INTERPOL's MIND/FIND network in curbing transnational terrorism

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Abstract

This paper investigates the role that the Mobile/Fixed INTERPOL Network Database (MIND/FIND) has played in the War on Terror. MIND/FIND allows countries systematically to screen people and documents at border crossings against INTERPOL databases. We find that, on average, countries using MIND/FIND in 2008 experienced 0.79 fewer transnational terrorist attacks per 100 million people than they would have experienced had they not used MIND/FIND, so that a country like France with a population above 64 million people would have had one half fewer transnational terrorist incidents, a sizeable proportional reduction of 39 per cent.

KEYWORDS: Treatment effects, MIND/FIND, INTERPOL, Counterterrorism, Transnational terrorism

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1 Introduction

The International Criminal Police Organization (INTERPOL) benefits member countries by coordinating their police efforts. Sandler, Arce, and Enders (2011) estimated that for every dollar invested in INTERPOL's counterterrorism activities, member countries receive $200 in average returns. This is a huge rate of return for public money. INTERPOL provides multiple services – e.g., police training, communication links, and coordinating the hunt for fugitives – to member countries. This paper focuses on one of these services – the control of transnational terrorism.

In 2005, INTERPOL introduced two networks, the Mobile INTERPOL Network Database (MIND) and the Fixed INTERPOL Network Database (FIND), which facilitate searches of people, motor vehicles, and documents at international transit or other points. The main difference between these networks is that FIND allows access to an online database, which is continously updated, whereas MIND provides access to an offline database, which is periodically downloaded in an updated form.

These technologies may be effective at curbing international crime and transnational terrorism, however, as of December of 2008 only 47 of the then 188 INTERPOL member countries had adopted these technologies. The associated crime-fighting transnational externalities derived from MIND/FIND were not fully internalized by member countries. In order to understand the reasons for these unexploited benefits, Enders and Sandler (2011) studied why some countries chose to join the MIND/FIND networks and others did not. They found that income per capita, population, and democratic freedoms were the main determinants of whether INTERPOL member countries installed MIND/FIND technologies. As of August 2012, more than a hundred members were connected to either the MIND or FIND networks or both. This increased membership came as INTERPOL pushed to educate its member countries about the benefits of MIND/FIND in fighting international crime and transnational terrorism.

The current paper differs from Enders and Sandler (2011), which investigated not only the determinants of MIND/FIND adoption, but also what could be done to encourage greater adoption. In the current paper, we ask whether the implementation and use of MIND/FIND technology reduced the amount of transnational terrorism in the implementing countries. A favorable answer to this question can provide strong positive inducements for other INTERPOL countries to adopt MIND/FIND. Countries must, however, remember that keeping transnational terrorists from moving about freely from country to country is a weakest-link problem, because terrorists will seek to transit the least-vigilant borders (Enders and Sandler 2012). If, in addition, MIND/FIND limits transnational terrorist attacks in adopting countries, then planned attacks are likely displaced to other countries, where similar technologies are not deployed (see Enders and Sandler 1993).

In order to establish a causal relationship between MIND/FIND adoption and reduced transnational terrorist incidents, we apply causal inference methods developed in the treatment-effects literature (Angrist and Pischke 2009; Wooldridge 2010). Applying causal inference methods to assess treatment effects at the country level is a challenging task. We are not the first to investigate causal effects at an aggregate level: for instance, Lin and Ye (2007) assessed the effectiveness of the inflation targeting policy; Gilligan and Sergenti (2008) looked at the effect of United Nations peacekeeping missions on building a sustainable peace after civil war; Nielsen et al. (2011) examined the effect of foreign aid on armed conflict; and Chang and Lee (2011) analyzed the trade-promoting effect of the World Trade Organization. Using the treatment-effects approach for causal inference, we find that MIND/FIND adopters, who used the technology, experienced fewer transnational terrorist attacks than non-adopters. Even though the reduction in incidents per adopter is small, the proportional reduction is large for 2008–2010. It is large for 2011 when we use a flexible functional form.

The remainder of the paper contains eight sections. Section 2 presents necessary preliminaries on INTERPOL and MIND/FIND, while Section 3 describes our data set. Section 4 indicates our methodology, followed by some caveats in Section 5. Section 6 addresses the issue of covariate balance; Section 7 presents our empirical treatment findings using both cross-sectional and panel estimates. Section 8 performs a robustness check allowing for flexible functional forms. Section 9 concludes with a discussion of our findings.

2 Preliminaries on INTERPOL and MIND/FIND

A relevant distinction for this study is between domestic and transnational terrorist attacks. Domestic terrorism is homegrown and home-directed with no international externalities for other countries. For domestic terrorism, the perpetrators, the victims, and the targets (e.g., the institution receiving terrorist demands) are all from the venue country, where the attack takes place. In contrast, transnational terrorism involves perpetrators, victims, and/or targets from two or more countries. If the terrorists stage an attack in another country, then the incident is transnational terrorism. When a terrorist attack in, say, England kills or injuries an American, the attack is a transnational terrorist event. As such, it generates transnational externalities for countries other than where the attack takes place. In some terrorist instances, INTERPOL's resources assist member countries' effort to capture transnational terrorists, given INTERPOL's international mission.

INTERPOL was established in 1923 as an independent international organization with the mission to promote international cooperation in fighting international crime. Currently, INTERPOL has 190 member countries, whose assigned membership fees mostly fund the organization's staff, infrastructure, and operations. The remainder of INTERPOL's funding comes from voluntary donations. INTERPOL links law enforcement agencies, the members' National Central Bureaus (NCBs), and INTERPOL General Secretariat (IPGS) in fighting transnational crime and terrorism. In particular, INTERPOL addresses six primary criminal concerns: corruption, drugs and organized crime, financial and high-technology crime, fugitives, trafficking in humans, and transnational terrorism (INTERPOL 2011). After the four skyjackings on September 11, 2001 (henceforth, 9/11), INTERPOL channelled up to 20-25% of its annual crime-fighting resources into coordinating international law enforcement efforts to address transnational terrorism (Sandler, Arce, and Enders 2011). INTERPOL provides its communication networks, its training facilities, its best practices, its data banks, and other assets to member countries to assist in their arrest of suspected terrorists. Many of these arrests occur as terrorists are identified when they attempt to transit countries' borders.

INTERPOL members and their law enforcement agents can communicate over INTERPOL's secure communication linkage, I–24/7, which is a restricted-access internet portal. When connected to I–24/7, members' law enforcement agents can share information and access INTERPOL databases and online resources. I–24/7 is also used by INTERPOL to issue arrest (red) notices and to broadcast country-initiated diffusions to alert member countries to detain suspected criminals and/or terrorists. Among many other things, INTERPOL databases contain information on suspected terrorists and stolen and lost travel documents (SLTD). Such documents have been used by terrorists and criminals to transit international borders.

The ability of member countries to apprehend criminals and terrorists at their borders was greatly enhanced at the end of 2005 when INTERPOL offered MIND and/or FIND to interested members. MIND/FIND provides a systematic means for checking people, motor vehicles, and travel documents with efficiency against INTERPOL's global databases. With MIND/FIND, countries can check all passports and motor vehicles at border crossings and other points. In a matter of seconds, scanned passports or vehicle documents are checked by MIND/FIND against national and INTERPOL data banks. In the absence of MIND/FIND, these searches would be prompted by suspicious behavior, which has a strong random component. Moreover, the border official would have to leave his/her duty post and key in the passport or other document numbers at the I–24/7 portal. Such action is subject to error.

Countries may rely on MIND, FIND, or both, depending on their infrastructure. One key difference between MIND and FIND involves the freshness of accessed infomation. FIND allows real-time online access to INTERPOL databases, while MIND contains a copy of these databases. This offline copy is updated periodically, usually within 48 hours (Enders and Sandler 2011). Thus, FIND provides somewhat more up-to-date data; however, this advantage is likely to dissipate over time as MIND is updated more regularly. Countries can still make arrests without having MIND/FIND when a person's behavior raises suspicions, an alert has been issued, or a person turns him- or herself in. Not all countries linked to MIND/FIND utilize the technology for searches. This is particularly true of countries whose MIND/FIND linkage was externally funded – e.g., some Caribbean and African countries. So possessing MIND/FIND is no guarantee that it will be applied to border and or other searches (Enders and Sandler 2011).

3 The data

Based on the treatment-effects literature jargon, INTERPOL member countries are the unit of analysis, the treatment is the connection to the MIND/FIND network, and the outcome variable is transnational terrorism.

IPGS provided us with the exact date of MIND/FIND connections, which ran from December 13, 2005 when Switzerland linked to the MIND network to July 19, 2012 when the Ivory Coast linked to the MIND network. Some countries joined MIND, others joined FIND, and some joined both. Despite minor differences between MIND and FIND, indicated earlier, we treat them as equivalent in this study. Figure 1 plots the number of countries connected to the MIND/FIND network from 2004 to 2011. During 2005, Switzerland and Liechtenstein were the first countries to join the network. By the end of 2006, Belgium, Lithuania, Spain, St. Kitts and Nevis, and Turkey had joined the network. The number of countries connected to the MIND/FIND network rose to 24 in 2007, 47 in 2008, 71 in 2009, 94 in 2010, and 102 in 2011.

