Jake Hawkesworth
Applied Econometrics Final
December 13, 2012

A Replication of Alan Krueger's What Makes a Terrorist?

Introduction

It is often assumed by politicians, academics and policy-makers that terrorists come from under-privileged backgrounds. But is this true? Post-9/11 research, perhaps most notably the work of the 9/11 Commission Report, shows that the who designed and carried out the terrorists who successfully attacked the United States in 2001 were in fact individuals from wealthy backgrounds.

Alan Krueger addresses the question What Makes a Terrorist? as the title of his book from 2007. Using a wide variety of descriptive and statistical techniques and data, he argues that poverty is not caused by terrorism. The focus of this replication is part of a chapter of the book where he addresses the economic foundations from which terrorism emerges. Here, Krueger uses data from the US State Department to create country pairs of every combination of nations in the world. Using these pairs as his unit of observation, he hypothesizes that when countries have lower GDP, they are more likely to spawn terrorists, who, if not poor themselves, are likely to be motivated to action by the poverty of their countrymen. The number of international terrorist events between any set of two countries between 1997 and 2003 is the dependent variable, and log GDP per capita of the terrorist home (origin) country is the independent variable of interest. Krueger uses a negative binomial regression model to test this causal relationship, and he succeeds in disproving his hypothesis. He then concludes that poverty cannot be assumed to be a cause of terrorism, and the burden of proof ought to be on those who claim a causal relation.

This book is based in a number of Krueger's earlier papers. The book, as well as these earlier studies, spawned extensive qualitative criticism in academic circles. But Krueger's work has nonetheless been cited and used by policy-makers to affect American foreign policy. The implications of such an argument are indeed quite serious: not only does it suggest that fighting global poverty is not a good way for America to protect its national security, it also suggests that cross-cultural education is not important for fighting poverty. Krueger may not have intended to argue against fighting poverty and education, but nonetheless, it is not a far jump for conservative policy-makers and politicians to make.

One major contribution which Krueger made through this book was the improvement of the US State Department's statistical reporting. In the process of researching this paper, Krueger identified startling discrepancies and problems with State Department record keeping, and is right to conclude from his paper that having a Statistical Bureau in the State Department would be an important and positive step.

Krueger's substantive findings are less impressive. The paper suffers from two major short-comings. The first is a methodological issue: Why would poverty in one country cause a terrorist count in another nation? Rather, what we would expect to find is that the discrepancy between poverty levels between two nations might inspire a terrorist to attack another country. Thus the log GDP per capita difference between origin and target is much more important, as an independent variable, than is the specific log GDP per capita of the origin or target nation.

With country pairs as the unit of observation, cross-national variables are important confounding factors in the causality story – but such variables are few and far between in Krueger's dataset. More specifically, I identify the second major shortcoming of Krueger's study to be its lack of a history of war variable, which relates the two countries in a pairing. This is a confounding factor of great importance. If there was ever a war between the two countries, this would doubtlessly impact the terrorist event count, as well as the log GDP of the origin nation – richer nations, data in this replication shows, are more frequently involved in warfare.

Alternative specifications of the model are run, in answer to these shortcomings as well as to perform some basic robustness tests, including standard error clustering problems, a zero inflation negative binomial, and a poisson model. We find Krueger's model to be robust to only two of these five alternative specifications. In the remaining three alternative specifications, we fail to reject the null hypothesis that poverty causes terrorism.

Data

This dataset includes one observation for each set of two countries, totaling at 21,462 observations with usable data. Each observation includes country-specific data from the 'origin' country and from the 'target' country, as well as some connecting variables (such as the terrorist events count, and the distance between the two countries). Human rights ratings for the origin/target nations are also included in each observation. The terrorist events count, the dependent variable of interest, includes terrorist events from 1997 to 2003. 956 terrorist events are included in the dataset.

Krueger's data comes from the United States State Department's National Counter-Terrorism Center (NCTC). 'Target' is defined as nationality of people most affected by the attack, not necessarily the country where the attack occurred. The terrorist event count is defined as "premeditated politically motivated violence, perpetrated against non-combatant targets by sub-national groups or clandestine agents, usually intended to influence an audience. The term 'international terrorism' means "terrorism involving citizens or the territory of more than one country" (qtd. in Krueger p54). Countries with under 1 million citizens were dropped.

