INTERPOL’s Surveillance Network in Curbing Transnational Terrorism

Javier Gardeazabal
Todd Sandler

Abstract

This paper investigates the role that International Criminal Police Organization (INTERPOL) surveillance—the Mobile INTERPOL Network Database (MIND) and the Fixed INTERPOL Network Database (FIND)—played in the War on Terror since its inception in 2005. MIND/FIND surveillance allows countries to screen people and documents systematically at border crossings against INTERPOL databases on terrorists, fugitives, and stolen and lost travel documents. Such documents have been used in the past by terrorists to transit borders. By applying methods developed in the treatment-effects literature, this paper establishes that countries adopting MIND/FIND experienced fewer transnational terrorist attacks than they would have had they not adopted MIND/FIND. Our estimates indicate that, on average, from 2008 to 2011, adopting and using MIND/FIND results in 0.5 fewer transnational terrorist incidents each year per 100 million people. Thus, a country like France with a population just above 64 million people in 2008 would have 0.32 fewer transnational terrorist incidents per year owing to its use of INTERPOL surveillance. This amounts to a sizeable average proportional reduction of about 30 percent. © 2015 The Authors. Journal of Policy Analysis and Management published by Wiley Periodicals, Inc. on behalf of Association for Public Policy and Management.

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. This large return can be contrasted with disappointing returns on U.S. homeland security spending, which was calculated as four to ten cents on a dollar by Sandler, Arce, and Enders (2009) in their Copenhagen Consensus study. More recently, Mueller and Stewart (2014) showed that U.S. homeland security did not come near to justifying the many tens of billions of dollars spent each year. Thus, INTERPOL surveillance methods, which cost millions of euros annually, appear to be excellent value as our analysis will show, given their effectiveness in curbing transnational terrorism. INTERPOL provides multiple services—for example, 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 surveillance 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 continuously updated, whereas MIND provides access to an offline database, which is periodically downloaded in an updated form every 24 to 48 hours.

These technologies may be effective at curbing international crime and transnational terrorism; however, as of December 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. However, not all connected countries used the network.

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 and use MIND/FIND. Countries must, however, remember that keeping transnational terrorists from moving about freely from country to country is a weakest-link public good problem because terrorists will seek to transit the least-vigilant borders (Enders & 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 & Sandler, 1993). Displacement effects are ameliorated when main airport hub countries are utilizing INTERPOL surveillance, so that terrorists must take circuitous routes and cannot enter their prime-target countries.

We apply causal inference methods developed in the treatment-effects literature (Angrist & Pischke, 2009; Wooldridge, 2010) in order to establish a causal relationship between the treatment, MIND/FIND adoption, and transnational terrorist incidents. Applying causal inference methods to assess treatment effects at the country level is a challenging task as some of the assumptions maintained in the treatment-effects literature might not hold at the aggregate level. However, 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

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1 The only other surveillance system used at border crossings is the Schengen Information System, which is an inferior alternative to MIND/FIND for European Union (EU) countries. It is inferior because, unlike MIND/FIND, Schengen does not possess global databases on stolen and lost travel documents or on suspected terrorists (Enders & Sandler, 2011). NATO and other alliances do not conduct border surveillance. Many NATO countries use MIND/FIND.
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 nonusers. Even though the reduction in incidents per adopter is small, the proportional reduction is large for the period 2008 to 2011, at about 30 percent on average for countries using the network.

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 (e.g., human trafficking). MIND/FIND also dissuades criminals other than terrorists from crossing international borders, thereby providing another benefit, not captured in our study.

The remainder of the paper contains six sections. The next section presents necessary preliminaries on INTERPOL and MIND/FIND, while the ensuing section describes our data set. The following sections indicate our methodology and report estimates of the treatment effects. The last section concludes with a discussion of our findings.

PRELIMINARIES ON INTERPOL AND MIND/FIND

Terrorism is the premeditated use or threat to use violence by individuals or subnational groups to obtain a political or social objective through the intimidation of a large audience beyond that of the immediate victims (Enders & Sandler, 2012). 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. The Oklahoma City bombing by Timothy McVeigh on April 19, 1995 is a domestic terrorist incident since the perpetrator and the victims were Americans from the venue country. In contrast, transnational terrorism involves perpetrators, victims, 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 injures an American, the attack is a transnational terrorist event. The Boston Marathon bombing by the Tsarnaev brothers on April 15, 2013 is a transnational terrorist incident because one of the perpetrators was a non-U.S. citizen and one of the murdered victims was a student from China. Our distinction between domestic and transnational terrorist incidents is the one used by the three terrorist event data sets, including the one used in this study, described in the next section. Transnational terrorism generates transnational externalities for countries other than where the attack takes place. INTERPOL’s international mission has, in some terrorist instances, assisted member countries’ efforts to capture transnational terrorists using INTERPOL’s resources.

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

2 On these definitions and terrorist event data sets, see Enders, Sandler, and Gaibulloev (2011).
four skyjackings on September 11, 2001 (henceforth, 9/11), INTERPOL channeled up to 20 to 25 percent of its annual crime-fighting resources into coordinating international law enforcement efforts to address transnational terrorism (Sandler, Arce, & 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 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—this was true of some 9/11 hijackers (Sandler, Arce, & Enders, 2011).

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 or FIND (or both) to interested members. MIND/FIND provides an efficient systematic means for checking people, motor vehicles, and travel documents 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 or 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 information. FIND allows real-time online access to INTERPOL databases, while MIND contains a copy of these databases. This offline copy is updated periodically, within 48 hours or less (Enders & 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. In practice, this short lag should not make any effective difference between MIND and FIND. MIND/FIND allows access to huge databases containing millions of records contributed by all INTERPOL member countries (whether connected to the MIND/FIND network or not). These databases are continuously updated; however, the magnitude of the flow of records is minuscule compared with the size of the stock of records already in the databases. Therefore, searching INTERPOL databases through the MIND network misses the flow of records since the last update. This could make a difference between MIND and FIND if, for instance, a new terrorist suspect surfaces since the last update, but then a red alert can be issued in real time to INTERPOL member countries. Terrorists are anticipated to use SLTD already in the database unless acquired within a day or so of travel, which is not a likely event. 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—for example, some Caribbean and African countries. So, possessing MIND/FIND is no guarantee that it will be applied to border or other searches (Enders & Sandler, 2011). In March 2014, this was made abundantly clear when two passengers
boarded Malaysian Airlines flight 370 with stolen passports and were not screened by Malaysia, a FIND country since June 2007.

THE DATA

We collected yearly data on INTERPOL member countries, the units of analysis, from 2005 to 2011. Definition of the treatment (i.e., the connection to or moderate use of the MIND/FIND network) requires a detailed explanation. 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 1,000 or more annual searches using the MIND/FIND network. 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. Table 1 reports the number of country-year cases and average number of searches, classified according to whether countries were formally connected to MIND/FIND and whether the
number of searches was above or below the 1,000 threshold. Table 1 shows that in 124 country-year cases, countries were formally connected to MIND/FIND but performed less than 1,000 searches on the network (on average 81.1 searches per year). These figures indicate that those countries, although formally connected to MIND/FIND, did not use the network systematically. In addition, our sample includes seven country-year cases where countries not formally connected to the network performed more than 1,000 searches on the network through their I-24/7 portal (on average 897,974.9 searches). Although these countries were not MIND/FIND countries, their volume of searches is sufficiently high to suggest a more than casual use of the network. In summary, Table 1 shows that the 1,000 searches threshold identifies a more systematic use of the network than the connection status. Henceforth, we consider a country as treated when it actually used the MIND/FIND or I-24/7 network to perform a minimum of a thousand searches per year. The choice of a particular threshold number of searches is certainly arbitrary. A good reason for our 1,000 searches threshold choice is that INTERPOL itself used the 1,000 searches threshold to classify countries into those which "used/did not use" their Automated Search Facility (ASF).

Therefore, a country in a particular year is considered as treated if the total number of searches (either MIND or FIND) exceeds 1,000. However, the time domain of our analysis runs from 2005 to 2011. It includes not only the 2008 to 2011 period for which the number of searches is available but also the 2005 to 2007 period with only information on MIND/FIND connection status but no information on the number of searches. For the 2005 to 2007 period, treatment is defined according to connection status with a few exceptions: a number of countries formally connected at some point during the 2005 through 2007 period have no searches (or searches below the 1,000 threshold) in 2008. It seemed reasonable to consider those cases as untreated.\(^3\) If this assumption were erroneous, then we would be biasing the treatment effect in the direction of finding a smaller treatment effect (in absolute value).

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 their country venue. Figure 2 shows a time series plot of the number of transnational terrorism incidents in our sample for the period 2000 to 2011. During the subperiod 2005 to 2011, the total number of incidents is split into the group of treated (MIND/FIND) countries and untreated (not MIND/FIND) countries. A simple comparison of the raw number of incidents across

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Table 1. Number of searches and MIND/FIND connection status.

| Number of searches | Connected | | | Not connected | | |
|--------------------|-----------|---|---|----------------|---|
|                    | Average searches | Country-year cases | | Average searches | Country-year cases |
| ≥1,000             | 11,005,625.0 | 135 | | 897,974.9 | 7 |
| <1,000             | 81.1 | 124 | | 3.0 | 298 |

*Notes:* This table shows the average number of searches and the number of country-year cases classified according to MIND/FIND connection status and whether countries performed at least 1,000 searches or not.

\(^3\) These countries are Cambodia, Indonesia, Lao PDR, Lithuania, Malaysia, South Africa, Thailand, Turkey, and Vietnam.
groups would lead to erroneous inference. To begin with, countries that joined MIND/FIND first had only a few incidents prior to joining the network or afterwards, for example, Switzerland experienced no incidents during the entire sample period, before or after joining MIND/FIND. Second, the number of incidents should be adjusted for various other risk factors affecting the number of transnational terrorist incidents. Third, as the number of treated countries increases, so will the number of terrorist incidents even when the treatment might be reducing incidents.

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, & Gurr, 2011).

We dropped from the analysis countries with incomplete data, resulting in a balanced panel of 141 countries as listed in the first panel of Table 2. The temporal framework of the analysis takes the years from 2000 to 2004 as the pretreatment or presample period, and uses years 2005 to 2011 as the sample or estimation period. The effect of MIND/FIND adoption and use on transnational terrorism is evaluated for the 2008 to 2011 period.

THE METHODS

Introducing the methods requires some definitions. Let \( Y_{it} \) be the number of transnational terrorist incidents that take place in country \( i \) during year \( t \). Let \( R_{it} \) be the...
transnational terrorism incidence rate (TTIR) defined as the number of transnational terrorist incidents divided by population, that is, $R_t = \frac{Y_{it}}{M_{it}}$, where $M_{it}$ is population of country $i$ in year $t$. Past studies normalized terrorism by population because more populated countries imply greater terrorist exposure (see, e.g., Gassebner & Luechinger, 2011). In our application, population is measured in hundreds of millions. The treatment status variable, $D_{it}$, equals one when country $i$ receives treatment as defined in the Data section in year $t$ and equals zero otherwise. To assess the treatment effects, we use a Rubin causal model (Rubin, 1974; Sekhon, 2007). Let $Y_{it}^1$ be the potential number of transnational terrorist incidents under treatment, and let $Y_{it}^0$ be the potential number of transnational terrorist incidents under no treatment. The observed number of transnational terrorist incidents, $Y_{it}$, is related to the potential numbers of transnational terrorist incidents according to $Y_{it} = Y_{it}^0 + D_{it}(Y_{it}^1 - Y_{it}^0)$.
We assume that the conditional expectation of the potential number of transnational terrorist incidents is exponential

\[
E\left( Y_{it}^j \mid X_{it}, \eta_i, \lambda_t \right) = \exp \left( Z'_{it}\beta_j + \eta_i + \lambda_t + \ln (M_{it}) \right),
\]

for \( j = 0, 1 \), where \( X_{it} \) is a vector of covariates, \( Z_{it} \) is a vector that includes powers and interactions of the covariates as well as unity, \( \beta_j \) is a conforming vector of parameters which depends on whether treatment is in place or not, \( \eta_i \) is a time-invariant country-specific unobserved effect, and \( \lambda_t \) is a unit-invariant period-specific unobserved effect.