In addition to the exact date of connection, IPGS also provided the number of searches by each member country for the years 2008 to 2011. The total number of MIND/FIND searches by member countries showed that some connected countries did not actually use the network and also that some formally unconnected countries made searches through their I–24/7 portal when prompted by suspicious behavior or international events. Figure 1 also plots the number of countries that carried out a total number of searches in the MIND/FIND network above 1,000 per year. Such a mild threshold makes a difference in terms of the number of countries that actually used MIND/FIND and therefore can be considered as treated. Henceforth, we define the treatment group as the set of countries that actually used the MIND/FIND or I–24/7 network to perform a minimum of a thousand searches per year. Relatively few non-MIND/FIND countries met the search threshold in a given year.

The outcome variable is the number of transnational terrorist incidents ending in a country, which is available from International Terrorism: Attributes of Terrorist Events (ITERATE) (Mickolus et al. 2012). ITERATE uses the news media to identify transnational terrorist incidents and where they occurred. Although transnational terrorism is a concern for many countries, the MIND/FIND network is not primarily intended to curb transnational terrorism; rather, it is meant to reduce international crime. The number of transnational terrorist incidents is a count variable; its support is the set of non-negative integers. We account for this characteristic of the outcome variable using count regression methods. Countries vary considerably in size, thus having different exposures to transnational terrorism. Accordingly, we measure the outcome variable as the Transnational Terrorist Incidence Rate (TTIR), based on population as a proxy for country size and, therefore, exposure.

In addition to the treatment and outcome variables, other covariates of interest for our analysis are those that are determinants of the treatment status and the outcome variable. Enders and Sandler (2011) found that income per capita, population, and democratic freedoms were the main determinants of whether INTERPOL member countries installed MIND/FIND technologies. We gather Real GDP per capita and population data from the World Bank and we obtain a measure of democratic freedoms, *polity*, from POLITY IV PROJECT (Marshall, Jaggers, and Gurr 2011).

The resulting data set contains the 148 countries listed in Table 1. Our quasi-experimental approach takes the five years from 2000 to 2004 as the pre-treatment period and looks for an effect of MIND/FIND adoption and use on TTIRs during the 2008-2011 period.

4 The methods

Let Y be the number of transnational terrorist incidents that takes place in a country during a year, which is a non-negative integer or count variable. The treatment status variable, D, equals one when a country uses MIND/FIND or the I-24/7 portal for a thousand or more searches per year and equals zero otherwise. Using the Rubin causal model (Rubin 1974, Sekhon 2007), we let Y_1 be the *potential* number of transnational terrorist incidents under treatment, and Y_0 the *potential* number of transnational terrorist incidents under no treatment. The observed number of transnational terrorist incidents, Y, is defined as

$$Y = \begin{cases} Y_1 & if \quad D = 1 \\ Y_0 & if \quad D = 0. \end{cases}$$

That is, for treated countries ($D = 1$), we observe the potential number of transnational terrorist incidents under treatment, Y_1, but do not observe potential outcome under no treatment, Y_0. Similarly, for untreated countries ($D = 0$), we observe potential outcome under no treatment, Y_0, but do not observe potential outcome under treatment Y_1.

Under the Stable Unit Treatment Value Assumption (SUTVA), potential outcomes for each unit do not depend on whether other units receive the treatment (no interference). Moreover, there are no different levels of the treatment that have different effects on potential outcomes (no different treatment levels). These assumptions are likely violated in our analysis of the effect of MIND/FIND on transnational terrorism. We return to these concerns in Section 5, but assume them away for now.

The effect of adopting MIND/FIND technology on the number of transnational terrorist incidents is $Y_1 - Y_0$. However, this treatment effect is country specific, and therefore attention is typically directed towards the Average Treatment Effect (ATE), $E(Y_1 - Y_0)$. We will assume that, conditional on a vector of covariates, X, the expected number of transnational terrorist incidents is given by

$$E(Y \mid X, D) = \exp\left(X'\beta + DX'\gamma + \ln(n)\right),$$

where n is the population of the country and accounts for differential exposures across countries. Thus, the expected TTIR is $E(Y \mid X, D)/n$, which is an exponential function of a vector of covariates. Under the exponential mean assumption, the ATE on the TTIR can be written as

$$ATE = E(Y_1 - Y_0) = E\left(E(Y \mid X, D = 1) - E(Y \mid X, D = 0)\right)$$

$$= E\left(\left(\exp(X'\theta) - \exp(X'\beta)\right) n\right),$$

where $\theta = \beta + \gamma$. Wooldridge (2010) suggested that, provided we can estimate the exponential regression functions consistently, an estimate of the ATE can be obtained as the average,

$$ATE = \frac{1}{N} \sum_{i=1}^{N} \left(\left(\exp(X_i'\widehat{\theta}) - \exp(X_i'\widehat{\beta})\right) n_i\right),$$

and its standard error can be obtained by bootstrap resampling. However, by Jensen's inequality, averaging a convex function overestimates the value of the function; hence, we do not follow this route. Instead, we follow Lee and Kobayashi (2001), who suggested the conditional Proportional Average Treatment Effect (PATE),

$$PATE(X) = \frac{E(Y_1 - Y_0 \mid X)}{E(Y_0 \mid X)} = \exp\left(X'\gamma\right) - 1.$$

To integrate out the covariates, we compute the geometric mean to obtain the unconditional PATE,

$$\left\{\prod_{i=1}^{N} \exp\left(X_i'\gamma\right)\right\}^{1/N} - 1 = \exp\left(\overline{X}'\gamma\right) - 1,$$

where $\overline{X} = \frac{1}{N}\sum_{i=1}^{N} X_i$. Thus, the unconditional PATE is equal to the conditional PATE with covariates evaluated at their sample means. The arithmetic average of the unconditional PATE would, by Jensen's inequality, return a bigger value; hence, by using the geometric average instead of the arithmetic mean, we are on the conservative side. We also note that the PATE is bounded below by -1, because the number of transnational terrorist incidents cannot be negative. When later reporting PATE estimates, we use the asymmetric confidence interval for the PATE, suggested by Lee and Kobayashi (2001). Similarly, the PATE on the treated can be computed as:

$$\prod_{i=1}^{N} \left\{\exp\left(X_i'\gamma\right)\right\}^{\frac{D_i}{N_1}} - 1 = \exp\left(\overline{X}_1'\gamma\right) - 1,$$

where $N_1 = \sum_{i=1}^{N} D_i$ is the number of treated units and $\overline{X}_1 = (N_1)^{-1}\sum_{i=1}^{N} D_i X_i$ the average value of the covariates for the treated.

For estimation, we assume that, conditional on the vector of covariates, the number of transnational terrorist incidents follows a Poisson distribution with density

$$f(Y_i \mid X_i, D_i) = \frac{\exp\left(\mu(X_i, D_i)\right)\left[\mu(X_i, D_i)\right]^{Y_i}}{Y_i!},$$

where the mean of the distribution is exponential, $\mu(X_i, D_i) = \exp\left(X_i'\beta + D_i X_i'\gamma + \ln(n_i)\right)$. The log-likelihood function is

$$\ell(\beta,\gamma) = \sum_{i=1}^{N}\left(-\ln(Y_i!) - \exp\left(X_i'\beta + D_i X_i'\gamma + \ln(n_i)\right) + Y_i\left(X_i'\beta + D_i X_i'\gamma + \ln(n_i)\right)\right),$$

and the first-order conditions for a maximum are

$$\sum_{i=1}^{N}\left(Y_i - \exp\left(X_i'\beta + D_i X_i'\gamma + \ln(n_i)\right)\right) X_i = 0,$$

$$\sum_{i=1}^{N}\left(Y_i - \exp\left(X_i'\beta + D_i X_i'\gamma + \ln(n_i)\right)\right) D_i X_i = 0.$$

The Poisson Quasi-Maximum Likelihood Estimator (QMLE) solves these first-order conditions which can be viewed as a set of sample moment conditions that can be used to construct a Generalized Method of Moments (GMM) estimator. Therefore, consistency of the Poisson QMLE/GMM estimator obtains even when the true distribution of Y, conditional on X, is not Poisson. This estimator is, thus, robust to overdispersion, a frequently observed characteristic of count data.

Although our analysis has so far dealt with cross-sectional estimation, our data set is a panel, which allows us to account for unobserved heterogeneity. Keeping track of countries and time periods, we assume that the conditional mean is exponential,

$$E(Y_{it} \mid X_{it}, D_{it}, \eta_i) = \exp\left(X_{it}'\beta + D_{it}X_{it}'\gamma + \ln(n_i) + \eta_i\right),$$

where η_i is a country-specific unobserved effect. Notice that the PATE does not include the country-specific effect and can be estimated, as in the cross-sectional case, as

$$PATE(X_{it}) = \frac{E(Y_{1it} - Y_{0it} \mid X)}{E(Y_{0it} \mid X)} = \exp\left(X_{it}'\gamma\right) - 1,$$

which can be evaluated at the overall mean or the cross-sectional average at time t, $\overline{X}_t = \frac{1}{N}\sum_{i=1}^{N} X_{it}$, to provide a time-varying effect of the treatment.