The major problem with the dataset is that there are major outliers which are difficult to effectively code. Events in Israel relating to the West Bank/Gaza were dropped, due to problematic coding, and events the State Department treated as domestic (within India) are recoded as events originating from Pakistan targeting India. Columbia has one of the highest terrorist event counts, and many of these events could be argued to be domestic. The dataset's validity is somewhat substantiated with its high correlation with other datasets, such as University of Southern California's ITERATE data (Krueger "Kto Kogo").

Krueger's cleaned dataset and Stata .do file was publicly available through Princeton University's DataSpace database ("What Makes a Terrorist? Appendix 2.1"). To account for omitted variable bias, I added data from the “Militarized Interstate Dispute Data” dataset, which is a part of the larger Correlates of War (COW) project. The data was compiled by Faten Ghosn and Glenn Palmer at Pennsylvania State University. Country paired data is provided, along with dispute numbers for each specific international war a set of countries was involved in. The data covers wars from 1816-2003. From this dataset, I took only one variable, and this was a warfare indicator dummy, which is coded as 1 if the set of nations had a war between 1816 and 2003, and 0 if otherwise. 7,868 of the 21,256 wars included in the dataset were between only two countries, while the rest involved 3 nations or more.

Model and Replication

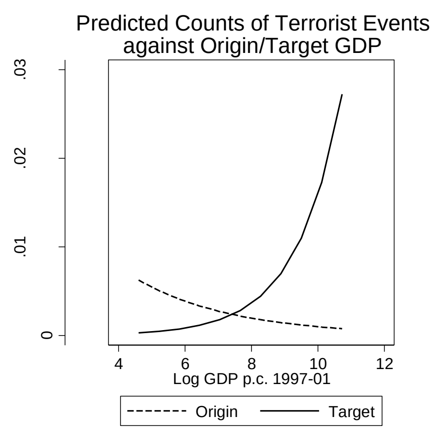
Krueger’s study (see Appendix 2) includes three negative binomial regressions. One includes only 4 controls, the second has 6 controls, and the third has 15 controls.

$$E\left(y_{ij} \mid x\right) = \exp(x_{ij}'\beta_1 + x_i'\beta_2 + x_j'\beta_3)$$

y_{ij} is the terrorist event count by terrorists from country *i* on people of country *j*. *x* is the explanatory variables (*i* for the origin country variables, *j* for the target country variables).

Using Krueger’s cleaned data and his uploaded .do file, I was able to recreate Krueger’s process and obtain identical results to those he published in Appendix 2.1. These results are printed in the attached Appendix 2.

Krueger’s results are displayed graphically on the right (this is my own graph – it is not exhibited in any of Krueger’s papers on this subject). The graph shows the predicted count of terrorist events across origin country’s log GDP per capita as a dotted line. The solid line is the equivalent finding for the target nation. The coefficients which these graph reflect are significant at the 5% level in the case of the target nation, and insignificant in the case of the origin nation. This means that we can say with 95% confidence that the data for the target line is reflective of the linear model presented, but not in the case of the dotted line. Using this information, and by comparing the size of the shown effect of target versus origin country data, Krueger concludes that the economic story of terrorism is in the target nation, not in the origin nation.



Alternative Specifications

Difference log GDP – Perhaps the biggest issue with the above model is that one cannot simply stratify the variables by country when looking for a causal relationship between event counts and economic foundations of terrorism. Using descriptive statistics, it might be important to note, as Krueger does, that target nations log GDP per capita is highly correlated with terrorism event counts, but origin nations log GDP per capita is not (reasons for this are discussed in the 'Findings' section). But from a perspective of identifying a causal relationship, it does not make any sense to separate the log GDP per capita of origin and target nations into two distinct variables. Neither the poorness of the origin country nor the richness of the target country in and of itself could cause terrorism: it is the relative levels of poverty which might be seen as inequality, and could breed hatred. Thus for this specification, the origin and target country log GDP per capita variables is replaced with a single variable, which is the log of the absolute value of the difference between raw GDP per capita of origin and target nations[1].

War Omitted Variable Bias – Another key problem with Krueger's model is that it lacks a variable for whether or not the two nations have a history of warfare. International wars often result in feuds and ill-will between nations which can last for centuries, and this ill-will could well present itself on the sub-national level. Furthermore, a history of warfare between two countries would be correlated with log GDP per capita rates, because richer countries more frequently involve themselves in international wars.

