivations for terrorism includes the nexus between culture, religion, and ethnicity. Extensive research has led to the conclusion that ethnic differences, religious diversity, or general cultural factors do not make a country more prone to civil war (Fearon and Laitin, 2003, p. 75). If terrorism is considered a tactic of a local insurgency, then the same diversity conclusion can be drawn regarding terrorism.

Religious fundamentalism is not seen as a cause of terrorism (Richardson, 2006, p. 68), but may provide the moral justification to the consequentialist end. It follows that a "culture of violence" (Richardson, 2006, p. 68) ordained by "God" may assist in sustaining a terrorist organization through ideological alignment of its membership (Richardson, 2006, p. 68). For example, the Tamil Tigers secular group in Sri Lanka used suicide bombing outside of a religious setting (Juergensmeyer, 2006, p. 137). Again, religion is not necessarily causal in the event of suicide bombings, but is exploited as the means of promised reward in the afterlife. Indeed, religion may be the impacted "victim" of extremist groups whose deviation from the core tenets may not resemble the popular faith at all (Juergensmeyer, 2006, p. 136).

Terrorist Motivations and Assumptions

Understanding the motivations for terrorism is a key component of a successful counterterrorism strategy. In the face of contrary evidence from the literature (Krueger and Maleckova, 2003, p. 30-31), I explore the potential relationship between demographics and terrorism using two different variables than previous research: cultural fractionalization and purchase price parity. Additionally, I regionally cluster observations to a subset of countries that have a high number of terrorist incidents relative to the rest of the world for the 1970-2010 time period. This combination of observations by country and year is intended to expose patterns which may only exist for a region over a specific and continuous time. Interestingly, research shows the predominant pattern of the attacker and terrorism victim hailing from the same democratic country (Eubank and Weinberg, 2001, p. 161). Likewise, another study finds that, "88 percent of the time, terrorist attacks occur in the perpetrators' country of origin [which]… implies that most international terrorism is in fact local" (Krueger, 2008, p. 71). Due to the high incidence of terrorism carried out by domestic actors I have aggregated the demographic details to the country level. My research question is the following:

Among the northern African and Middle East countries, which intra-country people characteristics affect the incidence of terrorist events? That is, are there characteristics of the populations being attacked that indicate a susceptibility to attack?

My model to explore this topic comprises a generalized linear model with a negative binomial regression using maximum likelihood estimation versus least squares because the data panel is not normally distributed (Pearce and Schafer, 1986, p. 977).

II. Data

The data compiled for my research represents a balanced panel for the following countries: Algeria, Djibouti, Egypt, Eritrea, Israel, Jordan, Lebanon, Libya, Morocco, Saudi Arabia, Somalia, Sudan, Syria, Tunisia, and Yemen. These countries were selected for analysis based on a high level of terrorist activity, the continuity of the panel, rich variation in the demographic covariates within and between countries, and spatial proximity to the economically important Mediterranean Sea and Panama Canal. An effort was made to minimize heteroskedasticity across the longitudinal panel data set by including only covariates that depend on the observed and discrete country populations. Table 1 summarizes the panel data structure.

Response Variable

The dependent variable terrorist events (counts) consists of nonnegative integers such as the values 0, 1, and 2. The terrorist events observations are taken from the Global Terrorism Database (GTD) for the years between 1970 and 2010 (National Consortium, 2012). The GTD definition of a terrorist attack is defined as, "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation" (National Consortium, 2012). Accordingly, each terrorist event count follows the attributes defined by the GTD criteria (National Consortium, 2012). I assume the terrorism events are carried out by local terrorists against their local countrymen for 100% of the time versus the previous research finding of 88% (Krueger, 2008, p. 71). This imposed assumption permits the analysis of national population characteristics relating to the perpetrators and also the victims.

Demographic Characteristics

The demographic characteristics are considered both subject- and occasion-specific covariates (Rabe-Hesketh and Skrondal, vol. I, 2012, p. 234). These variables span the entire 1970 – 2010 year horizon unless otherwise identified.