In the panel case, estimation of the exponential regression function is carried out differently. We use the Fixed Effects Poisson Maximum Likelihood Estimator (FEP-MLE), introduced by Hausman, Hall, and Griliches (1984), as well as the Pre-Sample Mean GMM (PSM-GMM) estimator, suggested by Blundell, Griffith, and Windmeijer (2002). If the number of transnational terrorist events follows a Poisson distribution, then the distribution of the number of transnational terrorist incidents, conditional on the covariates, the country effects, and the sum of the number of incidents over the sample period for each country, follows a Multinomial distribution, which simplifies computations. The Fixed Effects Poisson estimator allows for overdispersion or underdispersion and serial dependence of the outcome variable. The exponential mean assumption and strictly exogenous regressors are all that is required for consistency. The PSM-GMM estimator assumes that the country-specific effects can be accounted for by the pre-sample mean of the dependent variable (i.e., the number of transnational terrorist incidents during a pre-sample period). Let $\overline{Y}_i^* = \frac{1}{T^*}\sum_{r=1}^{T^*} Y_{i,0-r}$ be the average number of transnational terrorist incidents ending in country i during the T^* periods before the beginning of the sample period. The PSM-GMM estimator assumes that

$$E(Y_{it} \mid X_{it}, D_{it}, \overline{Y}_i^*) = \exp\left(X_{it}'\beta + D_{it}X_{it}'\gamma + \alpha \ln \overline{Y}_i^* + \ln(n_i)\right),$$

where α is a parameter to be estimated. As the PSM-GMM estimator does not require the assumption of strict exogeneity of regressors and allows for predetermined ones, this estimator can also be applied to a lagged dependent variable model of the form suggested by Crépon and Duguet (1997)

$$E(Y_{it} \mid Y_{i,t-1}, X_{it}, D_{it}, \overline{Y}_i^*) = h(Y_{i,t-1}; \delta) \exp\left(X_{it}'\beta + D_{it}X_{it}'\gamma + \alpha \ln \overline{Y}_i^* + \ln(n_i)\right),$$

where $h(Y_{i,t-1}; \delta) = \exp\{\delta d_{i,t-1}\}$ with $d_{i,t-1}$ being a dummy variable that equals one when the lagged number of transnational terrorism incidents is positive, $Y_{i,t-1} > 0$, and equals zero otherwise. As long as the parameter δ is constant, the $h(\cdot)$ function cancels out when computing the PATE, which can be estimated as explained earlier.

5 The caveats

The goal of this paper is to assess the effect of the MIND/FIND network on transnational terrorism using the treatment-effects methodology. This is not an easy task. To begin with, in sharp contrast to other observational studies, our empirical analysis is based on a sample of small size, limited by the number of countries and data availability. This inconvenience might be somewhat ameliorated by the fact that the units used in the analysis constitute almost the entire population of countries. External validity is not as much of a concern as in other observational studies, where the causal effect found in a sample is to be extrapolated to a target population from which the sample is drawn. In our case, the population of interest is precisely the sample used in the analysis.

A second important concern involves covariate balance. When the effect of a treatment is estimated using a randomized experiment, the distributions of the variables that affect the outcome are balanced across treatment and control groups, at least ex ante. However, in our application, countries are not randomly assigned to treatment and control groups, which results in an uneven distribution of covariates across treatment and control groups. To cope with this problem, we perform a pre-analysis covariate rebalancing process, constructing control groups that match as closely as possible the characteristics of the treatment group.

A third issue is that, under the SUTVA assumption, there is no interference across units, so that the treatment applied to a unit does not have an effect on other units. The no-interference assumption is unlikely to be satisfied in our analysis of the effect of MIND/FIND on transnational terrorism. The War on Terror is considered to be a weakest-link problem; that is, world security depends on the level of security in the least-secure country. Therefore, it could be argued that MIND/FIND adoption by a country might deflect some transnational terrorist incidents to countries, where this technology is not used, thus reducing the TTIR in treated countries and increasing the TTIR in untreated countries. This violation of the no-interference assumption is not as problematic as one might think. When interference causes the same effect on treated and untreated units, erroneous causal inference might be drawn if we conclude that there is no causal effect whenever the outcome for the treated is not significantly different from the control group. If the weakest-link effect exists, treatment in one country causes more transnational terrorist incidents in untreated ones, biasing the treatment effect upwards. Therefore, part of the estimated treatment effect should be attributed to the effect of the treatment on the control group rather than on the treated.

A second violation of the no-interference assumption might occur if MIND/FIND adoption generates peer effects, whereby countries benefit from tighter border controls elsewhere. Here, the effect of the treatment applied to a country affects the outcome of other countries, either treated or not, in the opposite direction from the weakest-link effect. For MIND/FIND, the peer effect may be associated, in part, with the hub-spoke system of air travel, where passengers must travel through major hubs (e.g., Heathrow in London, Charles de Gaulle in Paris, or Frankfurt Airport in Germany) to get to their final destination. If major hub airports are in MIND/FIND treatment countries, then peer effects will be more prevalent. One can envision that much less than 100 per cent MIND/FIND treatment may effectively protect all nations, not unlike the concept of herd immunity for contagious diseases. As the number of MIND/FIND countries grows in our later sample years, peer effects are more of a concern. As such, the treatment effect may become biased downward for, say, 2011. This is the year that Germany and the United Arab Emirates connected to MIND/FIND, both of which contain major hubs. Unfortunately, there is no easy way to tell whether the weakest-link and peer effects exist and whether one is going to dominate the other on balance.

In summary, the likely possibility of interference among countries implies that the estimated treatment effects account not only for the direct effect of the treatment on the treated, but also the indirect effect on the untreated, and therefore should be taken with caution. There is, however, theoretical grounds for believing that peer effects will dominate as the treatment countries increase in numbers.

6 Covariate balance

In computing the treatment effects, we make use of the assumption of covariate overlap. Imputed potential outcomes are more credible when covariates have similar distributions across treatments. Had assignment been randomized, covariate distributions would be identical, at least ex ante, thus providing the perfect set up for causal inference. However, in our analysis, assignment is not random and the distribution of covariates across treatment and control groups is far from identical. In order to cope with this problem, we perform some pre-analysis covariate rebalancing. To this end, we first introduce the propensity score function, $p(X) = P(D = 1 \mid X)$, which is the probability of adopting the MIND/FIND technology, conditional on the vector of covariates X. Enders and Sandler (2011) showed that the probability of observing that a country adopts the MIND/FIND technology depended on income per capita, population, and democratic freedoms. Using these determinants of treatment status, Table 2 reports estimates of the propensity score or probability of MIND/FIND adoption using a logit specification. As in Enders and Sandler (2011), we model the probability of receiving treatment as of the end of 2008. However, because we restrict the analysis to countries with available data on transnational terrorism, the sample is smaller. Column (1) uses contemporaneous values of the covariates, as in Enders and Sandler, to predict the probability of receiving treatment when treatment is defined according to connectivity. The results are qualitatively equivalent to those obtained by Enders and Sandler (2011), with income per capita, population, and the polity dummy having a positive and statistically significant effect on the probability of receiving treatment.[1] Column (2) differs from Column (1) in that treatment status is defined according to the criterion of performing at least 1,000 annual searches. This change in the definition of treatment does have an effect on the significance of the covariates, income per capita remains significant and so does the polity dummy marginally, but population loses significance. The actual polity score, however, turns out to be significant in Column (3). In summary, after properly defining treatment status, significance of population as a determinant of treatment status is questionable.

The binary choice models estimated by Enders and Sandler (2011) were not meant to be used for inference on the treatment effects of MIND/FIND adoption. However, in the treatment-effects literature, it is typically recommended that covariates should correspond to pre-treatment values. In addition, it is also recommended that the set of covariates should include pre-treatment values of the outcome to account for unobserved pre-treatment heterogeneity. In this regard, Columns (4) to (6) report logit estimates when covariates are dated as of 2004, the last year before the MIND/FIND begun functioning. Column (4) uses the definition of treatment according to connectivity and columns (5) and (6) use the 1,000 minimum number of searches criterion. Income per capita, population, and the polity dummy and polity score have qualitatively identical effects on the probability of receiving treatment. Columns (4)-(6) also include the cumulative number of transnational terrorist incidents as of 2004 as an additional regressor, which turns out to be insignificant.

[1] As in Enders and Sandler (2011), we include a polity dummy instead of the polity score itself. This polity dummy equals one when the polity score is seven or greater.

This finding indicates that transnational terrorism was not a significant determinant of treatment status; that is, joining and/or actually using MIND/FIND was not related to the previous history of transnational terrorism.