History of International War Stratified by log GDP per capita quartiles

	% Nations with history of warfare
Low log GDP	7%
Mid log GDP	12%
High log GDP	14%

The table to the left gives summary statistics which indicate this relationship between GDP and involvement in international wars. Stratifying by log GDP per capita, this table gives the percentage of origin/target countries which had a history of international warfare. We see that among the country pairings where origin and/or target nations have low log GDP per capita, only 7% of the time, was there a history of war with the other country in the pair. This statistic increases as we move up the log GDP per capita quartile range, indicating richer countries are twice as prone to involvement in war.

Because poorer countries are less likely to involve themselves in wars, to exclude this war indicator variable would also make it appear that they involved themselves in fewer terrorist events. Krueger does include a variable of 'occupied' and 'occupier' – that is, has the origin country ever been occupied by any other nation, and has the target country ever occupied another nation. But this is not specific to the country pairing and thus does not get at the omitted variable bias.

To add this variable to the model, it first had to be added to the dataset. The data was added from the Correlates of War (COW) "Militarized Interstate Dispute Data" dataset, as described in the above section. An indicator variable was used, which would list whether the two nations had ever been involved in a dispute.

Robustness Checks

Poisson Count Model Regression – Generally speaking, the most simple possible regression model ought to be considered before more complex specifications. The Poisson model is simpler than the negative binomial type regression, as it sets the model's variance equal to its mean. The alpha value of the Negative Binomial regression models which Krueger runs range from 22 to 28, and the magnitude of these values indicate that a Poisson model would suffer from overdispersion. While the Poisson model is not the most appropriate model for this analysis, it is an appropriate robustness.

Zero-Inflation Negative Binomial Regression – The zero inflation model mitigates the regression results in response to overly large zero counts in count model datasets such as the one used here. It allows for the model to take into account that the reason for a count to take a value of 0 as opposed to a value of 1

[1] A number of other methods were attempted, including log-ratios and interaction terms. This approach was most effective in obtaining meaningful results.

may be different than the reason for the count to take a value of 1 as opposed to 2, or 2 as opposed to 3. For this robustness check, the history of warfare dummy is used as the inflator. The logic in this choice is that countries with a history of war between them are more likely to have a count different from zero, but the history of war may have a more minor impact on the magnitude of the count after it surpasses the zero value.

Two-way clustering of standard errors – Because each country and the associated country-level data is repeated 149 times in the origin target and 149 more times in the target capacity, the standard errors are thrown off by more than just one variable. Krueger clusters for the origin country, but negative binomial regression models are difficult for two-way clustering. To check if this omission in the model is acceptable, I created an indicator variable for whether there was a count of 1 or greater terrorist events. I then ran a basic Ordinary Least Squares regression using two way clustering.

Findings

Log GDP Differencing – Trading origin and target log GDP per capita for a single differenced variable in each of Krueger's three regressions, the log GDP per capita difference is statistically significant at the 5% level in all but the third regression (see Appendix 1, Table 1). The incidents-rate ratios for this regression indicate that controlling for other factors, for a 1 unit change in log GDP difference per capita, there is a 6.3% to 30.7% increase in the predicted rate of terrorist event counts. In our first two regressions, we have reasonable certainty around this finding; for example, in the first regression, with minimal controls, the differenced GDP incidents-rate ratio falls between 23% and 38.4%. In the second regression, the range is 4.85% to 15.95%. The third regression's finding is statistically insignificant. Nonetheless, given the other two findings and the substantial size of these ratios, we can see this is a meaningful finding, and the log GDP difference per capita has a statistically significant effect.

Given that Krueger found a strong positive relationship between log GDP per capita and target country, it is not surprising that when this variable is folded back in to a differenced variable, that variable appears significant and large. Nonetheless, correlation is no substitute for theory, and there is no clear logic to Krueger's decision to separate out these variables.

Krueger of course did separate these variables for a reason, and from a descriptive statistics perspective, it is an interesting finding that origin country GDP is uncorrelated with terrorist activity, whereas target country GDP is highly correlated. This indicates that outliers, or countries where there are extremely high counts of terrorist activity, are not necessarily among the poorest of the poor. The data itself indicates this; Colombia, India, and Pakistan and India are not rich countries, but they are also not among the world's poorest, as would be the case with high levels of correlation.