Further assume that conditional on covariates, unobserved heterogeneity, and common time trends, potential outcomes and treatment status are mean independent, that is, \( E(Y_{it}^j \mid X_{it}, D_{it}, \eta_i, \lambda_t) = E(Y_{it}^j \mid X_{it}, \eta_i, \lambda_t) \). Therefore, the conditional mean of the observed number of transnational terrorist incidents is

\[
E\left( Y_{it} \mid X_{it}, D_{it}, \eta_i, \lambda_t \right) = \exp \left( Z'_{it}\beta_0 + D_{it}Z'_{it}\gamma + \eta_i + \lambda_t + \ln (M_{it}) \right),
\]

where \( \gamma = \beta_1 - \beta_0 \). Notice that (log) population enters the exponential mean function with the associated coefficient restricted to be unity. Thus, because the exponential and logarithm functions cancel out, the conditional mean is proportional to population, in other words, population is being used as a measure of exposure. Furthermore, moving population to the other side of equation (2) results in

\[
E\left( R_{it} \mid X_{it}, D_{it}, \eta_i, \lambda_t \right) = \exp \left( Z'_{it}\beta_0 + D_{it}Z'_{it}\gamma + \eta_i + \lambda_t \right),
\]

where the dependent variable is the TTIR. Therefore, we can use the predicted values generated using equation (3) and then average them over countries to compute average TTIRs.

A desirable feature of the specification in equation (2) is that it allows for different functional forms for treated and control units by including interactions of the treatment indicator with all elements of \( Z_{it} \), which includes unity. In addition, equation (2) permits a flexible parametric functional form by including powers and interactions of the covariates. These flexible functional forms are obtained after a careful specification search procedure. Details about the procedure are reported in an online appendix. In essence, the specification search procedure is as follows. We start with an initial specification including the baseline covariates, together with their interactions with the treatment indicator. The final specification is obtained after several rounds of regressions. At each round, a set of exponential regressions is estimated, each of these regressions includes all terms included in the previous round plus a pair of nonlinear terms: a squared covariate or interaction of two covariates and its interaction with the treatment indicator. Among all regressions in a round, we select the most statistically significant pair of nonlinear terms, which is then included in the next round of regressions. When no more pairs of terms turn out to be significant, we run a final round of regressions, in each of which an insignificant term is eliminated. Retaining only significant terms is important for the estimation of the treatment effects, which could otherwise be affected by large but insignificant parameter estimates. The specification search follows a procedure very similar to

\[\text{All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher’s Web site and use the search engine to locate the article at http://onlinelibrary.wiley.com.}\]

\[The use of quadratic covariates as determinants of transnational terrorism is consistent with Abadie (2006) and Enders, Hoover, and Sandler (2014).\]
the so-called stepwise regression. Using stepwise regression requires adjusting the significance levels to take into account the model building process. Had we adjusted the significance levels accordingly, confidence intervals (CIs) reported below would have been wider.7

Although the MIND/FIND network was not devised as a counterterrorism tool, it can be argued that MIND/FIND adoption is not entirely exogenous for the analysis of transnational terrorism. Countries that have a record of transnational terrorist incidents in the past could to a greater degree decide to adopt MIND/FIND technology. Anecdotally, one of the first countries to adopt MIND/FIND, Spain, joined the network on October 1, 2006, not long after the March 11, 2004 train attacks in Madrid. Accounting for country-specific unobserved effects, \( \eta_i \), is important because there might be unobserved factors that affect both the decision to join MIND/FIND and transnational terrorist incidents. For example, one such factor could be the stance against transnational terrorism, which could affect both the adoption of MIND/FIND technology and the level of transnational terrorism. Under these circumstances, treatment status is not independent from the unobserved factors (i.e., stance against transnational terrorism), thus generating a problem of endogenous treatment. This is an important challenge of this research. Some of the estimation methods described below account for it.

The number of transnational terrorist incidents is a count variable; its support is the set of nonnegative integers. We account for this characteristic of the outcome variable using count regression methods. We use three estimation procedures: the random-effects Poisson maximum likelihood estimator (REP-MLE) and the fixed-effects Poisson maximum likelihood estimator (FEP-MLE) introduced by Hausman, Hall, and Griliches (1984), as well as the presample mean generalized method of moments (PSM-GMM) estimator, suggested by Blundell, Griffith, and Windmeijer (2002). These estimation methods have different properties and use different subsets of the database.

The REP-MLE relies on strong distributional assumptions. Conditional on covariates and unobserved effects, this estimator assumes that the number of counts is Poisson distributed. Moreover, the REP-MLE assumes that the unobserved effects are Gamma distributed and independent from the covariates. The latter assumption implies that treatment status must be independent from unobserved factors. Therefore, it might lead to inconsistent estimates if MIND/FIND adoption and use (the treatment) is triggered by unobserved factors that also influence the incidence of transnational terrorism, such as the stance against transnational terrorism. The REP-MLE uses all the data in our sample, including information on countries that do not experience transnational terrorist incidents.

Although originally derived using strong distributional assumptions, the FEP-MLE can be obtained under weaker assumptions: the only assumptions needed are exponential mean and strictly exogenous regressors (Wooldridge, 1999). The FEP-MLE, however, allows for dependence between the unobserved factors and regressors, including the treatment indicator. Therefore, the FEP-MLE remains consistent even when treatment status depends on unobserved factors. The FEP-MLE restricts the analysis to units with a positive number of counts (transnational terrorist events) during the sample period. As a result of this restriction, the sample is significantly reduced. This sample selection might be reasonable, as there is not

7 There is, however, a fundamental difference between stepwise regression and our procedure. Stepwise regression uses an automatic procedure to choose a subset of predictive variables among a larger set of available variables. The specification search we use does not look for a set of predictive variables, we use those variables that have been found to be significant transnational terrorism determinants in the literature. Instead, the procedure searches for the best approximation to a nonlinear conditional mean.
much point in analyzing the effect of MIND/FIND use on countries that do not experience transnational terrorism. Unfortunately, it can also be argued that the sample selection imposed by the FEP-MLE cannot account for the effect of MIND/FIND use on countries that had a small number of transnational terrorist events, say one or two events, prior to the treatment period, but then had no transnational terrorist events during the sample period and therefore are dropped from the estimation sample. If this reduction in transnational terrorist events is due to MIND/FIND use, we would then be dropping countries from the sample, for which the proportional reduction in transnational terrorist incidents is a 100 percent.

Like the FEP-MLE, the PSM-GMM does not make distributional assumptions and the assumption of strictly exogenous regressors can be relaxed. The PSM-GMM estimator assumes that the unobserved country-specific effects can be accounted for by the presample mean of the dependent variable (i.e., the number of transnational terrorist incidents during a presample period). Under this assumption, the model can be written as

\[ E(Y_{it} | X_{it}, D_{it}, Y^*_{i}, \lambda_{it}) = \exp(Z'_{it} \beta_0 + D_{it} Z'_{it} \gamma + \alpha \ln Y^*_{i} + \lambda_{it} + \ln(M_{it})) , \]

where \( Y^*_{i} = \frac{1}{T^*} \sum_{t'=1}^{T^*} Y_{i,t} \) is the average number of transnational terrorist incidents ending in country \( i \) during the \( T^* \) periods before the beginning of the sample period and \( \alpha \) is a parameter to be estimated. By relying on the presample mean of transnational terrorist events as a proxy for the country effects, the PSM-GMM estimator is not affected by the endogenous treatment bias, as the country effects are an additional regressor that can be correlated with the other regressors.

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,

\[ E(Y_{it} | Y_{i,t-1}, X_{it}, D_{it}, Y^*_{i}, \lambda_{it}) = h(Y_{i,t-1}; \delta) \times \exp(Z'_{it} \beta_0 + D_{it} Z'_{it} \gamma + \alpha \ln Y^*_{i} + \lambda_{it} + \ln(M_{it})) , \]

where the lagged dependent variable enters the conditional mean through function \( h(Y_{i,t-1}; \delta) \). In our application, we use the functional form suggested by Crépon and Duguet (1997): \( h(Y_{i,t-1}; \delta) = \exp(\delta w_{i,t-1}) \) with \( w_{i,t-1} \) being a dummy variable that equals one when the lagged number of transnational terrorist incidents is positive, \( Y_{i,t-1} > 0 \), and equals zero otherwise. In equation (5), \( \delta \) is a parameter to be estimated.

As the presample mean of transnational terrorist incidents enters the exponential mean in logarithms, the PSM-GMM method restricts the sample to the set of countries with a positive number of transnational terrorist incidents during the presample period. As in the case of the FEP-MLE, imposing this restriction reduces the sample significantly. However, the PSM-GMM analysis focuses on countries with some transnational terrorist incidents during the presample (i.e., pretreatment) period, while the number of transnational terrorist incidents during the sample period is unrestricted. It seems to us that this sample restriction constrains the analysis to a more natural sample than in the FEP-MLE case.\(^8\)

\(^8\) As an example, suppose you are interested in analyzing the effect of some retroviral pharmaceutical on viral load. It seems pretty obvious that, in this case, you certainly want to use a sample of previously virus-infected individuals for your analysis. Similarly, the PSM-GMM estimator focuses on a sample of countries that experienced some transnational terrorist incidents prior to the treatment period.
Our estimation methods rely on the assumption of random sampling under which the number of transnational terrorist incidents is independent across countries. In particular, this assumption rules out the case where MIND/FIND adoption in one country has an effect on the number of transnational terrorist incidents in another country. In our study, there are at least two reasons why the no-interference assumption may not hold in opposing directions. First, the War on Terror is considered to be a weakest-link public good problem (Enders & Sandler, 2012); that is, world security depends on the level of security in the least-secure country. Therefore, MIND/FIND adoption by a country might deflect some transnational terrorist incidents to countries where this technology is not used, thus reducing transnational terrorism in treated countries and increasing it in untreated countries.

This violation of the no-interference assumption is not as problematic as one might think. Typically, when interference occurs, the treatment affects the treated and the control units in the same direction, but usually in different magnitudes. In this situation, if we use a comparison group whose units are affected by the treatment, we may erroneously conclude that there is no causal effect, or that the effect is smaller than it actually is. However, if the weakest-link effect exists, treatment in one country causes more transnational terrorist incidents in untreated ones, so that treatment affects treated and control units in the opposite direction. 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.

Second, another 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. Testing for the presence of peer effects is difficult, see Angrist and Pischke (2009, pp. 192–197). To illustrate this difficulty, suppose that peer effects are proportional to the average number of searches across countries, so that the greater the overall use of MIND/FIND, the greater the benefit to any individual country. Also suppose that to identify this form of peer effects we include the average number of searches as an additional regressor in our models. This strategy would not help to identify the peer effect if there are other country-invariant shocks that affect transnational terrorism and are correlated with the average number of searches. However, despite this difficulty, we can still account for the presence of peer effects and other time-varying country-invariant shocks by including time dummies in our regressions. In particular, we parameterize the time effect \( \lambda_t = \sum_{s=1}^T \delta_s d_{st} \), where \( d_{st} \) is a dummy variable that takes the value one when \( s = t \), and zero otherwise. By so doing, we are not able to identify the extent of peer effects but we are able to free our estimates from biases accruing from the existence of such effects.

In computing treatment effects, we follow Lee and Kobayashi (2001), who proposed the conditional proportional average treatment effect (PATE)

\[
\text{PATE}(X_{it}) = \frac{E(Y_{it}^1 - Y_{it}^0 | X_{it}, \eta_i, \lambda_t)}{E(Y_{it}^0 | X_{it}, \eta_i, \lambda_t)} = \exp(Z'_{it}\gamma) - 1.
\]

This is a particularly appropriate measure of the treatment effects for exponential conditional mean models. It does not depend on unobserved heterogeneity or time

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9 As an example, Rosenbaum (2007) argues that “vaccinating one child may prevent her from contracting a viral infection and spreading it to her unvaccinated brother.” That is, vaccination, the treatment, reduces the chances of a viral infection for the treated child and the untreated brother, although in the latter case probably to a lesser extent.

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effects as they cancel out in computing the ratio. The conditional PATE depends on the values of the covariates, so it requires evaluating the covariates at a particular point. To integrate out the covariates, we compute, for a given year, the geometric mean to obtain the unconditional PATE,

\[
\left\{ \prod_{i=1}^{N_t} \exp \left( Z'_{it} \gamma \right) \right\}^{1/N_t} - 1 = \exp \left( \bar{Z}'_{t} \gamma \right) - 1,
\]

where \( \bar{Z}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} Z_{it} \) and \( N_t \) is the number of units in period \( t \). Thus, the unconditional PATE is equal to the conditional PATE with (transformed) covariates evaluated at their sample means. Similarly, we can compute the geometric mean for the treated units to obtain the PATE on the treated (PATET),

\[
\prod_{i=1}^{N_t} \left\{ \exp \left( Z'_{i} \gamma \right) \right\}^{\frac{D_{it}}{N_t}} - 1 = \exp \left( \bar{Z}'_{1t} \gamma \right) - 1,
\]

where \( N_{1t} = \sum_{i=1}^{N_t} D_{it} \) is the number of treated units in period \( t \) and \( \bar{Z}_{1t} = \frac{1}{N_{1t}} \sum_{i=1}^{N_t} D_{it} Z_{it} \) is the average value of \( Z_{it} \) for the treated. Notice that the PATET depends on the estimate of \( \gamma \) which is obtained from the estimation of equation (2) when using the REP-MLE and the FEP-MLE and equations (4) and (5) when using the PSM-GMM with static or dynamic specifications, respectively.