1. Cultural Fractionalization

Culture, religion, and ethnicity are difficult to disaggregate because the classification of people into groups lacks a definitive criteria. This is a criticism of the ethno-linguistic fractionalization (ELF) index. Improved categorization of individuals within groups relies on language analysis rather than the constructivist assignment of populations to ethnic groups (Laitin and Posner, 2001, p. 14). Language and culture often go hand-in-hand. Hence, the overarching cultural umbrella could encompass ethnic, language, and religion.

In an attempt to overcome the criticism of the ELF index, cultural differences are captured within the cultural fractionalization (CF) index based on structural language differences (Laitin and Posner, 2001, p. 13). The CF is taken from two sources (Fearon, 2003, p. 215-219; Alesina,, Devleeschauwer, Easterly, Kurlat, and Romain, 2003). The CF is incorporated as an explanatory variable, versus the ethnolinguistic fractionalization index (ELF) for reasons mentioned before. Note that Malta and Qatar use a CF comprising the average of language and religion fractionalization because these countries were omitted from the original fractionalization analysis (Alesina et al., 2003). The CF is a dummy variable coded to 1 if the country observation by year is above the regional CF mean (0.2508667) and 0 otherwise.

2. Religious Fraction

According to the current definition for terrorism in the GTD, terrorist attacks are foremost political. The religious fraction contribution to the incidence of terrorist attack is implicitly assumed to be captured by the CF covariate.

3. Literacy Fraction

The demographic data including education is for adults only with the imposed assumption that adults are the perpetrators of terrorism. Children are included within the calculations of GDP per capita as well as the linearly similar income inequality variable (i.e., Gini index). However, the inclusion of the infant and school-age data with the Gini index resulted in a multicollinearity concern where the standard error of the estimators was large. Therefore, the literacy fraction-by-gender contains only the percentage of the population older than 15 years who can read (Worldbank, 2010). These two variables are the averaged combination of all present observations by country. Separate variables indicate the fraction-by-gender to facilitate covariate analysis per group. The variables are LITF and LITM with "F" indicating female and "M" meaning male. Each variable is coded as a dummy variable with 0 showing an observation above the mean (0.3342308 for females, 0.6742308 for males) and a 1 demonstrating an annual country observation lower than the regional mean. These variables are proposed as a potential proxy for education in the absence of available data.

4. Purchase Price Parity Index

To maintain non-varying comparisons between countries, the purchase price parity index (PPP) is used at current prices. The PPP index is derived from GDP per capita, is inflation adjusted, and is in the units of International dollars ($I) (Heston, Summers, Aten, 2012). This is a dummy variable constructed so that the value 0 means less than the mean (4259.12) and the value 1 indicates greater than the mean for all observations.

5. Income Inequality

The Gini index represents income inequality as a relative and not absolute measure based on comparisons of the varying proportions of income at specific levels (United Nations University, 2008). Hostile feelings between differing socioeconomic classes may escalate into conflict if the unequal rights distribution is considered illegitimate (Coser, 1956, p. 37). The Gini is fixed to the average of all available year observations (United Nations University, 2008). Note that the Gini coefficient used for Eritrea is set equal to the Gini for Djibouti due to an unavailable index and because the two countries were similar in other demographic features. The Egyptian Gini is used for Libya and Saudi Arabia for the same reasons. The Syrian Gini is an average of the Turkey and Lebanon Gini index values. The Gini is a dummy variable coded to 1 if the country observation by year is above the Gini mean (41.54) and 0 if below the mean for the region. Note that Table 2 shows the correlation between selected variables and is included because Gini and PPP both use GDP as an input to their derivation.

6. Total Years of Education

The data for the average years of education by gender, for individuals over 15 years old, is incorporated into the present research (Worldbank, 2010) as part of the robustness of the results analysis. This data is available from the year 1990 through 2010 in five year increments and is interpreted as a moving five-year average. The variable names are EDUF and EDUM where "F" means female and "M" indicates the male covariate. The dummy variable coded observations with a 0 show an observation above the mean (3.631264 for females, 5.262572 for males) and a 1 shows a below the overall regional mean value. Of note, available research suggests that education does not have a causal impact on terrorism at the country level (Krueger and Maleckova, 2008, p. 30-31).