The real question we seek to address is whether or not terrorists are more likely to strike out at countries that are significantly richer, when controlling for factors such as religion and civil liberties. The level of GDP a rich country is able to achieve is limitless, while the level of GDP a poor country can sink to is limited. The more absurdly rich a nation, the more likely said nation is to be targeted. The more absurdly poor a nation, a reciprocal effect cannot be expected. By separating the GDP into origin and target variables, then, Krueger is not breaking the variable down into its key components; rather he is breaking a variable down into factors that confound the results.

War Omitted Variable Bias – The inclusion of this warfare indicator variable brings statistical significance to the origin log GDP per capita variable in equations where it was insignificant in the original regressions (See Appendix 1, Table 1). The first regression's origin log GDP per capita beta coefficient becomes statistically significant at the 5% level, and the second and third regressions reach marginal significance. The incidents-rate ratios for the first regression indicates that controlling for other factors, for a 1 unit increase in origin log GDP per capita, there is a 21.6% to 34.2% decrease in the predicted rate of terrorist event counts. For the second regression, the ratio indicates a 7.04% to 22.8% decrease, and for the third regression 11.4% to 34% decrease.

This indicates that the origin GDP explanatory variable was picking up noise from history of warfare between the two nations. As illustrated above, richer nations participate in more wars, and more history of warfare leads to more terrorist activity between nations. That including this variable would decrease the origin nation log GDP per capita beta coefficient from -0.245 to -0.327 (see Appendix 3, Table 4), and decrease the error, indicates that the intervening warfare variable was stifling the predicted terrorist event count for poorer nations.

Two-Way Robust Clustering and Ordinary Least Squares Regression – The robustness check of two-way clustering and Ordinary Least Squares, as expected, increased standard error and erased the effect. While the effect is statistically significant at the 5% level in one of the three regressions, it is not significantly different from zero (see Appendix 3). This does not conflict with Krueger's original results in a substantial way; his major finding, after all, is the lack of a relationship. I believe this is at least partially because a straight-line regression line is inappropriate for this dataset, where there is exponential growth present.

Zero-Inflation Negative Binomial Regression – Krueger's model does not stand up to the Zero-Inflation Negative Binomial model, as he himself mentions in his paper. The Zero-Inflation method finds a strong negative relationship between origin nation log GDP per capita and terrorist event count, at the 5% level of statistical significance, across all three regressions (see Appendix 3). The incidents-rate ratios for the first regression indicates that controlling for other factors, for a one unit increase in origin log GDP per capita, there is a 29.2% to 43.6% decrease in the predicted rate of terrorist event counts. For the second regression, the ratio indicates a 5.62% to 23.6% decrease, and for the third regression 20.4% to 42.4% decrease.

This model indicates that a poorer country may not be much more likely to have a count of one than a count of zero, but once they have a count of one, the poorer they are the more likely they are to have a count higher than one. If a reader accepts the premise of the Zero Inflation method, then this seriously calls into question Krueger's findings. For a tangible example of the reason for using the Zero Inflation method, consider the case of Sweden and South Korea. If, for whatever reason, these two seemingly unconnected nations had a history of a war between them, then that would drastically increase their likelihood of having had at least one terrorist event in their history, but it would not significantly increase their likelihood of having two versus three events. For this reason, it makes sense to take this robustness check seriously.

Poisson Model – The Poisson model yields very similar results to Krueger's original model (see Appendix 3). In one of the regressions, origin log GDP per capita reaches a marginal level of significance, but this is not an important finding, particularly given the extensive limitations of the Poisson model.

Conclusion

In the end, neither Krueger's analysis nor this replication will get a 'yes' or 'no' answer to the question, "Does poverty induce terrorism?" At best, the answer will land somewhere on a spectrum: 'poverty plays a substantial role,' or 'there is no reason to believe there is a strong connection.' In Robert Pollin's critique of another Krueger study on the same question, he writes, "Krueger and Maleckova are themselves clear that relatively privileged people are drawn to terrorism because they hold strong political convictions. These convictions do not arise from thin air" (Pollin Contours of Descent pg.48). No statistical analyses can fully disentangle the way poverty plays into terrorists' political convictions.