Each panel in Table 3 reports statistics on the distribution of pre-treatment values of covariates for a given assignment of countries to the treatment and control groups. For instance, the first panel reports covariate distribution statistics when treatment and control groups are defined according to whether countries carried out a minimum of 1,000 searches in either MIND or FIND (treatment group) or not (control group) in 2008. The first two sets of columns report the size of the groups as well as the mean and standard deviation (SD) of each covariate. The treatment and control groups do not only differ in size but also in the mean and standard deviation of the covariates. To highlight this discrepancy, the third set of columns reports overlap rates, the standarized mean difference (SMD), and the log of the ratio of standard deviations (LRSD). The overlap rate is the proportion of observations in a group that fall within the 0.025 and 0.975 quantiles of the empirical distribution of the other group, thus 81 per cent of the observations in the treatment group have Log GDP per capita values that fall within the $(0.025, 0.975)$ quantile interval of the empirical distribution of Log GDP per capita among countries in the treatment group. A high overlap rate for the control (treatment) group indicates that it is reasonably easy to find countries in the control group with covariate values similar to those in the treatment (control) group. The standarized mean difference is defined as $(\bar{x}_1 - \bar{x}_0)/\sqrt{\left(\widehat{\sigma}_1^2 + \widehat{\sigma}_0^2\right)/2}$, where $\bar{x}_g$ and $\widehat{\sigma}_g$, $g = 0, 1$ are the sample mean and standard deviation of covariate x for the two groups. It measures the extent to which the two groups differ in mean values. As we are interested in *average* treatment effects, similar means across groups is crucial for robust inference. The log ratio of standard deviations is defined as $\log\left(\frac{\widehat{\sigma}_1}{\widehat{\sigma}_0}\right)$, with big absolute values indicating differences in dispersion across groups. Table 3 not only reports these statistics for the set of covariates but also for the propensity score and log odds ratio.

The third set of columns in Table 3 reports these statistics for the full sample. The first panel in this table shows that, when treatment and control groups are defined according to MIND/FIND effective use in 2008 or earlier, there is a poor overlap when we look at the propensity score or the log odds ratio. Differences in covariate means across groups is more evident and problematic, with all covariates reaching a SMD value above 0.25 (or almost in the case of log population), a yardstick that should raise caution. Similarly, the LRSD statistic shows values above the 0.25 yardstick in the case of the polity score, the propensity score, and the log odds ratio. The second, third, and fourth panels in Table 3 tell a very similar story, with some covariates exhibiting big differences in means and poor overlap. In sum, covariate distributions across treatment years are far from balanced.

Poor covariate balance is typical of observational studies and our analysis of the effect of MIND/FIND adoption on transnational terrorism is no exception. In order to cope with this problem, we follow standard procedures for covariate balancing, (e.g., Rosenbaum 2010; Imbens and Rubin forthcoming). The idea behind these methods is to use matching techniques to ensure balance in covariate distributions before the actual estimation of the treatment effects is carried out. To this end, for each period of analysis considered, we match each treated unit (country using MIND/FIND) with an untreated one from the control group. We match treated and untreated countries using a transformation of the propensity score, the log odds ratio, $\log(p(X)/(1-p(X))$. First, we order units according to the probability of receiving treatment in decreasing propensity score order. Second, for the first treated unit (the one with highest estimated propensity score), we find the unit in the control group with the closest log odds ratio. Then, we do the same for the second treated unit, and continue doing so until we find a match for each unit in the treatment group. We match units using the log odds ratio rather than the propensity score because, as argued by Imbens and Rubin (forthcoming), the log odds ratio is linear in the covariates, whereas the propensity score is not. In other words, differences in the propensity scores across treatment years are not equally important across all values of the propensity score. For instance, differences in propensity scores of 0.01 and 0.02 are more important than differences in propensity scores of 0.49 and 0.50, while this is not the case with the log odds ratio.

The fourth set of columns in Table 3 reports overlap rates, SMD, and LRSD for the matched samples. With few exceptions, overlap rates increase compared to the full sample. Standarized mean differences are much smaller, with only a few cases above the 0.25 yardstick. Figure 2 plots the distribution of the log odds ratio for the full and matched samples for different years. Covariate rebalancing does make a difference in 2008 and 2009, as the matched samples exhibit a more similar distribution across treatments than the full samples. However, for 2010 and 2011, matching does not achieve such a good covariate rebalancing in terms of the log odds ratio. There is a simple explanation for this, when treatment groups are defined according to the 2008 use of the MIND/FIND network, the treatment group includes only 19 countries and the control group contains 129 countries. Therefore, it is relatively easy to find a match for each treated country among the untreated ones. However, as more countries join MIND/FIND, and are included in the treatment group, there are fewer countries in the control group, making it more difficult to find a good match for each treated country. Although matching makes treatment and control groups much more similar, the small sample size precludes better pre-analysis covariate balancing. In any case, covariate rebalancing makes subsequent evidence more credible for the matched sample than the full sample.

7 The treatment effects

Table 4 reports cross-sectional Poisson regressions for different years. Column (1) shows results using the Poisson QMLE when the outcome, the number of transnational terrorist incidents, is measured as of 2008 when 19 countries performed at least a thousand searches in the MIND/FIND network. In addition to those 19 treated countries, another 19 untreated countries are included in the regression, the latter selected according to the procedure depicted above for covariate rebalancing. Similarly, Columns (2) to (4) report Poisson maximum likelihood estimates for the years 2009 to 2011 including 66 (33 treated plus 33 untreated), 76 (38 + 38), and 106 (53 + 53) countries in each case. The list of regressors includes those indicated earlier plus their interaction with the treatment indicator. Therefore, coefficients on the interaction terms can be interpreted as the differential effect of a particular covariate for the treated, with the treatment dummy included as the interaction with the constant term. Notice that coefficient estimates on the interaction terms experience changes in sign, size, and significance across columns, probably due to the changing treatment and control groups across columns. Only a few covariates and interactions turn out to be statistically significant. This might be a concern for causal inference, as our estimate of the treatment effects will be based on insignificant parameter estimates. We will return to this point in Section 8 where we allow for flexible functional forms.

Rows in the next-to-last panel of Table 4 report the PATE on the treated (PATET) and the 95 per cent confidence interval. The estimated PATET in 2008 is -0.6320, which indicates that the expected TTIR was a 63.20 per cent lower in treated countries than it would have been in the absence of treatment. The confidence interval for this estimate (-0.7273,-0.5217) does not include the origin, so the estimated PATET is significantly different from zero. In 2009, the PATET was -0.5617 and again significant, dropping to -0.4155 in 2010, but still retaining significance. However, in 2011, the estimated PATE is only -0.0836 and insignificantly different from zero. As covariates are better balanced in 2008 and 2009, our estimates of the PATET for 2008 and 2009 are more credible than those corresponding to the last years. The results in 2011 may also stem from peer effects, which may be washing out treatment effects, because some countries containing major hub airports joined MIND/FIND.

The last panel of Table 4 shows the expected TTIRs for the treated, conditional on having received treatment and having received no treatment as well as the actual TTIR for the treated. These expected TTIRs are estimated as the corresponding exponential means evaluated at the average covariate values for the treated. In all cases, incidence rates are measured per 100 million people, so for example, a 0.4669 TTIR for the treated in 2008 indicates that, on average, a country with a population of 100 million had less than half an incident. That is, an expected reduction from 1.4628 incidents under no treatment to 0.5383 incident under treatment results in 0.9245 fewer transnational terrorist incidents, or a 63 per cent reduction, as the PATET indicates. A similar interpretation can be made from the figures reported in the other columns. Comparing the expected TTIR for a treated country with 100 million population with its counterfactual under no treatment results in a reduction of transnational terrorist incidents as follows: 0.9159 in 2009, 1.5280 in 2010, and only 0.1361 in 2011. MIND/FIND use reduces transnational terrorist incidents by approximately 56.17 per cent in 2009, 41.55 per cent in 2010, and 8.36 per cent in 2011.

We now exploit the panel structure of our data set to account for unobserved country-specific factors which could be correlated with the covariates. All the subsequent panel data analysis uses contemporaneous values of the covariates. This could be a concern if the treatment had an effect on the covariates as it would bias our results. However, we are fairly confident that the treatment, MIND/FIND network use, does not affect GDP per capita, population, or democratic freedoms. Unfortunately, we are unable to carry out a covariate rebalancing as we did in the cross-sectional case, because the treatment and control groups of countries change during the period analyzed.

Table 5 reports panel regressions for the period 2005-2011. Column (1) reports Fixed Effects Poisson QML estimates, Column (2) reports PSM-GMM estimates for a static model, and Column (3) reports PSM-GMM estimates for the lagged dependent variable model. The earlier cross-sectional evidence included the cumulative number of transnational terrorism incidents as a covariate with the hope that it would capture unobserved pre-treatment differences in the outcome variable. The panel estimators used in Table 5 account for unobserved heterogeneity in different ways. The Fixed Effects Poisson estimator wipes out the country-specific unobserved effects by conditioning on the sum of transnational terrorism incidents for each country over the sample period and the PSM-GMMestimator accounts for it including the pre-sample mean of transnational terrorism incidents as a covariate.[2]

The Fixed Effects Poisson QML is conditional on having at least one transnational terrorist incident during the sample period, which results in a sample of 422 observations. The PSM-GMM estimates use pre-sample information (the pre-sample mean of the number of transnational terrorist incidents) to construct a proxy for the country fixed effects. Because the country-specific pre-sample mean enters the exponential mean in logarithms, the analysis is restricted to all countries that have had at least one transnational terrorist incident during the pre-sample period (2000-2004) for a total of 567 observations.

[2]Note that the pre-sample mean of transnational terrorism incidents is equal to the pre-treatment cumulative number of transnational terrorism events used earlier divided by the number of pre-sample periods.