III. Methodology and Model Specification

The data panel was first modeled using a Poisson distribution because the terrorist event observations, occurring on a continuous time continuum, were aggregated to yearly intervals from 1970 through 2010 for each country. The count variable y takes on nonnegative integer values only such that (y>0) R (Wooldridge, 2002, p. 472). The explanatory vector x contains the observed variables by country. The pure Poisson models that I tested violated the requisite distribution assumption that the conditional variance must equal the mean (equation 3.1).

$$Var(y| x)=E(y| x). \quad (3.1)$$

The model was then re-specified using the negative binomial from the Generalized Linear Models (GLM). This model uses a specific parameterization of the negative binomial distribution, which brings the model Pearson statistic to approximately one (Woolridge, 2002, p. 736). A fixed overdispersion parameter is included to capture variation in the data falling outside of the stricter Poisson distribution (Gelman and Hill, 2007, p. 114). Statistical fit using the Bayesian Information Criteria (BIC) and the log-likelihood function was used for model comparison.

In this random effects pooled negative binomial model, i represents the time interval whereby y_it terrorist events are observed over a yearly period t, x_it is 1×K vector of the observed explanatory variables (i.e., CF, PPP, Gini, LITF, and LITM) with unity as the first element, β_o is a K×1 vector, and c_i>0 is the unobserved heterogeneity (Woolridge, 2002, p. 758-9). The model form is given below:

$$y_i | x_i ,c_i \sim \text{Poisson}[c_i m(x_{it},\beta_o)], \quad (3.2)$$

$$m(x_{it},\beta_o)= \exp(x_{it},\beta_o), \quad (3.3)$$

c_i is independent of x_i and distributed as Gamma(δ_o,δ_o). (3.4)

The Gamma distribution is parameterized such that $E(c_i)=1$ and $Var(c_i)=1/\delta_o= \eta_o^2$, and y_i conditional on x_i is distributed according to the negative binomial (Woolridge, 2002, p. 726, 737, 760). The estimated overdispersion scalar parameter does not depend on the observed variables because no model variation is accounted for by this variable (Hardin and Hilbe, 2012, p. 292).

IV. Results

The log-linked negative binomial model consists of exponentiated coefficients (Hardin and Hilbe, 2012, p. 265). Interpretation of the coefficients is equivalent to that of the incidence-rate ratio (IRR) originating from the traditional Poisson model (Hardin and Hilbe, 2012, p. 257). This means that for every one point change in the covariate, the response variable (terrorist event count) increases by the estimated IRR (Hardin and Hilbe, 2012, p. 265). My empirical results, shown in Table 3, suggest that countries with a female literacy fraction above the regional mean are approximately nine and one half times as likely to suffer a terrorist attack (Gelman, 2007, p. 326-327). The probability of a terrorist event increases about fourfold for an above average male literacy fraction. A cultural fractionalization index larger than regional average increases the likelihood of in-country terrorism by roughly two-thirds of one percent. I consider this last result a negligible and non-contributing factor to the incidence of terrorism even in the presence of statistical significance to the 0.01 level. The Gini and PPP variables are considered non-contributory to the terrorism event risk from the regression statistics.

My outcomes support the general findings from the literature that cultural fractionalization (and perhaps ELF insofar as it is related to CF), income inequality, and level of national income per person are not necessarily important factors which impact the number of terrorist events for a given country within the studied region.

Robustness of the Results

The terrorist attacks occur in continuous time and the separation of country observations aggregated to an annual total is a form of interval-censoring (Rabe-Hesketh and Skrondal, vol. II, 2012, p. 743-747). The present paper is an observational study and the countries are assumed to be at risk for a terrorist incident prior to the analyzed time period. However, countries that did not experience a terrorist attack are included within the sample period and the conditional survival hazard is not required (Rabe-Hesketh and Skrondal, vol. II, 2012, p. 772). Another consideration is that the analyzed time period may omit structural changes present over a different time horizon. Additionally, any covariates missing from the model may cause inconsistency in the maximum likelihood estimators of the model (Woolridge, 2002, p. 469).