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. Thus, when later reporting PATE estimates, we use the asymmetric CI suggested by Lee and Kobayashi (2001).

THE RESULTS

Columns (1) through (4) of Table 3 report panel regression estimates for the determinants of transnational terrorist attacks for the period 2005 to 2011 using REP-MLE, FEP-MLE, and PSM-GMM for a static model, and PSM-GMM for the lagged dependent variable model, respectively. The list of countries used in each case is reported in Table 2. The estimates reported correspond to flexible functional forms obtained after the specification search procedure detailed in the previous section. The reading of the results reported in Table 3 is not straightforward. As the specification is nonlinear, marginal effects of covariates on the number of transnational terrorist events are also nonlinear and depend on covariate values, so they cannot be directly read from Table 3. Furthermore, marginal effects depend on unobserved country effects and therefore cannot be estimated for the REP-MLE and FEP-MLE estimates reported in columns (1) and (2), which account for unobserved heterogeneity but do not provide estimates of the country effects. However, because the treatment dummy and its interactions with several covariates are statistically significant in Table 3, we can tell that the transnational terrorism determinants are different for treated

\[\text{Notice that because the treatment status dummy enters the exponential mean interacted with all entries of } Z_{it}, \text{ the PATE depends on all elements of } Z_{it}. \text{ Should the exponential mean include just the treatment status dummy and no interactions, the PATE would be an exponential function of the coefficient on the treatment status dummy.} \]
Table 3. Model estimates using different estimation methods.

| Estimation method: | (1) REP-MLE | (2) FEP-MLE | (3) PSM-GMM | (4) PSM-GMM |
|-------------------|-------------|-------------|-------------|-------------|
| Dummy lagged transnational terror incidents |            |             |             | 1.2245***   |
| Log GDP pc        | 4.3899***   | -3.6665***  | 5.4184***   | 4.3420***   |
|                   | (1.6647)    | (1.1062)    | (1.3084)    | (1.1808)    |
| Log population    | 6.7313***   | 2.1918***   | 1.5208**    |             |
|                   | (2.6083)    | (0.6817)    | (0.6046)    |             |
| Polity score      | -0.8355***  | 1.2149***   | -0.3629**   | -0.2275*    |
|                   | (0.2512)    | (0.4182)    | (0.1618)    | (0.1374)    |
| Log population squared | -0.1429**  |             |             |             |
|                   | (0.0684)    |             |             |             |
| Polity score squared |           |             | -0.0221***  | -0.0174***  |
|                   |             |             | (0.0059)    | (0.0052)    |
| Log GDP pc x log population | -0.2548**  | -0.3199***  | -0.2562***  |             |
|                   | (0.0992)    | (0.0774)    | (0.0700)    |             |
| Log GDP pc x polity score | -0.1535*** | 0.0465**    | 0.0297*     |             |
|                   | (0.0531)    | (0.0193)    | (0.0159)    |             |
| Log population x polity score | 0.0473*** |             |             |             |
|                   | (0.0144)    |             |             |             |
| Treatment          | 31.5238**   | 50.2436**   | 94.9887***  | 85.3380***  |
|                   | (13.2842)   | (23.9211)   | (20.8831)   | (24.6531)   |
| Treatment x log GDP pc | -7.0165** | -10.7331**  | -14.2888*** | -9.0549***  |
|                   | (2.9412)    | (5.0947)    | (2.1939)    | (2.6161)    |
| Treatment x log population | -3.7867**  |             | -4.8737***  |             |
|                   | (1.4407)    |             | (1.4648)    |             |
| Treatment x polity score | 0.4384*    |             |             |             |
|                   | (0.2484)    |             |             |             |
| Treatment x log GDP pc squared | 0.3806**  | 0.5611**    | 0.3967***   |             |
|                   | (0.1611)    | (0.2696)    | (0.1039)    |             |
| Treatment x polity score squared |           |             | 0.0190**    | 0.0194***   |
|                   |             |             | (0.0080)    | (0.0068)    |
| Treatment x log GDP pc x log population | 0.4185***  |             | 0.5079***   |             |
|                   |             |             | (0.1500)    | (0.1550)    |
| Treatment x log GDP pc x polity score | -0.0518*   |             |             |             |
|                   |             |             | (0.0279)    |             |
| Presample mean transnational terror incidents | 0.4741***  | 0.3208***   |             |             |
|                   |             |             | (0.0969)    | (0.1069)    |
| Constant          | -77.7209*** | -40.4420*** | -29.7967*** |             |
|                   | (26.4761)   | (11.5677)   | (10.2754)   |             |
| Number of observations | 987        | 399         | 539         | 539         |
| Number of countries | 141        | 57          | 77          | 77          |

Notes: REP-MLE stands for random-effects Poisson maximum likelihood estimator, FEP-MLE for fixed-effects Poisson maximum likelihood estimator, and PSM-GMM for presample mean generalized method of moments. All regressions include year dummies. Standard errors in parentheses, ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.
Table 4. Proportional average treatment effects on the treated (PATET) and confidence intervals (CIs).

| Year | 2008     | 2009     | 2010     | 2011     |
|------|----------|----------|----------|----------|
|      | Random-effects Poisson (REP-MLE) |          |          |          |          |
| PATET | −0.2635  | −0.2536  | −0.2635  | −0.2595  |
| CI lower bound | −0.2738  | −0.2642  | −0.2739  | −0.2702  |
| CI upper bound | −0.2531  | −0.2429  | −0.2530  | −0.2488  |
|      | Fixed-effects Poisson (FEP-MLE) |          |          |          |          |
| PATET | −0.4530  | −0.3108  | −0.3633  | −0.3806  |
| CI lower bound | −0.4669  | −0.3299  | −0.4389  | −0.3547  |
| CI upper bound | −0.4389  | −0.2914  | −0.3950  | −0.2795  |
|      | Presample mean GMM—static |          |          |          |          |
| PATET | −0.4098  | −0.2815  | −0.1970  | −0.1854  |
| CI lower bound | −0.4244  | −0.2984  | −0.2161  | −0.2056  |
| CI upper bound | −0.3950  | −0.2644  | −0.1778  | −0.1649  |
|      | Presample mean GMM—lagged dependent variable |          |          |          |          |
| PATET | −0.2982  | −0.2835  | −0.3160  | −0.3315  |
| CI lower bound | −0.3167  | −0.3012  | −0.3333  | −0.3496  |
| CI upper bound | −0.2795  | −0.2656  | −0.2984  | −0.3132  |

Note: Confidence intervals correspond to 5 percent significance levels.

and untreated countries. Notice that the specification search procedure outlined in the Methods section results in a final specification, reported in Table 3, with no statistically insignificant terms. This guarantees that the treatment effects reported later are not the result of including large but insignificant coefficient estimates. Table 3 also reports the number of observations used with each method. The REP-MLE uses 987 observations from all 141 countries in our data set, the FEP-MLE uses 399 observations on 57 countries that experience at least one transnational terrorist incident during the sample period, and the PSM-GMM estimator uses 539 observations on 77 countries that experienced some transnational terrorist incident during the presample period.

Similarly, treatment effects cannot be read from the coefficient estimates reported in Table 3. Estimates of the proportional treatment effects on the treated, as defined in equation (6), are reported in Table 4 along with lower and upper CI bounds. For instance, the PATET for 2008 using the REP-MLE is −0.2635, a 26.35 percent reduction in the number of transnational terrorist incidents, which is a statistically significant estimate because the associated CI does not include zero. Similarly, the estimated PATETs for subsequent years indicate a significant 25 or 26 percent reduction in TTIRs. The PATET estimates from the FEP-MLE start at a high 45.30 percent reduction in TTIRs in 2008, then fall to a 27.95 percent reduction in 2009, increase to a 31.08 percent reduction in 2010 and increase further to a 36.33 percent reduction in 2011. Overall, the PATET obtained using the REP-MLE suggest a constant time pattern of the proportional treatment effect, while the treatment effects obtained from the FEP-MLE suggest a falling time pattern.

11 For instance, should the coefficient on the treatment dummy be the only significant term, the treatment effect would be an exponential function of that coefficient estimate. However, because several interactions with the treatment dummy are significant, the exponential function of the coefficient on the treatment dummy measures the treatment effect for a unit with covariate values equal to zero, which is a meaningless quantity.
Table 5. Transnational terrorism incident rates (TTIRs) per 100 million people. Geometric average estimates.

| Year | 2008   | 2009   | 2010   | 2011   |
|------|--------|--------|--------|--------|
| Presample mean GMM—static |        |        |        |        |
| Expected TTIR under treatment | 1.1821 | 1.3443 | 1.6417 | 1.5241 |
| Expected TTIR under no treatment | 2.0029 | 1.8710 | 2.0446 | 1.8709 |
| Difference in expected TTIRs | −0.8208 | −0.5267 | −0.4029 | −0.3468 |
| Presample mean GMM—lagged dependent variable |        |        |        |        |
| Expected TTIR under treatment | 1.1928 | 1.1034 | 1.1428 | 1.1298 |
| Expected TTIR under no treatment | 1.6997 | 1.5400 | 1.6707 | 1.6902 |
| Difference in expected TTIRs | −0.5069 | −0.4366 | −0.5279 | −0.5604 |

Despite the fact that the FEP-MLE estimates account for arbitrary dependence between unobserved heterogeneity and the treatment indicator while the REP-MLE does not, the estimated PATETs are not that different. As there are no big differences in proportional treatment effects among the REP-MLE and FEP-MLE estimates, one is tempted to conclude that the selection bias might not be that important. Notice, however, that the FEP-MLE estimates are conditional on having at least one transnational terrorist incident during the sample period, while the REP-MLE estimates refer to a sample of countries that, in addition to the 57 countries used in the FEP-MLE estimation, includes 84 additional countries with no transnational terrorist incidents during the sample period. In other words, the proportional treatment effects obtained from the REP-MLE and FEP-MLE estimates are of similar magnitude, but the REP-MLE estimates refer to a sample with a much lower number of transnational terrorist events. Therefore, the proportional treatment effects obtained from the FEP-MLE estimates suggest a deeper reduction in TTIRs as a result of MIND/FIND use.

As argued above, it might be more reasonable to base our inference on a sample of countries with some pretreatment transnational terrorist incidents, which is exactly what the PSM-GMM method does. The third and fourth panels of Table 4 report PSM-GMM PATET estimates using the static and dynamic specifications are all significant. Using the static specification, estimated PATET starts at a 40.98 percent reduction in 2008, falls to 28.15 percent in 2009, further falls to 19.70 percent in 2010 and 18.54 percent in 2011. Based on the dynamic specification, the PATET starts at a 29.82 percent reduction in 2008, experiences a slight fall to a 28.35 percent reduction in 2009 but then increases to 31.60 percent and 33.15 percent reductions in 2010 and 2011, respectively. The static specification suggests a falling time pattern while the dynamic specification indicates a flat or slightly increasing pattern.

Overall, we find negative and significant PATET estimates. These findings indicate a significant proportional reduction of transnational terrorism as a result of using the MIND/FIND network for searches.