Table 6 shows the PATETs obtained for each year using the three estimation methods. PATETs are always negative and significant, with the PATETs from the Fixed Effects Poisson being generally somewhat bigger than those obtained using the Pre-Sample Mean GMM. Estimates range from a low 15 per cent reduction in expected TTIRs to a high 35 per cent reduction. Comparing the panel results to the cross-sectional results, we see that the former are much smaller. Notice, however, that the panel estimates are conditional on having had at least one transnational terrorist incident during the sample period (Fixed Effects Poisson) or the pre-sample period (PSM-GMM estimates). Therefore, these PATETs are not directly comparable to those of the cross-sectional analysis, where the sample includes countries with no transnational terrorist incidents and therefore smaller average TTIRs. In other words, the cross-sectional analysis finds larger effects on samples with smaller TTIRs. In order to give a more directly comparable figure, we must compare the expected TTIRs under treatment and no treatment obtained in the panel analysis, as we did for the cross-sections. This is not possible for the Fixed Effect Poisson estimates, as we cannot estimate the constant term, which makes it impossible to recover the expected TTIRs. Therefore, we base our comparison using the PSM-GMM estimates from Table 5 Column (2). The last panel of Table 6 reports expected TTIRs for the treated under treatment and no treatment. The differences between these expected TTIRs, again for a country of 100 million population, are -0.2924 in 2008, -0.4596 in 2009, -0.5665 in 2010, and -0.4782 in 2011. These estimated reductions in TTIRs as a result of using the MIND/FIND network are smaller than those obtained in the cross-sectional analysis. In summary, the panel analysis suggests that as a result of using the MIND/FIND technology, a country with 100 million population that suffered from transnational terrorism would experience about a half fewer transnational terrorist incidents.

8 Flexible functional forms

A concern with the results reported in Tables 4 and 5 is that most regressors are not statistically significant. As a consequence, inference on the treatment effects makes use of some insignificant parameter estimates, which casts some doubts on the results. In this section, we assess the robustness of the previous results to permit flexible functional forms for the propensity score and the conditional mean functions. Flexible functional form for the propensity score function increases the goodness of fit, or the capacity of the model to predict treatment, thus providing an improved tool for subsequent matching. In addition, flexible functional form for the transnational terrorism incidents' conditional mean increases the statistical significance of regressors, thereby offering a more credible framework for inference on the treatment effects.

Table 7 reports estimates of the propensity score with flexible functional forms that permit selected power terms and interaction terms. The procedure, used to obtain the particular estimated functional forms reported in Table 7, is as follows. The four terms previously included in Table 2 (that is, log GDP per capita, log population, polity score, and cumulative transnational terrorism incidents) are included as the benchmark specification and additional terms are then sequentially included. A first round of logistic regressions is performed with each regression including the benchmark terms plus one additional term from the set of squared terms and interactions. After this first round, the propensity score specification is extended by including the term with the highest contribution to the log-likelihood function, as measured by the log-likelihood ratio test statistic. If none of the additional terms contribute significantly to the likelihood function, then the functional form search ends. Otherwise, another round of logistic regressions is performed, where the benchmark specification now includes the additional terms from previous rounds. Using this procedure, we end up with the extended propensity score functions in Table 7. When the outcome is measured as of 2008 in Column (1), the number of (pre-treatment) cumulative transnational terrorism incidents, which was previously insignificant in Column (6) of Table 2, now enters significantly when linear or squared. This is not the case in Columns (2) to (4), where the interaction of log GDP per capita with the polity score variable gains significance. A changing functional form across columns in Table 7 is not surprising, because the countries included in the treatment and control groups are changing from column to column in a non-random fashion.

Using the flexible functional form specification of the propensity score reported in Table 7, we match each treated country to an untreated one with the nearest log-odds ratio in order to come up with a more balanced sample. Table 8 reports flexible functional form specifications of the TTIR conditional mean functions. In addition to the variables included in benchmark specification in Table 4, several squared terms and interaction terms are included in the extended specifications by applying the same procedure as in the propensity score function, except for only two differences: (i) TTIR conditional mean functions are estimated using the Poisson-GMM estimation procedure, and (ii) additional terms includes itself and its interaction with the treatment indicator. As a result of using this procedure, several additional terms are included in the TTIR conditional mean functions. In addition, the benchmark terms, which were previously insignificant, turn out to be statistically significant when the additional terms are included in the extended conditional mean function. The estimates of the PATET, shown at the bottom of Table 8, are similar to those reported in Table 4 for 2008 and 2010, larger for 2009, and a lot larger for 2011. Thus, allowing for flexible functional forms in the conditional mean of transnational terrorism incidents reinforces our previous finding that MIND/FIND adoption had a significant effect in reducing transnational terrorism. The bottom panel in Table 8 shows that the reduction in the expected TTIRs as a result of MIND/FIND use is lower than previously found for the cross-section specifications in Table 4, 0.8527 less transnational terrorism incidents in 2008, 0.6043 less in 2009, 0.1570 less in 2010, and 0.6867 less in 2011.

Flexible functional forms for the panel estimates are reported in Table 9. The procedure used to reach the functional form reported follows a general-to-specific approach. Starting with a general specification with all squared terms and interactions, insignificant terms were eliminated one at a time. In sharp contrast to the results reported in Table 5, most regressors are statistically significant. Proportional treatment effects are reported in Table 10. The estimated PATET indicates a significant reduction of transnational terrorism as a result of using the MIND/FIND network for searches. These effects are somewhat bigger from those reported in Table 6. Using the PSM-GMM estimates in Table 9 Column (2), the estimated average reduction in TTIRs for the treated, again for a country of 100 million population, are 0.7868 fewer transnational terrorism incidents in 2008, 0.5970 less in 2009, 0.5180 in 2010, and 0.4342 in 2011. A remarkable feature of the estimated PATET is their decreasing time pattern, suggesting the existence of peer effects as non-using countries benefit from the users, which suggest a network externality even beyond the network.

9 Discussion

Our analysis indicates that INTERPOL countries that adopted MIND/FIND and also applied it to screen people and documents at border crossings and other key points suffered fewer transnational terrorist incidents than the control group, which either did not install MIND/FIND or else installed it but did not utilize it. Our panel estimates indicate that a country with 64 million people, like France in 2008, would experience slightly over one half fewer transnational terrorist incidents as a result of using MIND/FIND.[3] This figure would be even higher if we use the cross-section estimates. This reduction in such incidents might not seem like a lot, but it represents for most countries a sizeable proportional reduction in transnational terrorist incidents. Even for the panel estimates where the reduction was smaller, a 18 to 39 per cent reduction in such incidents characterized those countries experiencing transnational terrorism. Globally, this can translate into quite a reduction in attacks.

Although each transnational terrorist incident kills one person and injures two on average, the reduction of these incidents through MIND/FIND means the potential capture of terrorists and the disruption of terrorist groups. Additionally, on occasion a terrorist spectacular, such as 9/11 or the

[3] Back-of-the-envelope calculation using the extended panel estimates from Table10: Expected reduction in TTIR $\times$hundreds of millions population $= -0.7868 * (64.37/100) = -0.5065$.

Madrid commuter train bombings in 2004, may be stopped where the payoff is huge. However, we would argue that the payback is large even for small incidents, since curbing such incidents reduces media coverage of attacks, limits terrorist recruitment, and curtails society's anxiety. Moreover, a fall in transnational terrorist incidents worldwide allows countries to reduce somewhat homeland security spending. Non-adopting countries will come to realize that terrorists will transfer attacks to their soil, which should eventually foster more universal adoption of MIND/FIND.

The hub-spoke system of international air travel means that less than universal adoption of MIND/FIND may be sufficient to greatly curb transnational terrorist attacks, in which borders are transgressed by the perpetrator. Unfortunately, MIND/FIND cannot eliminate transnational terrorist incidents where a perpetrator attacks foreign assets (i.e., people or property) for political purposes on his/her home soil. Moreover, MIND/FIND cannot stop the transit of would-be terrorists, who are not in INTERPOL or national data banks as suspected terrorists. Thus, MIND/FIND can ameliorate transnational terrorism, as shown here, but it cannot eliminate it. A potential downside of MIND/FIND may be an increase in domestic terrorism, so that the authorities must be vigilant for this transference as MIND/FIND use expands. For domestic terrorist attacks, countries possess the proper incentives to take proactive measures because any resulting benefits are fully captured by the acting country – there are no transnational externalities. Thus, this MIND/FIND domestic transference of attacks does not pose too much of a concern.

Finally, we want to put the associated INTERPOL costs into perspective. The entire operating budget of INTERPOL was 60 million euros in 2011 (INTERPOL 2011). Based on past percentages calculated by Sandler, Arce, and Enders (2011) for 2006 and 2007, about 23 per cent of INTERPOL's budget goes to coordinating the fight against terrorism. This is a high-end estimate because these authors wanted to err on the high side to give more credence to their benefit-cost computations. For example, they included the entire costs of I-24/7 in INTERPOL's efforts to address terrorism. If we use their percentage, then less than 13.8 million euros were spent by INTERPOL in 2011 on assisting its member countries' counterterrorism activities. Of course, member countries using MIND/FIND have initial setup costs before their border officials can start using the technology and databases for searches. Nevertheless, the associated costs are minuscule compared to the tens of billions that the United States alone spends on homeland security. In 2011, the US Department of Homeland Security budget was $56.335 billion, of which about 66 per cent or $37 billion went to defensive measures against terrorism (Enders and Sandler 2012). Our analysis shows that the small INTERPOL costs have huge paybacks in thwarting transnational terrorism as borders are made more secure.