Both of the aforementioned structural and covariate omissions may be tested by constraining the era and by including other explanatory variables. The total education years separated by gender are included within the original model for the restricted period of years 1990 through 2010. In addition, the robustness check model uses a new overdispersion scalar parameterization appropriate to the inclusion of more information to the previously specified model.

The robust model demonstrates a better model fit as indicated by the decreased Bayesian Information Criteria (BIC) statistic when compared to the original model specification (Rabe-Hesketh and Skrondal, vol. I, 2012, p. 324). The original model specification was chosen for the increased panel observations present per year with the implicit assumption of increased model power (Rabe-Hesketh and Skrondal, vol. 1, 2012, p. 168-171) and because 20% of the country panel data for the years of education spanning 1970 through 1989 are unavailable. The new robust model appears to validate that years of education is an omitted covariate and thus the original model IRR estimates should be downward biased. The results of the robust model support this because the estimated IRRs for both the female and male literacy fractions are higher for the new model. Notably however, the standard errors of the IRR estimators are smaller for the first model with confidence intervals that almost contain the robust model values. I think that the robust model results confirm the original model fit to the data and are also an improvement in model specification. Note that my proposed use of literacy fraction as an indirect proxy for education is proven to be an incorrect assumption for the original specification.

Prospective Confounds

1) "A common statistical error is to summarize comparisons by statistical significance and to draw a sharp distinction between significant and non-significant results" (Gelman, 2007, p. 222-223). This warning is heeded within this paper by considering the feasibility of the estimates. For example, the IRR coefficient for cultural fractionalization appears statistically significant, but is impractically small in magnitude and thus not considered a factor in relation to the incidence of terrorist attack for an individual country or for the region.

2) ELF or CF does not account for changes over time, which could present incorrect regression coefficients. This may lead to consistent, but biased estimation of the relationship between diversity and the incidence of terrorism. However, the data set is considered large enough to provide a directional indication of the impact of a country's demographic mixture on the number of events. Moreover, this type of index has been used in the same manner in previous research (Fearon and Laitin, 2003, p. 79).

3) Income inequality shows some variation from

year-to-year. With the Gini index averaged across all years, no targeted interpretation on individual year contributions to the likelihood of terrorist event occurrence may be made. Future year-by-year forecasts of terrorism are beyond the scope of the present research, but would be an area for future research.

4) The somewhat strong assumption that the terrorism perpetrators are citizens of the country that they attack versus the 88% from the literature (Krueger, 2008, p. 71) potentially omits heterogeneity which may arise between the terrorists and the domestic population. This assumption of homogeneity means that estimates must be interpreted relative to the regional covariate mean summed across all countries. Moreover, the country-level aggregation of demographics imposes the further assumption that the terrorists are a representative sample of the population (e.g., middle class and better educated than the average person). This may remove variation and make my model less sensitive to capturing other demographic characteristics relevant to the incidence of terrorism.

V. Conclusion

Differences between people and groups of people, which may be perceived as unjust, are likely contributing factors motivating both individuals and groups to take up terrorism to meet objectives such as grievance. There is a difference between causality, statistical empiricism, and the determination of risk factors. For that reason a "one-size-fits-all" conclusion on terrorism motivations may be unwarranted based on my present research.

The results of my research points to a relationship between above average literacy fraction and the incidence of terrorism for a regional time-series data panel. The positive relationship between terrorism and both female and male literacy may result from a terrorist recruiting selection effect. This explanation coincides with prior research where, at least for suicide attacks, the literacy rate is a "positive predictor of suicide attacks" because terrorist organizations recruit from among the better educated and wealthier candidates with the assumption that these demographic characteristics reveal higher competencies (Piazza, 2008, p. 37). However, the increased likelihood of terrorism resulting from the higher female literacy fraction, relative the male literacy portion, is more difficult to explain. An argument about the openness of a country's society could made here to connect higher female literacy to a rise in the number of terrorist attacks. That is, a country with more literate women may be less hostile towards female participation within the political arena and therefore more susceptible to the coercive punishment provided by terrorism. The appeal of this explanation is that it complements the prior research result that democracies present a higher terrorist attack risk (Eubank and Weinberg, 2001, p. 161, 163).