Proportional treatment effects are to be interpreted relative to the number of transnational terrorist events. To provide an idea of the magnitude of the effects, we compute average TTIRs as the geometric average of the predictions generated by the estimated counterpart of equation (3), both under treatment and under no treatment. Notice that this is not feasible for the REP-MLE and FEP-MLE estimates, which do not provide estimates of the country effects, while the PSM-GMM estimates do allow us to average TTIRs. Table 5 reports the average TTIRs under treatment, under no treatment, and their difference, which is an estimate of the treatment effect. These quantities vary depending on whether we use estimates from the static or dynamic specifications. According to the estimates from the static
Table 6. Transnational terrorism incident rates (TTIRs) per 100 million people. Arithmetic average estimates.

| Year  | 2008  | 2009  | 2010  | 2011  |
|-------|-------|-------|-------|-------|
|        |       |       |       |       |
| Presample mean GMM—static         |       |       |       |       |
| Expected TTIR under treatment     | 1.4555| 2.1277| 2.6255| 2.5207|
| Expected TTIR under no treatment  | 3.8990| 3.6139| 4.1102| 4.0656|
| Difference in expected TTIRs      | −2.4435| −1.4862| −1.4848| −1.5450|
| Presample mean GMM—lagged dependent variable |       |       |       |       |
| Expected TTIR under treatment     | 1.4474| 1.5818| 2.0434| 2.4104|
| Expected TTIR under no treatment  | 2.7404| 2.9512| 3.9158| 3.3964|
| Difference in expected TTIRs      | −1.2930| −1.3693| −1.8724| −0.9860|

model as of 2008, treated countries experienced a reduction of 0.8208 transnational terrorist incidents per 100 million people. This figure fell in subsequent years to 0.5267, 0.4029, and 0.3468 fewer incidents. According to the estimates from the dynamic model, the effect of MIND/FIND use on TTIRs is initially smaller, 0.5069 fewer transnational terrorist incidents per 100 million people in 2008, 0.4366 fewer incidents in 2009, and then 0.5279 fewer incidents in 2010 and 0.5604 fewer incidents in 2011 per 100 million people.

We note that our estimates of the TTIRs and treatment effects are conservative because we use the geometric average of the exponential mean function instead of the arithmetic mean, which would, by Jensen’s inequality, result in larger estimates. Table 6 reports estimates of the average TTIRs for the treated obtained as the arithmetic average of the exponential mean function. As expected, estimated TTIRs are a lot larger than when using the arithmetic average. Differences in average TTIRs under treatment and under no treatment suggest treated countries experienced from 0.9860 to 2.4435 fewer transnational terrorist incidents than under no treatment.

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 estimates indicate that a country with 64 million people, like France in 2008, would on average experience 0.32 fewer transnational terrorist incidents each year as a result of using MIND/FIND. This terrorism reduction might not seem like a lot, but it represents for most countries a sizeable proportional reduction in transnational terrorist incidents of about 30 percent. 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 Madrid commuter train bombings in 2004, may be stopped, where the payoff is huge. However, we would argue that the payoff is large even for small incidents, since curbing such incidents reduces

\[ \text{Back-of-the-envelope calculation using the average reduction in transnational terrorist incidents during the 2008 to 2011 period gives: expected reduction in TTIR \times hundreds of millions population = -0.50 \times (64.37/100) = -0.32.} \]
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. Nonadopting countries will come to realize that terrorists will transfer attacks to their soil, which should eventually foster more universal adoption of MIND/FIND.

We acknowledge that our estimates of the treatment effect of MIND/FIND on transnational terrorism might be influenced by interference across countries. These interferences might be of two different types: weakest-link and peer effects. The weakest-link effect corresponds with potential displacement of transnational terrorist incidents from MIND/FIND countries to countries where this technology is not used. As argued above, the weakest-link effect would bias our estimates, as part of the treatment effect would correspond to an increase in the number of transnational terrorist incidents in non-MIND/FIND countries. The second type of interference across units is the peer effects whereby countries (MIND/FIND or not) benefit from the overall use of the technology. 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 percent 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. However, despite whether the peer effects exist or not, our estimates of the MIND/FIND treatment effects account for their presence provided they are country-invariant and can be captured by year-specific time dummies.

Unfortunately, MIND/FIND cannot eliminate transnational terrorist incidents where a perpetrator attacks foreign assets (i.e., people or property) for political purposes on his or 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 (Enders & Sandler, 2012). Thus, MIND/FIND-induced 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 percent 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.13

13 A rough rule of thumb is that MIND/FIND costs approximately one million euros per port of entry, with larger airports costing much more than smaller airports (INTERPOL, 2010). Once MIND/FIND infrastructure is installed, the day-to-day cost is minimal as agents scan passports.
Nevertheless, the associated costs are minuscule compared to the tens of billions that the United States alone spends on homeland security. Our analysis shows that the small INTERPOL costs have huge paybacks in thwarting transnational terrorism as borders are made more secure.

JAVIER GARDEAZABAL is a Professor of Economics at the University of the Basque Country UPV/EHU, Lehendakari Aguirre 83, 48015 Bilbao, Spain (e-mail: javier.gardeazabal@ehu.es).

TODD SANDLER is the Vibhooti Shukla Professor of Economics and Political Economy in the School of Economic, Political and Policy Sciences at the University of Texas at Dallas, 800 W. Campbell Road, Richardson, TX 75080 (e-mail: tsandler@utdallas.edu).

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APPENDIX A: THE DATA

- **Transnational terrorist events.** Yearly number of terrorist events ending in a particular country or territory. Source: ITERATE database (Mickolus et al., 2012). Please note that the number of transnational terrorist events ending in Cabinda were added to Angolan attacks, those ending in the 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 dollar. Source: World Bank.

- **Population.** Total population. Source: World Bank.

- **Polity score.** Polity2 variable. Source: POLITY IV PROJECT (Marshall, Jaggers, & Gurr, 2011).

- **MIND/FIND data.** Connection dates and number of searches. Source: INTERPOL General Secretariat.

APPENDIX B: SPECIFICATION SEARCH

All exponential conditional mean function estimates reported in Table 3 of the main text correspond to functional forms obtained after applying the following specification search procedure. We commence with an initial specification that includes log GDP per capita, log population, and the polity score, together with their interactions with the treatment indicator. The procedure conducts several rounds of exponential regressions using one of three estimators—REP-MLE, FEP-MLE, or PSM-GMM. In each round, a set of exponential regressions are estimated, each of which includes all previous rounds’ terms plus a pair of nonlinear terms. These terms involve a squared covariate or interaction of two covariates and its interaction with the treatment indicator. Among all regressions in a round, we select the most statistically significant pair of nonlinear terms to include in the next round of regressions. When no further pairs of terms are significant, we run a final round of regressions, during which any insignificant terms are eliminated. The procedure is a mixture of a bottom-up selection procedure, where additional terms are included in each step, and a top-down selection procedure, where insignificant terms are eliminated. The bottom-up part of the procedure selects a pair of terms at each round, which consists of a particular nonlinear term and its interaction with the treatment indicator. The method allows for different parameter values for treated and untreated groups. Frequently, one of the two terms (either the nonlinear term or its interaction with the treatment indicator) is not significant. Thus, if the procedure ended when no further pairs of terms turn out to be significant, the search procedure would select a specification where some of the regressors are not significant. The last round of regressions sequentially eliminates insignificant regressors, achieving a specification where all regressors are statistically significant at the 10 percent or lower significance level. Retaining only significant terms is essential for the estimation of the treatment effects, which could otherwise be affected by large, but insignificant, parameter estimates.

All regressions include a set of time dummies. Statistical significance at the 10, 5, and 1 percent level is indicated by one, two, and three asterisks. Each of the following sections reports all intermediate rounds of regressions for a particular column in Table 3 in the main text. For instance, Tables C1 to C4 report all intermediate rounds of regressions that lead to the results reported in column 1 in Table 3. Similarly, Tables C5 to C8 report all intermediate rounds of regressions that lead to the results reported in column 2 in Table 3.
### Table C1. REP-MLE specification search.

|                      | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     |
|----------------------|---------|---------|---------|---------|---------|---------|---------|
| Log GDPpc            | 0.1174  | 0.2277  | 0.1277  | 0.3060* | 3.5686**| 0.2626  | 0.1376  |
|                      | (0.1376)| (2.2157)| (0.1394)| (0.1755)| (1.5687)| (0.1720)| (0.1421)|
| Log population       | 0.1248  | 0.1261  | 2.1512  | 0.1239  | 0.8697  | 0.1317  | 0.1362  |
|                      | (0.0219)| (0.0221)| (0.0221)| (0.0204)| (0.0223)| (0.0230)| (0.0296)|
| Polity score         | 0.1936  | 0.1940  | 1.6769* | 0.1525  | 0.1663  | 0.2969  |
|                      | (0.1248)| (0.1261)| (0.1239)| (0.1239)| (0.1663)| (0.1362)| (0.1362)|
| Treatment            | 2.1504  | 20.8240 | 31.3272 | 1.4518  | 2.7483  |
|                      | (3.2696)| (27.5564)| (3.3345)| (6.9674)| (5.3141)|
| Treatment × log GDPpc| 0.1886  | 0.1993  | 0.2590  | 0.1737  | 0.2339  | 0.2992  |
|                      | (0.1675)| (3.1575)| (0.1233)| (0.1233)| (0.1677)| (0.2690)|
| Treatment × log population | 0.0001 | 0.0087  | 0.0048  | 0.0027  | 0.0016  |
|                      | (0.0452)| (0.0455)| (0.0460)| (0.0467)| (0.0456)| (0.0497)|
| Log GDPpc squared    | 0.0248  | 0.0258  | 0.0319  | 0.0445  | 0.0583  |
|                      | (0.0219)| (0.0221)| (0.0221)| (0.0221)| (0.0221)|
| Treatment × log GDPpc squared | 0.0001 | 0.0087  | 0.0048  | 0.0027  | 0.0016  |
|                      | (0.0452)| (0.0455)| (0.0460)| (0.0467)| (0.0456)| (0.0497)|
| Log population squared| 0.0436  |         |         |         | 0.0059  |
|                      | (0.0642)|         |         |         | (0.0922)|
| Treatment × log population squared | 0.0632  |         |         |         | 0.0065  |
|                      | (0.0922)|         |         |         | (0.0922)|
| Polity score squared | 0.0001  | 0.0248  | 0.0319  | 0.0445  | 0.0583  |
|                      | (0.0219)| (0.0221)| (0.0221)| (0.0221)| (0.0221)|
| Treatment × Polity score squared | 0.0001 | 0.0087  | 0.0048  | 0.0027  | 0.0016  |
|                      | 0.0001  | (0.0452)| (0.0455)| (0.0460)| (0.0467)| (0.0456)|
| Log GDPpc × log population | 0.0248  | 0.0258  | 0.0319  | 0.0445  | 0.0583  |
|                      | (0.0219)| (0.0221)| (0.0221)| (0.0221)| (0.0221)|
| Treatment × log GDPpc × log population | 0.0001 | 0.0087  | 0.0048  | 0.0027  | 0.0016  |
|                      | (0.0452)| (0.0455)| (0.0460)| (0.0467)| (0.0456)| (0.0497)|
| Log GDPpc × polity score | 0.0001  | 0.0248  | 0.0319  | 0.0445  | 0.0583  |
|                      | (0.0219)| (0.0221)| (0.0221)| (0.0221)| (0.0221)|
| Treatment × log GDPpc × polity score | 0.0001 | 0.0087  | 0.0048  | 0.0027  | 0.0016  |
|                      | 0.0001  | (0.0452)| (0.0455)| (0.0460)| (0.0467)| (0.0456)|
| Log population × polity score | 0.0001  | 0.0248  | 0.0319  | 0.0445  | 0.0583  |
|                      | (0.0219)| (0.0221)| (0.0221)| (0.0221)| (0.0221)|
| Treatment × log population × polity score | 0.0001 | 0.0087  | 0.0048  | 0.0027  | 0.0016  |
|                      | 0.0001  | (0.0452)| (0.0455)| (0.0460)| (0.0467)| (0.0456)|
| Constant             | −2.0130 | −2.5180 | −14.2711| −2.8270 | −32.8396**| −3.8147 | −0.8693 |
|                      | (0.1963)| (9.5730)| (18.1192)| (0.1982)| (14.3726)| (2.9179)| (2.7971)|
| Number of observations| 987     | 987     | 987     | 987     | 987     | 987     | 987     |
| Number of countries   | 141     | 141     | 141     | 141     | 141     | 141     | 141     |
|                      | Round 2 |             | Round 3 |             |
|----------------------|---------|-------------|---------|-------------|
|                      | (1)     | (2)         | (3)     | (4)         | (5)     | (6)      | (7)     |
| Log GDPpc            | 0.6168  | 0.1787      | 0.2675  | 3.9568**    | 0.1211  | 0.9957   | 0.1154  |
|                      | (2.2392)| (0.1465)    | (0.1788)| (1.7569*)   | (0.1796)| (2.2618) | (2.2856)|
|                      | 0.1371  | (2.3191)    | 0.1355  | (0.9518)    | (0.1417)|         |         |
| Log population       | 0.6792***| 0.8553***   | 0.6979**| 0.7169*     |         | 0.8320***| 0.6264***|
|                      | (0.1371)| (2.3191)    | (0.1355)| (0.9518)    | (0.1417)|         |         |
|                      |         |             |         | (2.2618)    | (2.2856)|         |         |
| Polity score         | −0.2698**| −0.2851**   | −0.2743*| 0.9957      | 0.1154  | 0.9957   | 0.1154  |
|                      | (2.2392)| (0.1465)    | (0.1788)| (1.7569*)   | (0.1796)| (2.2618) | (2.2856)|
|                      | 0.2273  | (0.2499)    | 0.2333  | (0.2414)    | (0.4196)| (0.2467) | (0.2335)|
| Treatment            | 37.8403**| 37.2633     | 32.4148 | 3.6377      | 0.2784**| 36.5127**| 0.1359  |
|                      | (15.2042)| (30.3890)   | (5.3175)| (2.3225)    | (3.8677)|         |         |
| Treatment × log GDPpc| −10.1958***| −2.2486     | −3.2281 | −9.6846***  | 9.8430**| 35.1071 | 16.0057|
|                      | (3.7668)| (0.2115)    | (0.2605)| (2.6528)    | (2.3225)| (3.8677)|         |
| Treatment × log population | 0.4342 | −4.1863     | 0.0572  | −0.0874     | 2.3415  | 0.4238  |         |
|                      | (0.3421)| (3.5934)    | (0.2918)| (1.5635)    | (1.3610)| (1.3517)|         |
| Treatment × polity score | 0.9325 | 0.3755      | 0.1458  | −0.1598     | 1.1130* | 0.8793  |         |
|                      | (0.6245)| (0.5698)    | (0.5190)| (0.4959)    | (0.6589)| (0.6333)|         |
|                      | (0.0132)| (0.0143)    | (0.0134)| (0.0139)    | (0.0142)| (0.0134)|         |
| Log population × polity score | 0.0383***| 0.0479***   | 0.0351**| 0.0387**    |         | 0.0361***|         |
|                      | (0.0132)| (0.0143)    | (0.0134)| (0.0139)    | (0.0142)| (0.0134)|         |
| Treatment × log population × polity score | −0.0561| −0.0211     | −0.0098 | 0.0025      | 0.0665* | 0.0530  |         |
|                      | (0.0382)| (0.0350)    | (0.0324)| (0.0306)    | (0.0401)| (0.0389)|         |
| Log GDPpc squared    | −0.0267 | (0.1279)    |         |             | −0.0466 | 0.0081  |         |
| Log GDPpc × log GDPpc squared | 0.5631***| (0.2084) |         |             |         |         |         |
| Log population squared | −0.1310*| (0.0687)    |         |             | −0.1171*| (0.0690)|         |
| Treatment × log population squared | 0.1239 | (0.1078)    |         |             | 0.0824  |         |         |
| Polity score squared  | −0.0076 | (0.0068)    |         |             | −0.0063 | (0.0071)|         |
| Treatment × polity score squared | 0.0109 | (0.0100)    |         |             | 0.0016  | (0.0108)|         |
| Log GDPpc × log population |         |             |         | −0.2319**   | (0.0160) |         |         |
| Treatment × log GDPpc × log population |         |             |         | 0.1778      | (0.1559)|         |         |
| Log GDPpc × polity score |         |             |         | 0.0033      | (0.0233)|         |         |
| Treatment × log GDPpc × polity score |         |             |         | 0.0136      | (0.0330)|         |         |
| Constant             | −2.9635 | −37.7031*   | −1.3891 | −34.6234**  | −0.6482 | −37.0598*| −0.8765|
|                      | (9.5779)| (19.7667)   | (2.8017)| (15.7974)   | (3.2036)| (22.5124)| (9.7484)|
| Number of observations| 987     | 987         | 987     | 987         | 987     | 987     | 987     |
| Number of countries  | 141     | 141         | 141     | 141         | 141     | 141     | 141     |
### Table C3. REP-MLE specification search (continued).