Krueger's analysis here purports to provide a glimpse of where these political convictions rise from, by looking for trends in where terrorists come from and where they attack. But even here, serious limitations and generalizations are unavoidable. For example, Pan-Arabism plays a crucial role in terrorism and poverty for an entire region of countries observed. Many nations of this region have a count of greater than one in their pairings. Systematic control of variables cannot get at the complexities of Pan-Arabism's connection with terrorism and poverty, particularly when the question is secondary to a broader research question, as is the case here. It is important to remember that quantitative work in this field, particularly on a world-wide scale, has inherent limitations.

Nonetheless, Krueger's analysis ought to be taken seriously. It has impacted policy-making and political discourse: he cast doubt on a causal relationship which many politicians and policy-makers took for granted. Controlling for other variables, Krueger finds a strong positive relationship between terrorist event counts and log GDP per capita with target countries, and only an insignificant, near-zero relationship between terrorist event counts and log GDP per capita with origin countries.

This replication illustrates clearly why Krueger obtains this result, and why policy-makers should not doubt that fighting poverty will reduce terrorism. In this replication, I find there is a major omitted variable bias which is having a dampening effect on the relationship between terrorist event counts and origin country poverty levels. I also find that when looking at relative levels of poverty between nations which are paired, rather than absolute levels of poverty of origin nations, a strong relationship is apparent. Finally, this replication shows that when controlling for zero inflation by using an adjusted count model, the relationship between origin nation log GDP per capita and terrorism is again visible.

This leads to the conclusion that Krueger's original findings and analyses, while interesting, are tied to flaws in the modeling and are therefore insubstantial. Given the limitations discussed earlier, exhaustive research on this topic is probably not merited. However, there are some possible extensions worth considering. For example, the use of Foreign Direct Investment (FDI) values in country pairings could present a good alternative dependent variable for analysis. An indicator variable for a target nation's ownership of military bases in a given origin nation might also be a useful control to consider.

Appendix 1

Table 1: Origin log GDP per capita Terrorist Event Incident-Rate Ratios by Regression

	Reg. 1	Reg. 2	Reg. 3
GDP differencing	1.307**	1.104**	1.063
	(0.0767)	(0.0555)	(0.0636)
War OVB	0.721**	0.851*	0.773*
	(0.0630)	(0.0786)	(0.113)
Zero Inflation	0.636**	0.854	0.686**
	(0.0720)	(0.0898)	(0.110)
Poisson	0.689**	0.736	0.924
	(0.109)	(0.158)	(0.199)
Robust Clustering[2]	-0.0017**	-0.0000568	-0.00122
	(0.000701)	(0.000835)	(0.00138)
Original	0.783**	0.918	0.828
	(0.0703)	(0.0913)	(0.127)

Table 2: Target log GDP per capita Terrorist Event Incident-Rate Ratios by Regression

	Reg. 1	Reg. 2	Reg. 3
GDP differencing	1.307**	1.104**	1.063
	(0.0767)	(0.0555)	(0.0636)
War OVB	1.771**	1.557**	1.548**
	(0.0981)	(0.0915)	(0.107)
Zero Inflation	2.190**	1.523**	1.560**
	(0.333)	(0.162)	(0.164)
Poisson	3.399**	1.0327	1.129
	(0.746)	(0.157)	(0.105)
Robust Clustering[2]	0.00638**	0.00513**	0.00609**
	(0.00193)	(0.00142)	(0.00168)
Original	1.889**	1.652**	1.646**
	(0.0822)	(0.882)	(0.101)

Reading the above tables: Robust standard errors in parentheses. ** indicates statistical significance at the 5% Level, * at the 10% level. Columns indicate which of Krueger's 3 Regressions is being replicated (Krueger gives three regressions in order to vary the number of controls he uses), the row represents the alternative specification of that regression which is being run. Krueger's original results are listed in the 'Original' row. Details about the method used in creating and running the alternative specifications can be found in the "Alternative Specifications" and "Robustness Checks" sections of this paper.

[2] The Robust Clustering Regressions listed here are Ordinary Least Squares, and thus do not have Incidents-Rate Ratios. Thus the beta coefficients and standard errors are listed instead.