Data Appendix

- Transnational terrorist events. Yearly number of terrorist events ending in a particular country or territory. Source: ITERATE data base. Note: the number of transnational terrorist events ending in Cabinda were added to Angolan attacks, those ending in Canary Islands were added to Spanish attacks, those ending in Corsica were added to French attacks, those ending in Scotland and Northern Ireland were added to the United Kingdom attacks, and those ending in Dubai were added to United Arab Emirates attacks.
- Gross Domestic Product per capita. GDP per capita, PPP, constant 2005 international $. Source: World Bank.
- Population. Total population. Source: World Bank.
- Polity score. Polity2 variable. Source: POLITY IV PROJECT.
- MIND/FIND data. Connection dates and number of searches. Source: INTERPOL General Secretariat.

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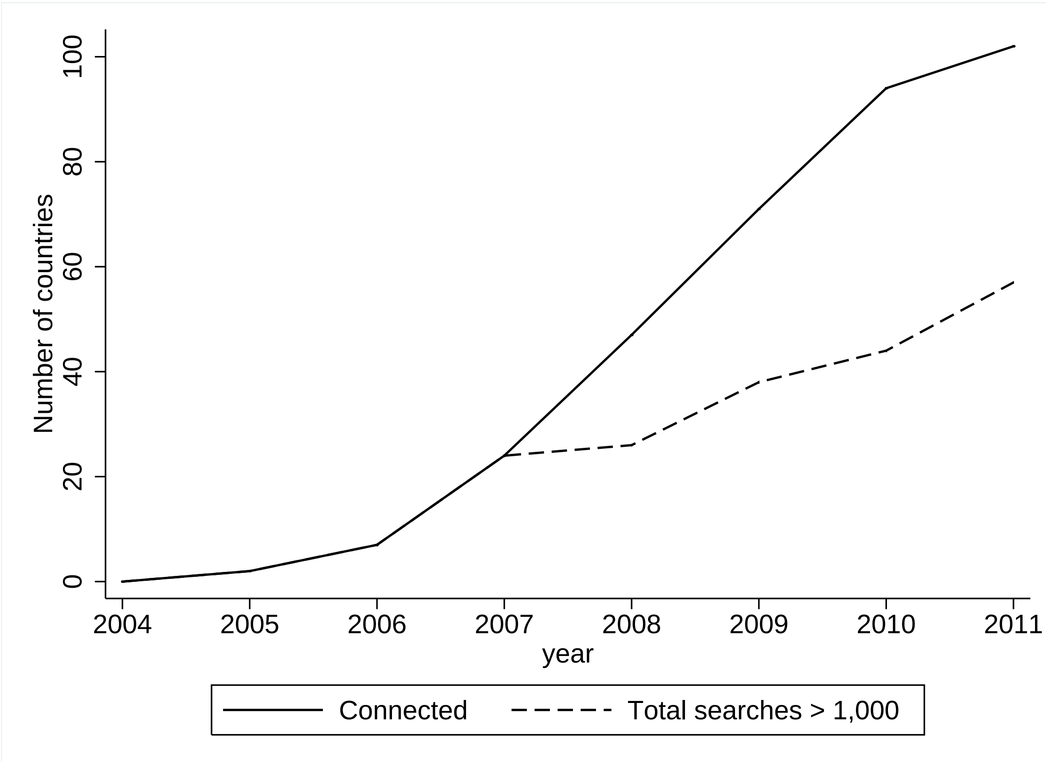

Figure 1: Number of countries connected to MIND/FIND network and number of countries with total searches above 1,000.

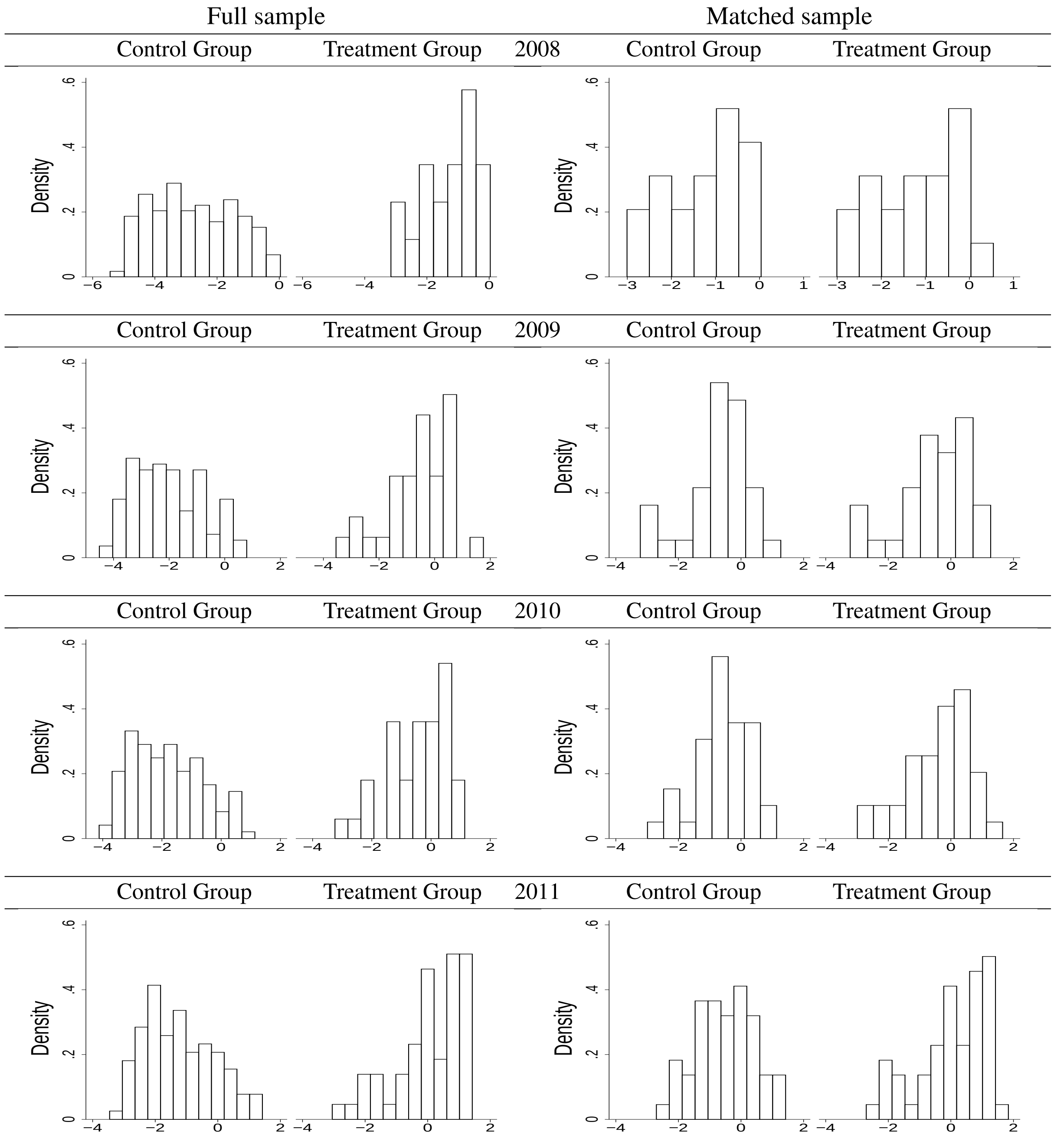

Figure 2: Log odds ratio distribution across treatment legs and periods

Table 1: List of Countries

Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Benin, Bhutan, Bolivia, Botswana, Brazil, Bulgaria, Burkina, Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Republic of the Congo, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Djibouti, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, India, Indonesia, Islamic Republic of Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Republic of Korea, Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lesotho, Liberia, Libya, Lithuania, Macedonia FYR, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovak Republic, Slovenia, Solomon Islands, South Africa, Spain, Sri Lanka, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela RB, Vietnam, Republic of Yemen, Zambia.