|                       | Round 3          | Round 4          | Round 5          |
|-----------------------|------------------|------------------|------------------|
| Log GDPpc             | 4.6451*          | 5.6199**         | 5.1828*          |
|                       | (2.8228)         | (2.7382)         | (2.7812)         |
| Log population        | 1.6482**         | 7.2759**         | 7.0760***        |
|                       | (0.9427)         | (2.6462)         | (2.6110)         |
| Polity score          | −0.6836***       | −0.8749***       | −0.8211***       |
|                       | (0.2364)         | (0.2466)         | (0.2532)         |
| Treatment             | 11.0922          | 37.4798          | 37.9310          |
|                       | (38.4938)        | (50.8731)        | (50.3994)        |
| Treatment × log GDPpc | −8.8006**        | −8.7391**        | −8.4504**        |
|                       | (4.0674)         | (4.0595)         | (4.1028)         |
| Treatment × log population | 2.4101          | −0.7113          | −0.8711          |
|                       | (2.6870)         | (5.0363)         | (5.0567)         |
| Treatment × polity score | 1.0872          | 1.2419*          | 1.1563*          |
|                       | (0.6799)         | (0.7048)         | (0.7141)         |
| Log GDPpc × polity score | 0.0389***       | 0.0496***        | 0.0473***        |
|                       | (0.0137)         | (0.0141)         | (0.0143)         |
| Treatment × log GDPpc × polity score | −0.0654       | −0.0743          | −0.0423          |
|                       | (0.0414)         | (0.1274)         | (0.1323)         |
| Log GDPpc squared     | −0.0519          | −0.0743          | −0.0423          |
|                       | (0.0233)         | (0.1285)         | (0.1245)         |
| Treatment × log GDPpc squared | 0.6618***      | 0.6235**         | 0.5904**         |
|                       | (0.2449)         | (0.2433)         | (0.2546)         |
| Log GDPpc × log population | −0.2193**     | −0.2534**        | −0.2529**        |
|                       | (0.1050)         | (0.0984)         | (0.0975)         |
| Treatment × log GDPpc × log population | −0.1808       | −0.1460          | −0.1312          |
|                       | (0.2454)         | (0.2407)         | (0.2394)         |
| Log GDPpc × polity score | 0.0079         | 0.0079           | 0.0079           |
|                       | (0.0036)         | (0.0252)         | (0.0252)         |
| Treatment × log GDPpc × polity score | −0.0144       | −0.0528          | −0.0520          |
|                       | (0.0074)         | (0.0394)         | (0.0394)         |
| Log population squared | −0.1596**       | −0.1596**        | −0.1540**        |
|                       | (0.0687)         | (0.0697)         | (0.0674)         |
| Treatment × log population squared | 0.0825        | 0.0825           | 0.0826           |
|                       | (0.1249)         | (0.1249)         | (0.1258)         |
| Polity score squared  | −0.0145         | −0.0145          | −0.0057          |
|                       | (0.0071)         | (0.0100)         | (0.0071)         |
| Treatment × polity score squared | 0.0011        | 0.0011           | 0.0027           |
|                       | (0.0100)         | (0.0110)         | (0.0110)         |
| Constant              | −36.3189**       | −87.6208***      | −84.0469***      |
|                       | (18.1982)        | (28.7806)        | (28.7821)        |
| Number of observations| 987              | 987              | 987              |
| Number of countries   | 141              | 141              | 141              |
## Table C4. REP-MLE specification search (continued).

|                        | Round 6 |
|------------------------|---------|
|                        | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     |
| Log GDPpc              | 5.6619**| 5.7421**| 5.6723***| 4.4550***| 4.5572***| 4.4391***| 4.3899***|
|                        | (2.7382)| (2.7466)| (2.7194) | (1.6588) | (1.6805) | (1.6547) | (1.6647) |
| Log population         | 7.2759**| 7.4291***| 7.1082***| 7.0614***| 7.0600***| 6.9508***| 6.7313***|
|                        | (2.6462)| (2.6321)| (2.5883) | (2.6183) | (2.6245) | (2.6122) | (2.6321) |
| Polity score           | −0.8749***| −0.8773***| −0.8548***| −0.8527***| −0.8370***| −0.8488***| −0.8355***|
|                        | (0.2466)| (0.2459)| (0.2436) | (0.2467) | (0.2498) | (0.2492) | (0.2512) |
| Treatment              | 37.4798 | 58.5682| 37.0296**| 35.7081**| 32.7409**| 33.2505**| 31.5238**|
|                        | (50.8731)| (35.2525)| (15.0237)| (14.9181)| (13.5228)| (13.4835)| (13.2842)|
| Treatment × log GDPpc  | −8.7391**| −9.8914***| −10.3183***| −9.9652***| −7.6480***| −7.4264***| −7.0165**|
|                        | (4.0595)| (3.6996)| (3.7355) | (3.6978) | (3.0381) | (2.9896) | (2.9412) |
| Treatment × log population | −0.7113| −2.2630| 0.5040| 0.4905| 0.0856| 0.0856| 0.0856| 0.0856|
|                        | (5.0363)| (4.1420)| (0.3465)| (0.3455)| (0.1948)| (0.1948)| (0.1948)| (0.1948)|
| Treatment × polity score| 1.2419*| 1.0832*| 0.9353| 0.9118| 0.0270| 0.0358| 0.0358| 0.0358|
|                        | (0.7048)| (0.6521)| (0.6247)| (0.6234)| (0.0471)| (0.0428)| (0.0428)|
| Log GDPpc squared      | −0.0743| −0.0731| −0.0713| −0.0743| −0.0731| −0.0713| −0.0713| −0.0713|
|                        | (0.1273)| (0.1274)| (0.1269)| (0.1269)| (0.1269)| (0.1269)| (0.1269)| (0.1269)|
| Treatment × log GDPpc squared | 0.6235**| 0.5460***| 0.5713***| 0.5513***| 0.4143***| 0.4016**| 0.3806**| 0.3806**|
|                        | (0.2433)| (0.2059)| (0.2070)| (0.2047)| (0.1664)| (0.1634)| (0.1611)| (0.1611)|
| Log population squared | −0.1596**| −0.1627**| −0.1538**| −0.1517**| −0.1503**| −0.1487**| −0.1429**| −0.1429**|
|                        | (0.0687)| (0.0683)| (0.0675)| (0.0679)| (0.0681)| (0.0682)| (0.0684)| (0.0684)|
| Treatment × log population squared | 0.0825| 0.0819| 0.0819| 0.0825| 0.0819| 0.0819| 0.0819| 0.0819|
|                        | (0.1249)| (0.1224)| (0.1224)| (0.1249)| (0.1224)| (0.1224)| (0.1224)| (0.1224)|
| Log GDPpc × log population | −0.2534**| −0.2592***| −0.2570**| −0.2588**| −0.2645**| −0.2574**| −0.2548**| −0.2548**|
|                        | (0.0984)| (0.0979)| (0.0970)| (0.0991)| (0.1003)| (0.0987)| (0.0992)| (0.0992)|
| Treatment × log GDPpc × log population | −0.1460| −0.1460| −0.1460| −0.1460| −0.1460| −0.1460| −0.1460| −0.1460|
|                        | (0.2407)| (0.2407)| (0.2407)| (0.2407)| (0.2407)| (0.2407)| (0.2407)| (0.2407)|
| Log population × polity score | 0.0496***| 0.0497***| 0.0485***| 0.0482***| 0.0472***| 0.0479***| 0.0473***| 0.0473***|
|                        | (0.0141)| (0.0141)| (0.0140)| (0.0141)| (0.0143)| (0.0143)| (0.0144)| (0.0144)|
| Treatment × log population × polity score | −0.0741*| −0.0648| −0.0561| −0.0547| −0.0547| −0.0547| −0.0547| −0.0547|
|                        | (0.0428)| (0.0397)| (0.0382)| (0.0381)| (0.0382)| (0.0381)| (0.0382)| (0.0382)|
| Constant               | −87.6208***| −89.2869***| −86.2618***| −80.7400***| −81.1627***| −79.7933***| −77.7209***| −77.7209***|
|                        | (28.7806)| (28.7068)| (28.1517)| (26.6840)| (26.7795)| (26.5409)| (26.4761)| (26.4761)|
| Number of observations | 987     | 987     | 987     | 987     | 987     | 987     | 987     | 987     |
| Number of countries    | 141     | 141     | 141     | 141     | 141     | 141     | 141     | 141     |
Table C5. FEP-MLE specification search.