Appendix 2 (Krueger's Original Appendix 2.1)

Table 3: Negative Binomial Regressions for Number of International Terrorist Incidents with Origin-by-Target-Level Data

Explanatory Variable	(1)	(2)	(3)
Intercept	-24.711	-24.878	-26.411
	(1.919)	(2.308)	(2.637)
Distance between Origin	-0.262	-0.254	-0.233
and Target Country	(0.049)	(0.048)	(0.046)
Volume of Trade per Capita	---	---	-0.750
			(0.650)
Different Predominant	---	---	-0.600
Religion			(0.239)
Origin Country's Variables			
Log Population	0.418	0.395	0.614
	(0.090)	(0.101)	(0.108)
Log GDP	-0.245	-0.085	-0.189
Per Capita	(-0.090)	(0.099)	(0.153)
Low Civil Liberties	---	0.251	0.270
(7=low; 1=high)		(0.092)	(0.124)
Proportion Muslim	---	---	-0.028
			(0.641)
Proportion Buddhist	---	---	-1.417
			(1.011)

Proportion Hindu		---	---	-2.475
				(1.003)
Proportion Other		---	---	-3.026
Religion				(1.669)
Female Illiteracy Rate		---	---	-0.002
(Percent)				(0.010)
Occupied				0.223
				(0.523)
Target Country's Variables				
Log Population		0.694	0.692	0.646
		(0.059)	(0.056)	(0.056)
Log GDP		0.636	0.502	0.498
Per Capita		(0.044)	(0.053)	(0.061)
Low Civil Liberties		---	-0.167	-.176
(7=low; 1=high)			(0.064)	(0.061)
Occupier	---	---	0.585	
				(0.224)
Pseudo-R^2	0.20	0.22	0.26	
Sample Size	22,052	21,462	17,802	

Notes: The dependent variable is the number of international terrorist events in the cell, 1997-2003. The mean (standard deviation) of the dependent variable is .03 (1.7). The average female illiteracy rate is 27.6 percent. GDP per capita is the average from 1997-2001, and is derived from World Bank data. The distance between countries is the distance between origin and target countries' capitals, measured in thousands of miles by the haversine formula. Average distance between capitals is 4,482 miles. Occupied is a dummy variable that equals 1 if the origin country is occupied by any another country; occupier is a dummy variable that equals 1 if the target occupies any country in the world. The sample excludes pairs in which the origin and target countries are identical. Standard errors that allow for correlated errors within country of origin are shown in parentheses.

Appendix 3

Table 4: Krueger Regression 1 Full Replication, plus Alternative Specifications

VARIABLES	(1) Original	(2) GDP Differencing	(3) War OVB	(4) Zero Inflation	(5) Poisson	(6) Robust Clustering
Intercept	-24.71***	-22.52***	-22.16***	-28.97***	-34.70***	-0.223***
	(1.919)	(1.619)	(2.110)	(1.796)	(3.892)	(0.0701)
Distance: Origin to Target Country	-0.262***	-0.245***	-0.211***	-0.352***	-0.591**	-0.00198***
	(0.0490)	(0.0430)	(0.0511)	(0.0408)	(0.283)	(0.000453)
History of Warfare			0.811***			
			(0.309)			
Log GDP Difference per Capita		**0.268*** **				
		(0.0587)				
Origin Country's Variables						
Log Population	0.418***	0.434***	0.373***	0.673***	0.592***	0.00494***
	(0.0902)	(0.0832)	(0.0916)	(0.0733)	(0.0933)	(0.00148)
Log GDP per Capita	**-0.245*** **		**-0.327*** **	**-0.453*** **	**-0.372*** **	**-0.00170** **
	(0.0898)		**(0.0874)**	**(0.0646)**	**(0.121)**	**(0.000701)**
Target Country's Variables						
Log Population	0.694***	0.626***	0.627***	0.784***	1.223***	0.00774***
	(0.0586)	(0.0453)	(0.0647)	(0.0569)	(0.229)	(0.00261)
Log GDP	0.636***		0.572***	0.657***	0.536***	0.00638***
	(0.0436)		(0.0554)	(0.0599)	(0.102)	(0.00193)
Observations	22,052	22,052	22,052	22,052	22,052	22,052
R-squared						0.029