Table 2: Probability of joining MIND/FIND as of 2008

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP per capita (2008)	0.6018***	0.6892**	0.6960**			
	(0.2030)	(0.2935)	(0.3069)			
Log Population (2008)	0.5422***	0.1426	0.1357			
	(0.1517)	(0.1570)	(0.1618)			
Polity Dummy (2008)	1.0858**	1.2257*				
	(0.5112)	(0.6866)				
Polity Score (2008)			0.1210**			
			(0.0515)			
Log GDP per capita (2004)				0.5792***	0.6498**	0.6476**
				(0.2109)	(0.2855)	(0.2986)
Log Population (2004)				0.5647***	0.1160	0.0877
				(0.1712)	(0.1558)	(0.1635)
Polity Dummy (2004)				1.0749**	1.2455*	
				(0.5242)	(0.6988)	
Polity Score (2004)						0.1286**
						(0.0544)
Cum. Trans. Terror Incidents (2004)				-0.0109	0.0105	0.0161
				(0.0222)	(0.0223)	(0.0243)
Constant	-15.9806***	-11.4022***	-11.2375***	-15.9578***	-10.5691***	-10.0405***
	(3.2081)	(3.9729)	(3.9068)	(3.4988)	(3.8987)	(3.8326)
Observations	149	149	149	148	148	148

As in Enders and Sandler (2011), Polity Dummy = 1 if Polity score ≥ 7.
Standard errors in parentheses, *** p-value<0.01, ** p-value<0.05, * p-value<0.1

Table 3: Covariate overlap

	Treatment			Control			Full sample				Matched sample			
							Overlap				Overlap			
	Size	Mean	SD	Size	Mean	SD	Treat	Cont	SMD	LRSD	Treat	Cont	SMD	LRSD
Treatment and control group as of 2008 effective connection to MIND/FIND														
Log GDP pc	19	9.58	1.09	129	8.42	1.28	0.95	0.81	0.97	-0.16	0.79	1.00	0.07	0.10
Log Pop	19	16.43	1.48	129	16.06	1.58	0.95	0.92	0.24	-0.07	1.00	0.89	-0.21	-0.17
Polity score	19	8.11	3.16	129	3.05	6.58	1.00	0.73	0.98	-0.73	1.00	0.95	0.06	-0.18
Cum Terror	19	6.05	7.20	129	3.81	8.19	1.00	0.96	0.29	-0.13	1.00	0.89	-0.29	-0.54
Prop. score	19	0.26	0.15	129	0.11	0.12	0.84	0.53	1.11	0.25	0.89	0.95	0.06	0.07
Log odds rat	19	-1.26	0.94	129	-2.73	1.33	0.84	0.53	1.27	-0.35	0.89	0.95	0.03	0.04
Treatment and control group as of 2009 effective connection to MIND/FIND														
Log GDP pc	33	9.53	1.14	115	8.30	1.23	0.88	0.97	1.04	-0.08	0.91	1.00	0.15	0.11
Log Pop	33	16.51	1.61	115	15.99	1.54	0.97	0.92	0.33	0.05	0.94	0.97	-0.00	0.16
Polity score	33	7.18	4.89	115	2.70	6.54	0.97	1.00	0.78	-0.29	1.00	1.00	0.09	-0.19
Cum Terror	33	5.6	8.29	115	3.66	8.00	0.97	0.98	0.24	0.04	1.00	0.97	-0.06	-0.30
Prop. score	33	0.40	0.21	115	0.17	0.16	0.79	0.77	1.22	0.24	0.94	0.97	0.23	0.17
Log odds rat	33	-0.55	1.12	115	-2.03	1.24	0.79	0.77	1.25	-0.10	0.94	0.97	0.16	0.12
Treatment and control group as of 2010 effective connection to MIND/FIND														
Log GDP pc	38	9.50	1.13	110	8.25	1.22	0.89	0.97	1.07	-0.08	0.95	1.00	0.16	0.08
Log Pop	38	16.32	1.56	110	16.03	1.57	1.00	0.92	0.18	-0.01	1.00	0.89	0.07	-0.10
Polity score	38	6.87	5.38	110	2.6	6.47	0.95	1.00	0.72	-0.19	0.95	1.00	0.07	-0.06
Cum Terror	38	5.37	9.07	110	3.66	7.71	1.00	0.98	0.20	0.16	1.00	0.97	-0.03	-0.08
Prop. score	38	0.42	0.20	110	0.20	0.18	0.79	0.78	1.18	0.13	0.95	0.97	0.24	0.15
Log odds rat	38	-0.41	1.02	110	-1.79	1.21	0.79	0.78	1.23	-0.17	0.95	0.97	0.17	0.12
Treatment and control group as of 2011 effective connection to MIND/FIND														
Log GDP pc	53	9.42	1.17	95	8.09	1.14	0.74	0.91	1.15	0.02	0.87	0.98	0.54	0.20
Log Pop	53	16.15	1.55	95	16.08	1.58	1.00	0.94	0.04	-0.02	1.00	0.92	0.03	-0.14
Polity score	53	5.38	6.49	95	2.76	6.30	0.94	1.00	0.41	0.03	0.91	1.00	0.03	0.11
Cum Terror	53	4.45	7.92	95	3.91	8.21	1.00	0.97	0.07	-0.04	1.00	0.96	0.10	-0.05
Prop. score	53	0.52	0.22	95	0.27	0.20	0.85	0.85	1.19	0.12	0.83	0.98	0.62	0.17
Log odds rat	53	0.04	1.08	95	-1.25	1.11	0.85	0.88	1.17	-0.02	0.83	0.98	0.53	0.17

SD, SMD, and LRSD stand for Standard Deviation, Standarized Mean Difference, and Log-Ratio of Standard Deviations

Table 4: Cross-sectional Poisson regressions

	(1)	(2)	(3)	(4)
Year when outcome is measured	2008	2009	2010	2011
Log GDP per capita	-0.8190**	-0.8279***	0.9625***	0.6444
	(0.3383)	(0.3194)	(0.3728)	(0.6213)
Log Population	-0.4551**	-0.9155***	-0.6326***	-0.4851**
	(0.1981)	(0.1442)	(0.2004)	(0.2201)
Polity score	-0.0888	-0.0497	0.0643	-0.1223**
	(0.0946)	(0.0393)	(0.0681)	(0.0622)
Cum. Trans. Terror Incidents	0.0026	0.0266*	0.0499***	0.0426*
	(0.0293)	(0.0143)	(0.0162)	(0.0228)
Treatment	-7.6090	-22.6007***	9.8474	2.6326
	(7.9758)	(8.2651)	(8.0476)	(11.1020)
Treatment×Log GDP per capita	0.5105	0.6449	-0.7530	-0.4580
	(0.4090)	(0.4646)	(0.7314)	(0.8069)
Treatment×Log Population	0.1165	0.9049**	-0.1875	0.0410
	(0.3856)	(0.3776)	(0.2677)	(0.3091)
Treatment×Polity score	-0.1090	0.0803	-0.0129	0.1691**
	(0.1374)	(0.1673)	(0.0875)	(0.0834)
Treatment×Cum. Trans. Terror Incidents	0.1136*	0.0208	-0.0148	0.0053
	(0.0628)	(0.0270)	(0.0345)	(0.0265)
Constant	11.8021**	19.0903***	-2.8383	-1.8891
	(5.3553)	(4.3956)	(5.0047)	(8.7040)
Number of countries	38	66	76	106
Proportional Average Treatment Effect	-0.6320	-0.5617	-0.4155	-0.0836
Confidence interval lower bound	-0.7273	-0.6399	-0.4877	-0.1896
Confidence interval upper bound	-0.5217	-0.4757	-0.3384	0.0291
Transnational Terrorism Incidence Rates for the treated				
Expected TTIR under treatment	0.5383	0.7147	2.1494	1.4914
Expected TTIR under no treatment	1.4628	1.6306	3.6774	1.6275
Actual TTIR	0.4669	0.8495	2.2949	1.9638

Standard errors in parentheses, *** p-value<0.01, ** p-value<0.05, * p-value<0.1
Covariates measured as of 2004 and outcomes in different years by columns.

Table 5: Panel count regressions

	(1)	(2)	(3)
	FE Poisson	PSM-GMM	PSM-GMM
Dummy Lagged Trans. Terror Incidents			1.3560***
			(0.2385)
Log GDP per capita	-3.7980***	-0.2220**	-0.2121**
	(1.0816)	(0.1005)	(0.0937)
Log Population	-2.2309	-0.5820***	-0.7067***
	(2.1779)	(0.0614)	(0.0642)
Polity score	0.0165	-0.0178	-0.0144
	(0.0323)	(0.0153)	(0.0165)
Treatment	5.4839	-0.5612	-0.3012
	(3.8003)	(5.0589)	(4.7801)
Treatment×Log GDP per capita	-0.2743	0.1734	0.1820
	(0.1932)	(0.2834)	(0.2579)
Treatment×Log Population	-0.1880	-0.0968	-0.1196
	(0.1784)	(0.1897)	(0.2015)
Treatment×Polity score	0.0034	0.0385	0.0490
	(0.0482)	(0.0324)	(0.0426)
Pre-Sample Mean Trans. Terror Incidents		0.5885***	0.4078***
		(0.0905)	(0.1069)
Constant		7.7294***	9.0706***
		(1.0530)	(1.1671)
Observations	422	567	567
Countries	61	81	81

Standard errors in parentheses, *** p-value<0.01, ** p-value<0.05, * p-value<0.1
All regressions include year dummies.