|                  | Round 1          |                  |                  |                  |                  |                  |                  |
|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
|                  | (1)             | (2)             | (3)             | (4)             | (5)             | (6)             | (7)             |
| Log GDP\text{pc} | $-4.2496^{***}$ | $-1.4100$       | $-4.9254^{***}$ | $-4.2717^{***}$ | $-5.9724$       | $-3.7063^{***}$ | $-4.0484^{***}$ |
|                  | (1.0884)        | (7.9809)        | (1.1962)        | (1.0840)        | (7.5240)        | (1.1028)        | (1.0883)        |
| Log population   | $-1.6070$       | $-3.1648$       | $-20.1099$      | $-2.1276$       | $-2.2974$       | $-0.8201$       | $-1.0414$       |
|                  | (2.1504)        | (2.2134)        | (13.4106)       | (2.1680)        | (4.4601)        | (2.1964)        | (2.2986)        |
| Polity score     | 0.0077          | 0.0156          | $-0.0021$       | 0.0138          | 0.0145          | 1.4266***       | $-1.0715^*$     |
|                  | (0.0323)        | (0.0326)        | (0.0331)        | (0.0354)        | (0.0327)        | (0.4608)        | (0.6385)        |
| Treatment        | 4.5485          | 55.4218*        | 35.7154         | 5.4743          | 69.3739         | 9.4504***       | 4.6367          |
|                  | (3.8469)        | (28.5727)       | (31.7438)       | (4.0476)        | (44.1837)       | (4.5368)        | (6.7620)        |
| Treatment $\times$ log GDP\text{pc} | $-0.3789^*$ | $-11.8472^{**}$ | $-0.4311^*$    | $-0.6490^{**}$ | $-6.6517$       | $-0.7983^{***}$ | $-0.3238$       |
|                  | (0.2120)        | (6.0078)        | (0.2404)        | (0.3075)        | (4.2541)        | (0.2970)        | (0.2572)        |
| Treatment $\times$ log population | $-0.0769$ | $-0.0124$       | $-3.6116$       | $-0.0242$       | $-3.7982$       | $-0.1103$       | $-0.1216$       |
|                  | (0.1873)        | (0.2027)        | (3.5839)        | (0.1930)        | (2.5072)        | (0.1875)        | (0.3296)        |
| Treatment $\times$ polity score | $-0.0044$ | $-0.0065$       | 0.0007          | $-0.0413$       | $-0.0103$       | $-0.6568^*$     | $-0.0926$       |
|                  | (0.0505)        | (0.0509)        | (0.0527)        | (0.0553)        | (0.0501)        | (0.3877)        | (0.5877)        |
| Log GDP\text{pc} squared | -0.1535 | (0.4609)        | 0.6227**        | (0.3164)        |                  |                  |                  |
| Log population squared |               | 0.6018          | (0.4380)        |                  |                  |                  |                  |
| Treatment $\times$ log population squared |               | 0.1013          | (0.1039)        |                  |                  |                  |                  |
| Polity score squared |               | $-0.0049$       | (0.0092)        |                  |                  |                  |                  |
| Treatment $\times$ polity score squared |               | 0.0139          | (0.0106)        |                  |                  |                  |                  |
| Log GDP\text{pc} $\times$ log population |               | 0.1062          | (0.4189)        |                  |                  |                  |                  |
| Treatment $\times$ log GDP\text{pc} $\times$ log population |               | 0.3608          | (0.2418)        |                  |                  |                  |                  |
| Log GDP\text{pc} $\times$ polity score |               | $-0.1796^{***}$ | (0.0581)        |                  |                  |                  |                  |
| Treatment $\times$ log GDP\text{pc} $\times$ polity score |               | 0.0636*         | (0.0386)        |                  |                  |                  |                  |
| Log population $\times$ polity score |               | 0.0586*         | (0.0346)        |                  |                  |                  |                  |
| Treatment $\times$ log population $\times$ polity score |               | 0.0063          | (0.0363)        |                  |                  |                  |                  |
| Number of observations | 399            | 399             | 399             | 399             | 399             | 399             | 399             |
| Number of countries | 57             | 57              | 57              | 57              | 57              | 57              | 57              |
|                     | (1)            | (2)            | (3)            | (4)            | (5)            | (6)            |
|---------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Log GDPpc           | -3.7063***     | -0.4055        | -4.4112***     | -3.7177***     | -12.1312       | -3.5619***     |
|                     | (1.1028)       | (7.9125)       | (1.2094)       | (1.0999)       | (7.7258)       | (1.0961)       |
| Log population      | -0.8201        | -2.8450        | -19.6454       | -1.4305        | -5.5725        | -0.9769        |
|                     | (2.1964)       | (2.3165)       | (13.6313)      | (2.1893)       | (4.6055)       | (2.2116)       |
| Polity score        | 1.4266***      | 1.5124***      | 1.4366***      | 1.5350***      | 1.5104***      | 0.3263         |
|                     | (0.4608)       | (0.4668)       | (0.4655)       | (0.4616)       | (0.4845)       | (0.8980)       |
| Treatment           | 9.4504**       | 68.6438**      | 42.3566        | 11.3972**      | 80.6872*       | 10.9186        |
|                     | (4.5368)       | (32.3225)      | (31.1472)      | (4.8240)       | (48.7364)      | (7.5773)       |
| Treatment × log GDPpc | -0.7983***   | -14.1865**     | -0.8397***     | -1.2140**      | -7.7225        | -0.7079*       |
|                     | (0.2970)       | (6.7032)       | (0.3232)       | (0.3890)       | (4.7176)       | (0.3696)       |
| Treatment × log population | -0.1103      | -0.0302        | -3.8680        | -0.0503        | -4.2523        | -0.2648        |
|                     | (0.1875)       | (0.2076)       | (3.5037)       | (0.1945)       | (2.8287)       | (0.3202)       |
| Treatment × polity score | -0.6568*     | -0.5083        | -0.6123        | -0.7773**      | -0.3935        | -0.8118        |
|                     | (0.3877)       | (0.3954)       | (0.3928)       | (0.3846)       | (0.4563)       | (0.8094)       |
| Log GDPpc × polity score | -0.1796***   | -0.1902***     | -0.1821***     | -0.1935***     | -0.1900***     | -0.1817***     |
|                     | (0.0581)       | (0.0589)       | (0.0588)       | (0.0583)       | (0.0611)       | (0.0599)       |
| Treatment × log GDPpc × polity score | 0.0636*      | 0.0476         | 0.0596         | 0.0707*        | 0.0365         | 0.0425         |
|                     | (0.0386)       | (0.0396)       | (0.0392)       | (0.0381)       | (0.0459)       | (0.0436)       |
| Log GDPpc squared   | -0.1846        |               |               |               |               |               |
|                     | (0.4545)       |               |               |               |               |               |
| Treatment × log GDPpc squared | 0.7287**     |               |               |               |               |               |
|                     | (0.3503)       |               |               |               |               |               |
| Log population squared |               | 0.6091        |               |               |               |               |
|                     |               | (0.4416)       |               |               |               |               |
| Treatment × log population squared |               | 0.1080        |               |               |               |               |
|                     |               | (0.1017)       |               |               |               |               |
| Polity score squared |               | 0.0009         |               |               |               |               |
|                     |               | (0.0102)       |               |               |               |               |
| Log GDPpc × log population |               | 0.0188*        |               |               |               |               |
|                     |               | (0.0107)       |               |               |               |               |
| Treatment × log GDPpc × log population |               | 0.4818        |               |               |               |               |
|                     |               | (0.4334)       |               |               |               |               |
| Log population × polity score |               | 0.4034         |               |               |               |               |
|                     |               | (0.2747)       |               |               |               |               |
| Treatment × log population × polity score |               | 0.0606         |               |               |               |               |
|                     |               | (0.0398)       |               |               |               |               |
| Number of observations | 399           | 399           | 399           | 399           | 399           | 399           |
| Number of countries | 57            | 57            | 57            | 57            | 57            | 57            |
Table C7. FEP-MLE specification search (continued).

|                          | (1)          | (2)          | (3)          | (4)          | (5)          |
|--------------------------|--------------|--------------|--------------|--------------|--------------|
| Log GDPpc                | −0.4055      | −6.0958      | −0.2300      | −11.1212     | 0.7652       |
|                          | (7.9125)     | (8.8456)     | (7.9286)     | (13.8130)    | (7.9807)     |
| Log population           | −2.8450      | −22.7888     | −2.9165      | −6.7127      | −2.1032      |
|                          | (2.3165)     | (14.6129)    | (2.3183)     | (4.6943)     | (2.3569)     |
| Polity score             | 1.5124***    | 1.5045***    | 1.5299***    | 1.6497***    | 0.1717       |
|                          | (0.4668)     | (0.4709)     | (0.4644)     | (0.4964)     | (0.9173)     |
| Treatment                | 68.6438**    | 69.4936*     | 66.2946*     | 74.5708      | 84.8080**    |
|                          | (32.3225)    | (41.1456)    | (35.7739)    | (93.6365)    | (41.1695)    |
| Treatment × log GDPpc    | −14.1865**   | −14.8013**   | −13.6456*    | −14.6538     | −20.4414***  |
|                          | (6.7032)     | (7.4419)     | (7.5306)     | (11.2044)    | (9.5599)     |
| Treatment × log population| −0.0302     | 0.2023       | −0.0272      | −0.3757      | 0.5717       |
|                          | (0.2076)     | (4.2415)     | (0.2095)     | (4.6834)     | (0.4792)     |
| Treatment × polity score | −0.5083      | −0.4387      | −0.5449      | −0.5602      | 1.2358       |
|                          | (0.3954)     | (0.4025)     | (0.4073)     | (0.4395)     | (1.1532)     |
| Log GDPpc × polity score | −0.1902***   | −0.1908***   | −0.1929***   | −0.2073***   | −0.1691***   |
|                          | (0.0589)     | (0.0595)     | (0.0587)     | (0.0626)     | (0.0611)     |
| Treatment × log GDPpc × polity score | 0.0476 | 0.0401 | 0.0505 | 0.0536 | −0.0041 |
|                          | (0.0396)     | (0.0405)     | (0.0400)     | (0.0447)     | (0.0480)     |
| Log GDPpc squared        | −0.1846      | 0.1037       | −0.1937      | −0.0079      | −0.2562      |
|                          | (0.4545)     | (0.4962)     | (0.4550)     | (0.4953)     | (0.4595)     |
| Treatment × log GDPpc squared | 0.7287** | 0.7665* | 0.6976* | 0.7181** | 1.0935** |
|                          | (0.3503)     | (0.3926)     | (0.4046)     | (0.3536)     | (0.5106)     |
| Log population squared   | 0.6636       | 0.5482       | 0.4812       | 0.1230       | 0.2160       |
| Treatment × log population squared | 0.0080 | (0.1230) | 0.0040 | (0.0104) | 0.0021 |
| Polity score squared     | 0.0040       | (0.0104)     | 0.0021       | (0.0136)     | 0.0001       |
| Treatment × polity score squared | 0.0021 | (0.0136) | 0.0040 | (0.0104) | 0.0021 |
| Log GDPpc × log population | 0.4374       | 0.4374       | 0.4374       | 0.4374       | 0.4374       |
|                          | (0.4607)     | (0.4607)     | (0.4607)     | (0.4607)     | (0.4607)     |
| Treatment × log GDPpc × log population | 0.0636 | 0.0636 | 0.0636 | 0.0636 | 0.0636 |
|                          | 0.0636       | 0.0636       | 0.0636       | 0.0636       | 0.0636       |
| Treatment × polity score | 0.0749       | 0.0749       | 0.0749       | 0.0749       | 0.0749       |
|                          | (0.0546)     | (0.0546)     | (0.0546)     | (0.0546)     | (0.0546)     |
| Number of observations   | 399          | 399          | 399          | 399          | 399          |
| Number of countries      | 57           | 57           | 57           | 57           | 57           |
Table C8. FEP-MLE specification search (continued).