While other research at the global level (Fearon and Laitin, 2003) runs counter to my findings, there could be structural differences at a regional level yielding indications of terrorist events prior to occurrence. For instance, it could be that demographic factors presented at a point in time and across a specific region increase the probability of terrorism for the reasons that I have presented. Alternatively, my research could suffer from selection bias caused by the a priori knowledge that multiple terrorist events occurred across the Near East region within a specified time period. In either case, my results cast doubt on the out-of-hand dismissal of demographic factors.

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Appendix

TABLE 1: PANEL DATA SUMMARY

Characteristic		Mean	Std. Dev.	Min.	Max.
Terrorist Event	overall	13.72358	36.40142	0	344
	between		20.30267	0.219512	63.78049
	within		30.65482	-50.0569	293.9431
Cultural Fractionalization	overall	0.250867	0.179909	0	0.698
	between		0.186072	0	0.698
	within		1.60E-16	0.250867	0.250867
PPP	overall	4259.12	5255.744	186.02	29376.05
	between		4707.931	407.8734	14044.11
	within		3009.81	-6934.58	19591.06
Gini	overall	41.54	5.819404	32.9	54.5
	between		6.018756	32.9	54.5
	within		2.52E-14	41.54	41.54
Literacy Fraction - female	overall	0.334231	0.049712	0.269	0.457
	between		0.051693	0.269	0.457
	within		2.47E-16	0.334231	0.334231
Literacy Fraction - male	overall	0.674231	0.037231	0.601	0.741
	between		0.038715	0.601	0.741
	within		4.96E-16	0.674231	0.674231
Total Education - female	overall	3.631264	2.896801	0.01	11.5
	between		2.494136	0.576342	10.05366
	within		1.650362	-0.008	8.351996
Total Education - male	overall	5.262572	2.691763	0.09	11.24
	between		2.402897	1.795854	10.62732
	within		1.408868	2.259645	8.346718

TABLE 2: CORRELATIONS BETWEEN SELECTED CHARACTERISTICS

	CF	Gini	PPP
CF	1.0000		
Gini	0.1646	1.0000	
PPP	- 0.0716	- 0.2850	1.0000

TABLE 3: ORIGINAL MODEL: NEGATIVE BINOMIAL REGRESSIONS (COUNTRY-LEVEL DATA)

Dependent Variable: Number of Terrorist Events Originating from Each Country, 1970-2010

Explanatory Variable	IRR (above mean)
Intercept	2.62
	(2.95)
Cultural Fractionalization	0.07**
	(-8.91)
Gini	1.56
	(1.67)
PPP	1.38
	(1.39)
Literacy Fraction – female	9.42**
	(7.06)
Literacy Fraction – male	4.12**
	(5.45)
P-Value for Cultural Fractionalization	0.00
P-Value for Gini	0.094
P-Value for PPP	0.17
P-Value for Literacy Fraction – female	0.00
P-Value for Literacy Fraction – male	0.00
Log Likelihood	-1589
Sample Size	615

* Statistically significant at .05 level.

** Statistically significant at .01 level.

TABLE 4: ROBUST MODEL: NEGATIVE BINOMIAL REGRESSIONS (COUNTRY-LEVEL DATA)

Dependent Variable: Number of Terrorist Events Originating from Each Country, 1990-2010	
Explanatory Variable	IRR (above mean)
Intercept	3.85
	(3.68)
Cultural Fractionalization	0.13**
	(-5.59)
Gini	0.77
	(-0.88)
PPP	1.30
	(0.90)
Literacy Fraction – female	12.31**
	(7.30)
Literacy Fraction – male	4.27**
	(4.98)
Years of Education – female	0.80
	(-0.45)
Years of Education – male	1.09
	(0.16)
P-Value for Cultural Fractionalization	0.00
P-Value for Literacy Fraction – female	0.00
P-Value for Literacy Fraction – male	0.00
Log Likelihood	-976
Sample Size	615

* Statistically significant at .05 level.

** Statistically significant at .01 level.