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Krueger Regression 2 Full Replication, plus Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Original Column 2	GDP Differencing	War OVB	Zero Inflation	Poisson	Robust Clustering
Intercept	-24.88***	-21.29***	-22.27***	-29.80***	-29.37***	-0.227***
	(2.308)	(2.011)	(2.345)	(2.105)	(2.643)	(0.0677)
History of Warfare			0.788**			
			(0.306)			
Log GDP Difference per Capita		**0.0990****				
		(0.0503)				
Distance: Origin to Target Country	-0.254***	-0.251***	-0.208***	-0.347***	-0.587**	-0.00196***
	(0.0476)	(0.0431)	(0.0496)	(0.0407)	(0.250)	(0.000453)
Origin Country's Variables						
Log Population	0.395***	0.400***	0.337***	0.655***	0.616***	0.00463***
	(0.101)	(0.104)	(0.107)	(0.0730)	(0.127)	(0.00145)
Log GDP per Capita	**-0.0850**		**-0.161***	**-0.158****	**-0.307***	**-5.68e-05**
	(0.0994)		**(0.0923)**	**(0.0769)**	**(0.181)**	**(0.000835)**
Low Civil Liberties (7=low; 1=high)	0.251***	0.292***	0.254***	0.454***	0.118	0.00249**
	(0.0925)	(0.0841)	(0.0909)	(0.0717)	(0.123)	(0.00111)
Target Country's Variables						
Log Population	0.692***	0.692***	0.628***	0.777***	1.214***	0.00807***
	(0.0564)	(0.0467)	(0.0632)	(0.0573)	(0.218)	(0.00271)
Log GDP per Capita	0.502***		0.443***	0.421***	0.0322	0.00513***
	(0.0534)		(0.0588)	(0.0857)	(0.178)	(0.00142)
Low Civil Liberties (7=low; 1=high)	-0.167***		-0.159**	-0.295***	-0.804***	-0.00223*
		-0.519***				
	(0.0639)	(0.0738)	(0.0633)	(0.0786)	(0.257)	(0.00114)
Observations	21,462	21,462	21,462	21,462	21,462	21,462
R-squared						0.031

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Krueger Regression 3 Full Replication, plus Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Original Column 3	GDP Differencing	War OVB	Zero Inflation	Poisson	Robust Clustering
Intercept	-26.41***	-23.73***	-24.06***	-31.70***	-41.49***	-0.227***
	(2.637)	(1.853)	(2.773)	(2.450)	(4.218)	(0.0661)
Distance: Origin to Target Country	-0.233***	-0.233***	-0.199***	-0.336***	-0.552***	-0.00189***
	(0.0464)	(0.0454)	(0.0511)	(0.0440)	(0.121)	(0.000549)
Volume of Trade per Capita	-0.750	-0.661	-0.671	-1.133	-1.989***	-0.00829
	(0.651)	(0.524)	(0.628)	(0.720)	(0.718)	(0.00957)
Different Predominant Religion	-0.600**	-0.634***	-0.573**	-0.931***	-0.800***	-0.00158
	(0.239)	(0.239)	(0.236)	(0.233)	(0.242)	(0.00321)
History of Warfare			0.611**			
			(0.310)			
Log GDP Difference per Capita		**0.0615**				
		(0.0598)				
Origin Country's Variables						
Log Population	0.614***	0.623***	0.558***	0.761***	1.100***	0.00537***
	(0.108)	(0.113)	(0.110)	(0.0795)	(0.159)	(0.00161)
Log GDP per Capita	**-0.189**		**-0.257***	**-0.377*****	**-0.0796**	**-0.00122**
	(0.153)		**(0.146)**	**(0.110)**	**(0.123)**	**(0.00138)**
Low Civil Liberties (7=low; 1=high)	0.270**	0.353***	0.299**	0.480***	0.182	0.00262
	(0.124)	(0.0966)	(0.124)	(0.0981)	(0.114)	(0.00160)
Proportion Muslim	-0.0285	-0.327	-0.138	-0.0694	-0.338	-0.000185
	(0.641)	(0.551)	(0.624)	(0.424)	(0.575)	(0.00745)
Proportion Buddhist	-1.417	-1.433	-1.515	-2.378***	-2.501***	-0.0145*
	(1.011)	(1.002)	(1.022)	(0.749)	(0.670)	(0.00880)
Proportion Hindu	-2.475**	-2.377**	-2.138**	-3.037***	-10.61*	-0.0110
	(1.003)	(1.074)	(1.024)	(1.159)	(5.816)	(0.00713)
Proportion Other Religion	-3.026*	-3.127*	-3.084*	-3.087***	-5.105***	-0.0212
	(1.669)	(1.712)	(1.620)	(0.812)	(1.157)	(0.0133)
Female Illiteracy Rate	-0.00211	0.00521	-0.00260	-0.00954*	0.0268***	-6.66e-05
	(0.00978)	(0.00891)	(0.00946)	(0.00556)	(0.0104)	(0.000107)
Occupied	0.223	0.145	0.173	-0.0646	-0.720	0.0105
	(0.523)	(0.477)	(0.510)	(0.345)	(0.504)	(0.0117)
Target Country's Variables						
Log Population	0.646***	0.658***	0.599***	0.922***	1.288***	0.00779***
	(0.0558)	(0.0508)	(0.0655)	(0.0667)	(0.129)	(0.00217)
Log GDP per Capita	0.498***		0.437***	0.445***	0.121	0.00609***
	(0.0611)		(0.0689)	(0.0887)	(0.0885)	(0.00168)
Low Civil Liberties (7=low; 1=high)	-0.175***	-0.550***	-0.179***	-0.341***	-0.776***	-0.00253**
	(0.0611)	(0.0693)	(0.0592)	(0.0835)	(0.145)	(0.00120)
Occupier	0.585***	0.596***	0.516**	0.415	0.118	0.0201
	(0.224)	(0.231)	(0.221)	(0.258)	(0.259)	(0.0140)
Observations	17,802	17,802	17,802	17,802	17,802	17,802
R-squared						0.039