|                      | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       |
|----------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| Log GDPpc            | −0.4055   | −0.2954   | −0.2927   | −0.9766   | −3.7143***| −3.6665***|
|                      | (7.9125)  | (7.8815)  | (7.8818)  | (7.8598)  | (1.0807)  | (1.1062)  |
| Log population       | −2.8450   | −3.6769*  | −3.6975*  | −3.0316   | −2.8521   |           |
|                      | (2.3165)  | (2.0444)  | (2.1879)  | (1.9761)  | (1.9085)  |           |
| Polity score         | 1.5124*** | 1.2599*** | 1.2590*** | 1.2191*** | 1.2148*** | 1.2149*** |
|                      | (0.4668)  | (0.4153)  | (0.4154)  | (0.4155)  | (0.4143)  | (0.4182)  |
| Treatment            | 68.6438** | 60.6545** | 60.8920** | 60.2813** | 59.9746*  | 50.2436** |
|                      | (32.3225) | (28.1474) | (28.0648) | (28.0066) | (27.8489) | (23.9211) |
| Treatment × log GDPpc| −14.1865**| −13.0219**| −13.0119**| −12.9096**| −12.8461**| −10.7331**|
|                      | (6.7032)  | (5.9399)  | (5.9560)  | (5.9439)  | (5.9108)  | (5.0947)  |
| Treatment × log population | −0.0302 | 0.0153 |          |           |           |           |
|                      | (0.2076)  | (0.2043)  |           |           |           |           |
| Treatment × polity score | −0.5083 | −0.0335 | −0.0338   |           |           |           |
|                      | (0.3954)  | (0.0513)  | (0.0475)  |           |           |           |
| Log GDPpc × polity score | −0.1902***| −0.1592***| −0.1591***| −0.1542***| −0.1537***| −0.1535***|
|                      | (0.0589)  | (0.0528)  | (0.0528)  | (0.0528)  | (0.0527)  | (0.0531)  |
| Treatment × log GDPpc × polity score | 0.0476 |          |           |           |           |           |
|                      | (0.0396)  |           |           |           |           |           |
| Log GDPpc squared    | −0.1846   | −0.1996   | −0.1999   | −0.1585   |           |           |
|                      | (0.4545)  | (0.4520)  | (0.4520)  | (0.4509)  |           |           |
| Treatment × log GDPpc squared | 0.7287** | 0.6844** | 0.6836**  | 0.6772**  | 0.6739**  | 0.5611**  |
|                      | (0.3503)  | (0.3132)  | (0.3139)  | (0.3132)  | (0.3115)  | (0.2696)  |
| Number of observations | 399       | 399       | 399       | 399       | 399       | 399       |
| Number of countries  | 57        | 57        | 57        | 57        | 57        | 57        |
Table C9. PSM-GMM specification search.

|                        | Round 1       | Round 2       |
|------------------------|---------------|---------------|
|                        | (1)           | (2)           | (3)           | (4)           | (5)           | (6)           |
| Log GDPpc              | −0.2027**     | 0.0257        | 2.9926***     | −0.2814***    | −0.2017**     | 3.2421***     |
|                        | (0.0994)      | (0.0922)      | (0.9645)      | (0.1015)      | (0.0983)      | (1.8374)      |
| Log population         | −0.5905***    | −0.5202***    | 0.9581*       | −0.5800***    | −0.6015***    | 0.9591*       |
|                        | (0.0603)      | (0.0826)      | (0.5122)      | (0.0593)      | (0.0614)      | (0.5307)      |
| Polity score           | −0.0201       | 0.0206        | −0.0169       | −0.1763       | −0.0712       | −0.0169       |
|                        | (0.0154)      | (0.0223)      | (0.0155)      | (0.1183)      | (0.1514)      | (0.0153)      |
| Treatment              | −0.4535       | 2.3466        | 95.2532***    | 3.8786        | 6.1917        | 73.8708***    |
|                        | (5.0954)      | (5.0769)      | (23.7109)     | (3.6836)      | (5.2969)      | (20.1508)     |
| Treatment × log GDPpc  | 0.0916        | −0.1884       | −10.0839***   | −0.2906       | −0.0332       | −12.1941***   |
|                        | (0.2788)      | (0.2887)      | (2.5256)      | (0.2567)      | (0.2655)      | (2.3749)      |
| Treatment × log population | −0.0594     | −0.1214       | −5.5431***    | −0.0877       | −0.3928*      | −2.4450*      |
|                        | (0.1955)      | (0.1979)      | (1.3712)      | (0.1780)      | (0.2073)      | (1.3840)      |
| Treatment × polity score | 0.0358       | −0.0127       | 0.0211        | −0.6486**     | −0.7272*      | 0.0347        |
|                        | (0.0329)      | (0.0387)      | (0.0331)      | (0.3054)      | (0.4314)      | (0.0318)      |
| Polity score squared   | −0.0171***    | (0.0055)      | 0.0202***     | (0.0073)      |               |               |
| Treatment × polity score squared |         |               |               |               |               |               |
| Log GDPpc × log population | −0.1879***  | (0.0600)      |               |               |               |               |
| Treatment × log GDPpc × log population | 0.5842***   | (0.1457)      |               |               |               |               |
| Log GDPpc × polity score | 0.0180       | (0.0138)      |               |               |               |               |
| Treatment × log GDPpc × polity score | 0.0668**     | (0.0321)      |               |               |               |               |
| Log Population × polity score | 0.0028       | (0.0083)      |               |               |               |               |
| Treatment × log population × polity score | 0.0460*      | (0.0256)      |               |               |               |               |
| Log GDPpc squared      |               |               |               |               |               |               |
| Treatment × log GDPpc squared |          |               |               |               |               |               |
| Presample mean transnational terrorist incidents | 0.5699***   | 0.5318***     | 0.5443***     | 0.5891***     | 0.5761***     | 0.5522***     |
|                        | (0.0920)      | (0.0930)      | (0.0913)      | (0.0972)      | (0.0918)      | (0.0943)      |
| Constant               | 7.7707***     | 5.2807***     | −18.5863***   | 8.1918***     | 7.9506***     | −19.5935*     |
|                        | (1.0531)      | (1.3317)      | (8.3724)      | (1.1109)      | (1.1522)      | (1.1952)      |
| Number of observations | 539           | 539           | 539           | 539           | 539           | 539           |
| Number of countries    | 77            | 77            | 77            | 77            | 77            | 77            |
|                     | Round 2                      | Round 3                      |
|---------------------|-------------------------------|-------------------------------|
|                     | (1)                          | (2)                          |
| Log GDPpc           | 4.2427***                    | 3.6746***                    |
|                     | (1.2104)                     | (1.0124)                     |
| Log population      | 1.5106**                    | 1.3637**                    |
|                     | (0.6299)                     | (0.5334)                     |
| Polity score        | 0.0327                      | −0.2835**                   |
|                     | (0.0230)                     | (0.1155)                     |
| Treatment           | 103.5221***                  | 89.5876***                  |
|                     | (23.9329)                    | (29.2239)                    |
| Treatment × log GDPpc| −11.0487***                  | −9.5494***                  |
|                     | (2.5538)                     | (3.0763)                     |
| Treatment × log population | −5.9151***                  | −5.1861***                  |
|                     | (1.3955)                     | (1.7219)                     |
| Log GDPpc × log population | −0.2437***                  | −0.2342***                  |
|                     | (0.0721)                     | (0.0626)                     |
| Treatment × log GDPpc × log population | 0.6231***                  | 0.5513***                  |
|                     | (0.1488)                     | (0.1811)                     |
| Treatment × log GDPpc × log population | 0.0306**                   | 0.0465**                   |
|                     | (0.0132)                     | (0.0367)                     |
| Log population × log GDPpc | −0.0197***                  | −0.0197***                  |
|                     | (0.0054)                     | (0.0054)                     |
| Treatment × log GDPpc × log population | 0.0211***                  | 0.0187**                   |
|                     | (0.0073)                     | (0.0078)                     |
| Log GDPpc squared   | 0.1277                      | 0.1277                      |
|                     | (0.0800)                     | (0.0767)                     |
| Treatment × log GDPpc squared | 0.2773**                   | 0.2773**                   |
|                     | (0.1294)                     | (0.0977)                     |
| Presample mean transnational terrorist incidents | 0.4871***                  | 0.5437***                  |
|                     | (0.0924)                     | (0.0954)                     |
| Constant            | −29.8261***                  | −24.6921***                  |
|                     | (10.6351)                    | (8.7597)                     |
| Number of observations | 539                         | 539                         |
| Number of countries  | 77                           | 77                           |
|                                | (1)          | (2)          | (3)          | (4)          | (5)          |
|--------------------------------|--------------|--------------|--------------|--------------|--------------|
| Log GDPpc                      | 3.1805       | 1.8073       | 3.5021*      | 3.1805       | 5.4184***    |
|                               | (2.0106)     | (1.9443)     | (2.0720)     | (2.0107)     | (1.3084)     |
| Log population                 | 2.0908***    | 1.4436**     | 2.1274***    | 2.0908***    | 2.1918***    |
|                               | (0.6312)     | (0.6496)     | (0.6555)     | (0.6312)     | (0.6817)     |
| Polity score                   | −0.3301**    | 0.0679       | −0.6820**    | −0.3301**    | −0.3629**    |
|                               | (0.1453)     | (0.1892)     | (0.3251)     | (0.1453)     | (0.1618)     |
| Treatment                      | 85.4385***   | 72.9658***   | 86.7638***   | 85.4385***   | 94.9887***   |
|                               | (21.4896)    | (21.1486)    | (21.8654)    | (21.4894)    | (20.8831)    |
| Treatment × log GDPpc          | −12.1326***  | −10.7300***  | −12.7107***  | −12.1326***  | −14.2888***  |
|                               | (2.6422)     | (2.6473)     | (2.7956)     | (2.6422)     | (2.1939)     |
| Treatment × log population     | −3.6812***   | −2.8918**    | −3.6596**    | −3.6812***   | −3.7867***   |
|                               | (1.4210)     | (1.4545)     | (1.4682)     | (1.4210)     | (1.4407)     |
| Treatment × polity score       | 0.4032*      | 0.0676       | 0.8631       | 0.4032*      | 0.4384*      |
|                               | (0.2381)     | (0.0638)     | (0.6494)     | (0.2381)     | (0.2484)     |
| Log GDPpc × log population     | −0.3035***   | −0.2289***   | −0.3137***   | −0.3035***   | −0.3199***   |
|                               | (0.0723)     | (0.0739)     | (0.0752)     | (0.0723)     | (0.0774)     |
| Treatment × log GDPpc × log population | 0.4012***   | 0.3141**     | 0.4096***    | 0.4012***    | 0.4185***    |
|                               | (0.1477)     | (0.1487)     | (0.1505)     | (0.1477)     | (0.1500)     |
| Polity score squared           | −0.0237***   | −0.0218***   | −0.0246***   | −0.0237***   | −0.0221***   |
|                               | (0.0058)     | (0.0055)     | (0.0060)     | (0.0058)     | (0.0059)     |
| Treatment × polity score squared | 0.0205***   | 0.0188**     | 0.0215**     | 0.0205***    | 0.0190**     |
|                                | (0.0079)     | (0.0077)     | (0.0080)     | (0.0079)     | (0.0080)     |
| Log GDPpc squared              | 0.1158       | −0.0019      | 0.1059       | 0.1158       |              |
|                                | (0.0827)     | (0.0103)     | (0.0831)     | (0.0827)     |              |
| Treatment × log GDPpc squared  | 0.2861**     | −0.0012      | 0.3131**     | 0.2861**     | 0.3967***    |
|                                | (0.1310)     | (0.0353)     | (0.1419)     | (0.1310)     | (0.1039)     |
| Log GDPpc × polity score       | 0.0427**     | 0.0551***    | 0.0427**     | 0.0427**     | 0.0465**     |
|                                | (0.0170)     | (0.0205)     | (0.0170)     | (0.0170)     | (0.0193)     |
| Treatment × log GDPpc × polity score | −0.0477*   | −0.0619**    | −0.0477*     | −0.0477*     | −0.0518*     |
|                                | (0.0264)     | (0.0269)     | (0.0264)     | (0.0264)     | (0.0279)     |
| Log GDPpc squared              |              |              | 0.1286       |              |              |
|                                |              |              | (0.0815)     |              |              |
| Treatment × log GDPpc squared  |              |              | 0.2824**     |              |              |
|                                |              |              | (0.1403)     |              |              |
| Log population × polity score  |              |              | 0.0140       |              |              |
|                                |              |              | (0.0114)     |              |              |
| Treatment × log population × polity score | −0.0194 |              |              |              |              |
|                                |              |              | (0.0344)     |              |              |
| Presample mean transnational terrorist incidents | 0.4919***     | 0.5118***     | 0.5047***     | 0.4919***     | 0.4741***     |
|                                | (0.0969)     | (0.0921)     | (0.0987)     | (0.0969)     | (0.0969)     |
| Constant                      | −30.5568**   | −19.5500**   | −31.6964**   | −30.5568**   | −40.4420***   |
|                                | (12.6926)    | (12.5603)    | (13.1639)    | (12.6929)    | (11.5677)    |
| Number of observations        | 539          | 539          | 539          | 539          | 539          |
| Number of countries           | 77           | 77           | 77           | 77           | 77           |
Table C12. PSM-GMM with lagged specification search.