Table 6: Panel Proportional Average Treatment Effects for the Treated

Year	2008	2009	2010	2011
Fixed Effects Poisson				
PATET	-0.3515	-0.3173	-0.3156	-0.3185
Confidence interval lower bound	-0.3704	-0.3346	-0.3336	-0.3390
Confidence interval upper bound	-0.3323	-0.2998	-0.2973	-0.2976
Pre-Sample Mean GMM				
PATET	-0.1869	-0.2549	-0.2635	-0.2525
Confidence interval lower bound	-0.2062	-0.2711	-0.2796	-0.2699
Confidence interval upper bound	-0.1674	-0.2386	-0.2472	-0.2348
Pre-Sample Mean GMM - Lagged Transnational Terror Model				
PATET	-0.1576	-0.2419	-0.2550	-0.2429
Confidence interval lower bound	-0.1775	-0.2581	-0.2712	-0.2608
Confidence interval upper bound	-0.1375	-0.2256	-0.2387	-0.2248
TTIR for the treated				
Expected TTIR under treatment	1.2716	1.3434	1.5836	1.4160
Expected TTIR under no treatment	1.5640	1.8030	2.1501	1.8942
Actual TTIR	0.6824	1.3349	2.4360	3.8548

Table 7: Extended Propensity Score

	(1)	(2)	(3)	(4)
	2008	2009	2010	2011
Log GDP pc	1.0323**	-2.3994	-2.7239	-5.9753**
	(0.4759)	(2.1625)	(2.0418)	(2.8427)
Log Population	-0.1663	-1.7657	-2.1999*	-1.3095
	(0.1924)	(1.2190)	(1.2108)	(1.2215)
Polity score	0.3339***	1.0630***	0.9439***	0.8787**
	(0.1000)	(0.4121)	(0.3646)	(0.3468)
Cum. Trans. Terror	0.2365**	-0.0022	-0.5999*	-0.0255
	(0.0961)	(0.0248)	(0.3317)	(0.0251)
Log GDP pc squared				0.2686**
				(0.1361)
Log Population squared	-0.0346*			
	(0.0186)			
Cum. Trans. Terror squared	-0.0074***			
	(0.0028)			
Log GDP pc $\times$ Polity score		-0.1028**	-0.0924**	-0.0957**
		(0.0437)	(0.0396)	(0.0385)
Log GDP pc $\times$ Log Population		0.2311*	0.2529*	0.1691
		(0.1378)	(0.1355)	(0.1400)
Log Population $\times$ Cum. Trans. Terror			0.0351*	
			(0.0191)	
Constant	-9.0362**	14.6067	21.7230	28.0874
	(3.8756)	(19.2974)	(18.3238)	(19.3063)
Observations	148	148	148	148

Table 8: Extended Conditional Mean Functions

	(1)	(2)	(3)	(4)
	2008	2009	2010	2011
Benchmark terms				
Log GDP pc	13.8735***	17.3231***	-28.1528***	-12.0233***
	(5.0673)	(5.9338)	(4.9680)	(4.1653)
Log Population	-0.9779***	9.6558***	5.3107*	-0.3345
	(0.3681)	(3.3747)	(3.1076)	(0.2468)
Polity score	13.0621**	0.0732	-0.0607	-0.2915***
	(6.2852)	(0.0651)	(0.1623)	(0.0850)
Cum. Trans. Terror	0.1207	0.2148**	2.2923***	0.3777
	(0.0877)	(0.0886)	(0.7222)	(0.3149)
Treatment	127.4506**	271.4819***	-124.4583*	35.2168
	(49.9672)	(61.5962)	(68.0675)	(23.3934)
Treat. $\times$ Log GDP pc	-14.7089***	-28.3012***	3.1967	-7.8601
	(5.1029)	(6.4876)	(8.5243)	(6.1610)
Treat. $\times$ Log Population	0.5935	-15.7483***	13.1549	-0.3327
	(0.4969)	(3.5736)	(8.5207)	(0.2885)
Treat. $\times$ Polity score	-13.8558**	-0.2350**	0.2364	0.4206***
	(6.3114)	(0.1007)	(0.2094)	(0.1069)
Treat. $\times$ Cum. Trans. Terror	-0.0014	0.2103*	-4.0644***	2.3365***
	(0.1049)	(0.1214)	(0.9672)	(0.8135)
Additional terms				
Log GDP pc squared			1.5250***	0.7073***
			(0.2779)	(0.2554)
Log Population squared			-0.1386	
			(0.0872)	
Cum. Trans. Terror squared		-0.0043**		-0.0089**
		(0.0019)		(0.0039)
Log GDP pc $\times$ Log Pop.		-1.0299***		
		(0.3516)		
Log GDP pc $\times$ Polity score	-1.4074**			
	(0.6596)			
Log GDP pc $\times$ Cum. Trans. Terror				0.0002
				(0.0296)

Continued in next page

Table 8 Continued: Extended Conditional Mean Functions

	(1)	(2)	(3)	(4)
Log Population × Cum. Trans. Terror			-0.1580***	
			(0.0359)	
Polity score × Cum. Trans. Terror			0.0595*	
			(0.0325)	
Treat. × Log GDP pc squared			-0.0645	0.4504
			(0.4933)	(0.3673)
Treat. × Log Population squared			-0.4412*	
			(0.2421)	
Treat. × Cum. Trans. Terror squared		-0.0046*		-0.0029
		(0.0026)		(0.0052)
Treat. × Log GDP pc × Log Pop.		1.6377***		
		(0.3786)		
Treat. × Log GDP pc × Polity score	1.4710**			
	(0.6627)			
Treat. × Log GDP pc × Cum. Trans. Terr.				-0.2285***
				(0.0729)
Treat. × Log Pop. × Cum. Trans. Terr.			0.2680***	
			(0.0515)	
Treat. × Polity score × Cum. Trans. Terr.			-0.0684**	
			(0.0328)	
Constant	-117.6167**	-168.4538***	74.3357*	50.9296***
	(49.2272)	(57.6660)	(39.5327)	(14.1868)
Observations	38	66	76	106
PATET	-0.6117	-0.7303	-0.4260	-0.6970
Confidence interval lower bound	-0.7070	-0.7804	-0.6047	-0.7483
Confidence interval upper bound	-0.5023	-0.6748	-0.2119	-0.6408
Expected TTIR under treatment	0.5412	0.2232	0.2116	0.2986
Expected TTIR under no treatment	1.3939	0.8275	0.3686	0.9853
Actual TTIR	0.4669	0.8495	2.2949	1.9638

Standard errors in parentheses, *** p-value<0.01, ** p-value<0.05, * p-value<0.1

Table 9: Panel estimates extended specifications

	(1)	(2)	(3)
	FE Poisson	PSM-GMM	PSM-GMM
Dummy Lagged Trans. Terror Incidents			1.2519***
			(0.2366)
Log GDP pc	1.4639	3.1860	-1.6542
	(8.0965)	(2.0004)	(1.1843)
Log Population	-3.2356	2.0885***	-0.6066***
	(2.4051)	(0.6284)	(0.0910)
Polity score	1.5473***	-0.3375**	0.0245
	(0.4546)	(0.1477)	(0.0229)
Log GDP pc squared	-0.2726	0.1138	0.0989
	(0.4727)	(0.0825)	(0.0711)
Polity score squared		-0.0240***	-0.0173***
		(0.0059)	(0.0056)
Log GDP pc $\times$ Log Pop.		-0.3027***	
		(0.0722)	
Log GDP pc $\times$ Polity score	-0.1935***	0.0438**	
	(0.0573)	(0.0172)	
Treatment	50.3615**	92.4280***	23.4566***
	(19.9927)	(19.8411)	(7.5804)
Treat. $\times$ Log GDP pc	-10.2115**	-12.4381***	-4.9475**
	(4.2682)	(2.5989)	(2.0734)
Treat. $\times$ Log Population	-0.1107	-4.3011***	-0.1395
	(0.1972)	(1.2613)	(0.1722)
Treat. $\times$ Polity score	-0.4628	0.5278**	-0.0011
	(0.3758)	(0.2476)	(0.0476)
Treat. $\times$ Log GDP pc squared	0.5292**	0.2486**	0.2681**
	(0.2280)	(0.1221)	(0.1226)
Treat. $\times$ Polity score squared		0.0184**	0.0156*
		(0.0079)	(0.0084)
Treat. $\times$ Log GDP pc $\times$ Log Pop.		0.4639***	
		(0.1343)	
Treat. $\times$ Log GDP pc $\times$ Polity score	0.0444	-0.0603**	
	(0.0382)	(0.0279)	
Pre-Sample Mean Trans. Terror Incidents		0.5013***	0.4200***
		(0.0988)	(0.1079)
Constant		-30.5557**	13.0367***
		(12.6009)	(4.3854)
Number of observations	422	567	567
Number of countries	61	81	81

Standard errors in parentheses, *** p-value<0.01, ** p-value<0.05, * p-value<0.1

All regressions include year dummies.

Table 10: Treatment effects with the panel extended specification

Year	2008	2009	2010	2011
Fixed Effects Poisson				
PATET	-0.3763	-0.1812	-0.2257	-0.2255
Confidence interval lower bound	-0.3952	-0.2044	-0.2473	-0.2497
Confidence interval upper bound	-0.3572	-0.1577	-0.2038	-0.2009
Pre-Sample Mean - GMM				
PATET	-0.3880	-0.2893	-0.2285	-0.2008
Confidence interval lower bound	-0.4020	-0.3058	-0.2470	-0.2208
Confidence interval upper bound	-0.3729	-0.2725	-0.2098	-0.1805
PSM- GMM - Lagged transnational terror model				
PATET	-0.3036	-0.2811	-0.2624	-0.1990
Confidence interval lower bound	-0.3216	-0.2981	-0.2801	-0.2198
Confidence interval upper bound	-0.2854	-0.2640	-0.2444	-0.1780
TTIR for the treated				
Expected TTIR under treatment	1.2411	1.4669	1.7486	1.7284
Expected TTIR under no treatment	2.0279	2.0639	2.2665	2.1626
Actual TTIR	0.6824	1.3349	2.4360	3.8548