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 4

Table 7: Origin Log GDP Per Capita Marginal Effects Statistics, all else held at means

	Reg. 1	Reg. 2	Reg. 3
GDP differencing	0.0015	0.0002	0.0001
if count>1	0.0163	0.0061	0.0078
War OVB	-0.0011	-0.0004	-0.0005
if count>1	-0.0495	-0.0246	-0.0506
Zero Inflation	-0.0036	-0.0009	-0.0014
if count>1	-0.0824	-0.0311	-0.0844
Original	-0.0008	-0.0002	-0.0004
if count>1	-0.030	-0.0080	-0.0383

Table 8: Target Log GDP Per Capita Marginal Effects Statistics, all else held at means

	Reg. 1	Reg. 2	Reg. 3
GDP differencing	0.0015	0.0002	0.0001
if count>1	0.0163	0.0061	0.0078
War OVB	0.0014	0.0008	0.0006
if count>1	0.0667	0.0492	0.0616
Zero Inflation	0.0053	0.0025	0.0016
if count>1	0.1548	0.1058	0.1255
Original	0.0017	0.0011	0.0006
if count>1	0.0650	0.0489	0.0634

The above two tables show the Marginal Effects of first origin, then target log GDP per capita on the event count. These figures indicate the instantaneous change which results from a 1 unit increase in log GDP per capita. The rows with a clear background and a 'if count>1' heading represent the subsample where the count is greater than or equal to 1. They are otherwise calculated exactly the same as the row which directly precedes.

Words Referenced

Ghosn, Faten, and Glenn Palmer. *Militarized Interstate Dispute Data, Version 3.0*. Correlates of War 2 Project, 2003. Pennsylvania State University. Web. 12 Dec. 2012.

Kean, Thomas H., and Lee H. Hamilton. *9/11 Commission Report: Final Report of the National Commission on Terrorist Attacks upon the United States; with Interim Reports, Press Releases, and Index of the Final Report.* New York: Barnes & Noble, 2004. Print.

Krueger, Alan B. *What Makes a Terrorist? Appendix 2.1*. Princeton DataSpace, 2012. Web. 12 Dec. 2012.

--. *What Makes a Terrorist: Economics and the Roots of Terrorism*. Princeton: Princeton UP, 2007. Print.

Krueger, Alan B., and David D. Laitin. "Kto Kogo?: A Cross-Country Study of the Origins and Targets of Terrorism." *Terrorism, Economic Development, and Political Openness*. Ed. Philip Keefer and Norman Loayza. New York: Cambridge UP, 2008. 148-73. Print.