|                      | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
|----------------------|--------------|--------------|--------------|--------------|--------------|--------------|
| Dummy lagged transnational terrorist incidents | 1.3743***    | 1.3453***    | 1.3029***    | 1.3239***    | 1.3574***    | 1.3873***    |
|                      | (0.2424)     | (0.2450)     | (0.2404)     | (0.2387)     | (0.2445)     | (0.2498)     |
| Log GDPPc            | -0.2005**    | 0.1192       | -0.0019      | 2.2506**     | -0.2461**    | -0.2019**    |
|                      | (0.0938)     | (1.0619)     | (0.0968)     | (0.8786)     | (0.1009)     | (0.0939)     |
| Log population       | -0.7134***   | -0.7215***   | -0.6601***   | 0.4820       | -0.7060***   | -0.7072***   |
|                      | (0.0636)     | (0.0662)     | (0.0801)     | (0.4589)     | (0.0617)     | (0.0660)     |
| Polity score         | -0.0158      | -0.0152      | 0.0223       | -0.0129      | -0.1051      | 0.0176       |
|                      | (0.0167)     | (0.0165)     | (0.0233)     | (0.0169)     | (0.1151)     | (0.1661)     |
| Treatment            | -0.4018      | 29.8511***   | 2.2406       | 78.9674**    | 4.2008       | 7.1916       |
|                      | (4.7464)     | (7.6270)     | (4.6372)     | (25.2918)    | (3.6248)     | (5.1257)     |
| Treatment × log GDPPc| 0.1486       | -6.9856***   | -0.1651      | -8.1707***   | -0.2835      | 0.0272       |
|                      | (0.2516)     | (2.0153)     | (0.2652)     | (2.6520)     | (0.2693)     | (0.2350)     |
| Treatment × log population | -0.0947      | -0.0420      | -0.1304      | -4.6682***   | -0.1134      | -0.4864**    |
|                      | (0.2063)     | (0.1717)     | (0.2043)     | (1.4971)     | (0.1954)     | (0.2320)     |
| Treatment × polity score | 0.0424      | 0.0320       | -0.0131      | 0.0291       | -0.7007**    | -0.8644*     |
|                      | (0.0430)     | (0.0395)     | (0.0477)     | (0.0435)     | (0.3274)     | (0.4704)     |
| Log GDPPc squared    | -0.0188      |             |             |             |             |             |
|                      | (0.0629)     |             |             |             |             |             |
| Treatment × log GDPPc squared | 0.3995***   |             |             |             |             |             |
|                      | (0.1177)     |             |             |             |             |             |
| Polity score squared |             |             |             |             |             | -0.0140***   |
|                      |             |             |             |             |             | (0.0051)     |
| Log GDPPc × log population | -0.1442***  |             |             |             |             |             |
|                      |             |             |             |             |             | (0.0079)     |
| Treatment × log GDPPc × log population | 0.4804***   |             |             |             |             |             |
|                      |             |             |             |             |             | (0.1566)     |
| Log GDPPc × polity score |             |             |             |             | 0.0103      |             |
|                      |             |             |             |             | (0.0134)     |             |
| Treatment × log GDPPc × polity score | 0.0735**    |             |             |             |             |             |
|                      |             |             |             |             | (0.0351)     |             |
| Log population × polity score |             |             |             |             |             | -0.0019     |
|                      |             |             |             |             |             | (0.0093)     |
| Treatment × log population × polity score |             |             |             |             |             | 0.0544**    |
|                      |             |             |             |             |             | (0.0285)     |
| Presample mean transnational terrorist incidents | 0.3869***   | 0.4082***   | 0.3656***   | 0.3716***   | 0.4012***   | 0.3879***    |
|                      | (0.1089)     | (0.1120)     | (0.1057)     | (0.1080)     | (0.1128)     | (0.1088)     |
| Constant             | 9.1304***    | 7.9481*      | 7.1056***    | -11.1608     | 9.3629***    | 9.0217***    |
|                      | (1.1742)     | (4.1793)     | (1.4311)     | (7.5708)     | (1.2496)     | (1.2810)     |
| Number of observations | 539          | 539          | 539          | 539          | 539          | 539          |
| Number of countries  | 77           | 77           | 77           | 77           | 77           | 77           |
|                                | Round 2 | Round 3 |                                | Round 3 |
|--------------------------------|---------|---------|--------------------------------|---------|
|                                | (1)     | (2)     | (3)                            | (4)     |
| **Dummy lagged transnational**  | 1.3066***| 1.2540***| 1.3080***                      | 1.3506***|
| **terrorist incidents**         | (0.2400) | (0.2388) | (0.2432)                       | (0.2475) |
| **Log GDPpc**                   | 2.6496  | 3.5500***| 2.8881***                      | 2.5178***|
|                                | (1.7096)| (1.1044) | (0.9628)                       | (1.0253) |
| **Log population**              | 0.4897  | 1.0540*  | 0.8559*                        | 0.6429  |
|                                | (0.4768)| (0.5643) | (0.5006)                       | (0.5436) |
| **Polity score**                | -0.0123 | 0.0359   | -0.2212**                     | 0.1123  |
|                                | (0.0166)| (0.0248) | (0.1113)                       | (0.1596) |
| **Treatment**                   | 53.1987**| 86.3230***| 72.9080***                     | 79.7426***|
|                                | (23.1660)| (24.4753)| (27.2273)                      | (22.7683) |
| **Log GDPpc **× log GDPpc**     | -9.5204***| -9.1284***| -7.6247***                     | -7.6274***|
|                                | (2.6193)| (2.5820) | (2.8381)                       | (2.3708) |
| **Treatment **× log population**| -1.5112| -4.9622***| -4.2451***                     | -4.8866***|
|                                | (1.5888)| (1.4565) | (1.6439)                       | (1.3602) |
| **Treatment **× polity score**  | 0.0277  | -0.0338  | -0.1678                       | -0.9242*|
|                                | (0.0396)| (0.0488) | (0.3318)                       | (0.5197) |
| **Log GDPpc × log population** | -0.1461*| -0.2045***| -0.1866**                      | -0.1600**|
|                                | (0.0573)| (0.0655) | (0.0595)                       | (0.0628) |
| **Treatment **× log GDPpc **× log population** | 0.1723 | 0.5157***| 0.4423***                      | 0.4474***|
|                                | (0.1593)| (0.1534) | (0.1713)                       | (0.1422) |
| **Log GDPpc squared**           | -0.0213 | -0.0071  | 0.0239*                        | (0.0138) |
|                                | (0.0698)| (0.0412) | (0.0017)                       | (0.0136) |
| **Polity score squared**        | -0.0172**| -0.0172**| -0.0186**                      | -0.0170***|
|                                | (0.0052)| (0.0079) | (0.0054)                       | (0.0052) |
| **Treatment **× polity score squared** | 0.0226***| 0.0226***| 0.0260***                      | 0.0202***|
|                                | (0.0079)| (0.0083) | (0.0081)                       | (0.0081) |
| **Log GDPpc × polity score**    | 0.0239* | 0.0127   | 0.0188                        | (0.0142) |
|                                | (0.0129)| (0.0360) | (0.0173)                       | (0.0136) |
| **Treatment **× log GDPpc **× polity score** | -0.0071| -0.0071  | 0.0089                         | (0.0010) |
|                                | (0.0079)| (0.0089) | (0.0010)                       | (0.0010) |
| **Log population × polity score** | 0.0854*| 0.0854* | 0.0854*                       | (0.0031) |
|                                | (0.0310)| (0.0301) | (0.0031)                       | (0.0031) |
| **Presample mean transnational terrorist incidents** | 0.3793***| 0.3297***| 0.3635***                      | 0.3575***|
|                                | (0.1107)| (0.1031) | (0.1132)                       | (0.1091) |
| **Constant**                   | -12.8243| -22.5389**| -16.8757**                     | -13.9288|
|                                | (10.2153)| (9.5699) | (8.2598)                       | (9.0666) |
| **Number of observations**     | 539     | 539     | 539                            | 539     |
| **Number of countries**        | 77      | 77      | 77                             | 77      |
Table C14. PSM-GMM with lagged specification search (continued).

|                              | Round 3          |          | Round 4          |          |
|------------------------------|------------------|----------|------------------|----------|
|                              | (1)              | (2)      | (3)              | (4)      | (5)      |
| Dummy lagged transnational terrorist incidents | 1.2013***        | 1.2050***| 1.2275***        | 1.2255***| 1.2245***|
|                               | (0.2418)         | (0.2443) | (0.2387)         | (0.2391) | (0.2379) |
| Log GDPPc                     | 2.5996           | 4.5801***| 4.4980***        | 4.5252***| 4.3420***|
|                               | (1.8871)         | (1.2176) | (1.2015)         | (1.1895) | (1.1808) |
| Log population                | 1.5491***        | 1.6224***| 1.6037***        | 1.6201***| 1.5208***|
|                               | (0.5712)         | (0.6275) | (0.6159)         | (0.6079) | (0.6046) |
| Polity score                  | −0.2360**        | −0.4554  | −0.2531*         | −0.2621*| −0.2275* |
|                               | (0.1359)         | (0.3271) | (0.1469)         | (0.1368) | (0.1374) |
| Treatment                     | 55.5118**        | 77.3681***| 79.1288***       | 83.4372***| 85.3380***|
|                               | (22.8329)        | (26.4401)| (26.7814)        | (24.5499)| (24.6534)|
| Treatment × log GDPPc        | −8.4997***       | −7.7241***| −8.5166***       | −8.9470***| −9.0549***|
|                               | (2.8621)         | (2.7741) | (2.8074)         | (2.5760) | (2.6161) |
| Treatment × log population    | −2.1380          | −4.3450***| −4.4580***       | −4.7416***| −4.8737***|
|                               | (1.5116)         | (1.5937) | (1.6112)         | (1.4658) | (1.4648) |
| Treatment × polity score      | 0.0274           | −0.8878  | −0.2034          | −0.0839  |           |
|                               | (0.2301)         | (0.6637) | (0.2858)         | (0.0557) |           |
| Log GDPPc × log population    | −0.2550***       | −0.2713***| −0.2658***       | −0.2676***| −0.2562***|
|                               | (0.0666)         | (0.0722) | (0.0712)         | (0.0704) | (0.0700) |
| Treatment × log GDPPc × log population | 0.2407         | 0.4240**  | 0.4716***        | 0.5003***| 0.5079***|
|                               | (0.1542)         | (0.1676) | (0.1689)         | (0.1534) | (0.1550) |
| Polity score squared          | −0.0202***       | −0.0194***| −0.0186***       | −0.0187***| −0.0174***|
|                               | (0.0055)         | (0.0056) | (0.0054)         | (0.0054) | (0.0052) |
| Treatment × polity score squared | 0.0213**        | 0.0242**  | 0.0260***        | 0.0256***| 0.0194***|
|                               | (0.0085)         | (0.0085) | (0.0081)         | (0.0083) | (0.0068) |
| Log GDPPc × polity score      | 0.0317***        | 0.00409** | 0.0337*          | 0.0347***| 0.0297***|
|                               | (0.0158)         | (0.0202) | (0.0173)         | (0.0161) | (0.0159) |
| Treatment × log GDPPc × polity score | −0.0096        | 0.0090    | 0.0122           |          |           |
|                               | (0.0251)         | (0.0333) | (0.0316)         |          |           |
| Log GDPPc squared             | 0.1012           |          |                  |          |          |
|                               | (0.0828)         |          |                  |          |          |
| Treatment × log GDPPc squared | 0.2325           |          |                  |          |          |
|                               | (0.1512)         |          |                  |          |          |
| Log population × polity score |                  |          | 0.0080           |          |          |
|                               |                  |          | (0.0118)         |          |          |
| Treatment × log population × polity score |          |          | 0.0427           |          |          |
|                               |                  |          | (0.0338)         |          |          |
| Presample mean transnational terrorist incidents | 0.3334***        | 0.3276***| 0.3117***        | 0.3106***| 0.3208***|
|                               | (0.1078)         | (0.1089) | (0.1070)         | (0.1067) | (0.1069) |
| Constant                     | −23.0267**       | −31.3279***| −31.1350***      | −31.3909***| −29.7967***|
|                               | (11.4824)        | (10.6759) | (10.4666)        | (10.3534) | (10.2753) |
| Number of observations        | 539              |          | 539              |          | 539      |
| Number of countries           | 77               |          | 77               |          | 77       |