Not so different after all: Arrests and convictions (but not sentence length) deter terrorism

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Abstract

While countries differ in how they handle terrorism, in the West, criminal justice systems treat terrorism similar to other crime, with police, prosecutors, judges, courts, and penal systems carrying out similar functions of investigations, apprehension, charging, convicting, and overseeing punishments respectively. We address a dearth of research on potential deterrent effects against terrorism by analyzing data on terrorism offending, arrests, charges, convictions, and sentencing over 16 years in 28 EU-member states. Applying both count and dynamic panel data models across multiple specifications, we find that increased probability of apprehension and punishment demonstrate an inverse relationship with terrorism offending, whilst the rate of charged individuals is associated with a small increase in terrorism. The results for sentence length are less clear but also indicate iatrogenic effects. The findings unveil significant overlaps between crime and terrorism in terms of deterrent effects and have implications for both the research agenda and policy discussion.

Main

In recent years, criminologists have increasingly devoted attention to the study of terrorism, making significant contributions to a field of study that suffered from severe stagnation[1,2]. These contributions show that whilst differences certainly exist, ordinary crime and terrorism display significant overlaps. These include socio-demographics of offenders, with most offenders being relatively young males, especially those with criminal backgrounds, as well as psychological characteristics such as low self-control[3]. Overlaps have also been identified in terms of spatial and temporal clustering[4-7], patterns of recidivism[8], cycles of violence[4], target selection[9], and network organization[10]. Importantly, strategies found to be effective in combatting crime also appear effective in combatting terrorism, particularly situational prevention[11-16].

There is an extensive array of factors which can account for variation in the occurrence of terrorism, including but not limited to cultural, political, and socio-economic conditions[17-19]. However, the role of criminal justice factors has hereto remained under-researched, this despite the relatively consistent role of the criminal justice system in combatting terrorism: police are responsible for arrests, prosecutors are responsible for proceedings, judges are responsible for convicting/acquittal and sentencing, and the prison service for managing prison sentences[20,21]. Whether a country experiences terrorism or not (or how much) is a function of its socio-political climate, the differential opportunities that exist, as well as the effectiveness of authorities in both prevention and deterrence[22].

These considerations underpin the deterrence model which holds that decisions to engage in offending are the product of the weighing the risks of offending against the rewards, against the background rewards for abstaining from offending. Here, the risks for an individual to be subject to punishment, whatever its severity, are dependent on the risk of apprehension, prosecution, and conviction. Accordingly, deterrence is a function of the probability of arrest, the probability of conviction given arrest, the probability of imprisonment conditional on conviction, and the expected severity of punishment conditional on imprisonment[23, 24].

However, evidence for this model is mixed, with punishment severity displaying small effects, and in some cases even a positive relationship, in which it is associated with an increase in crime [25-29]. Even where punishment severity is associated with reduced crime, it has been suggested that this is an artifact of incapacitation effects, and not deterrence[30]. While there is also mixed evidence concerning the effects of certainty of apprehension and punishment, a meta-analysis found that certainty operates in the hypothesized direction and is of a meaningful magnitude[29].

Analytically, many issues, such as measurement[31] and specification biases[32,] may impact results. Few studies examine the full range of deterrence factors in a single model, with most limited to analyzing certainty of punishment[32]. This is especially problematic given the theorized negative correlation between certainty and severity[33]. In the cross-national research context, whilst in some countries greater likelihood of punishment is associated with a reduction in crime, in others the opposite is true, and differences exist across crime categories as well[34]. Others have found that police performance, which includes case clearance, has a negative relationship with homicide rates[35]. There are no real examples of cross-national studies that test the full deterrence model, in part due to a lack of data[36]. With regard to measurement, using the probability of conviction ignores the likelihood of being charged as a function of arrest. There is evidence that omission of this variable is a potential source of specification bias as its inclusion has been found to impact the statistical significant of other deterrence variables[32, 37, 38]. In light of these challenges, much of deterrence research focus on policies conceptualized as proxies for either certainty or severity of punishment. For example, researchers focused on how laws targeting gangs, which resulted in widescale arrests—thereby increasing the likelihood of punishment—impact a range of crime outcomes. Classically, research on severity of punishment research has focused on the effects of the death penalty, which can also be characterized by mixed results, and studies of policies such as California's (no longer practiced) 'Three strikes and you're out' approach. Whilst these avenues of research are certainly important, they are limited methodologically, and in terms of what they can tell us about deterrence[39].

Returning to the issue of terrorism, while significant overlaps with crime have been found, there are also important differences. Ordinary offenders are primarily motivated by the maximization of financial gains. Even the maximization of power is more of a means to achieving financial goals than a goal in and of itself. Terrorism is motivated more by grievances and seeks to maximize changes to social, political, or other norms and systems viewed as the sources of those grievances[40-42]. As a result, terrorists more often act out of altruistic motivations than ordinary offenders do. Relatedly, even if most ordinary offenders seek to avoid detection, terrorism has traditionally been used as a means of garnering maximum attention[43].

These differences led some to theorize that terrorists were irrational, and thereby undeterrable[44], mirroring some positions on homicide that view general or marginal deterrence through increasing the costs of offending as unachievable[45]. However, as in the case of homicide[45], there is evidence that (potential) terrorism offenders engage in rational choice making, weighing potential rewards against potential risks[12-14, 46-48]. Some argue that this is the point at which terrorism and crime are most similar, at least as much as the overlaps between general (e.g., ordinary violence) and specialty crimes such as hate-crime or gang-violence[49]. Evidence for rational choice making in terrorism, like in the case of crime, has been further deduced from how it responds to situational prevention efforts, with findings that increasing the difficulty of successful attacks, and of apprehension, are associated with reductions in terrorism[12, 14, 15, 50]. Additional evidence for this claim can be deduced from the impact of routine activities on incident rates. During the recent Coronavirus pandemic, lockdowns were found to be associated with significant decreases in crime, due to changes in routine activities leading to fewer opportunities for crime[51]. This similarly reduced opportunities for terrorism, with a lack of crowds at public venues, and increased police presence[52-54].

Most deterrence studies on terrorism follow the approach of analyzing policies as proxies for deterrence, partly due data availability issues. These studies generally rely on time-series analyses in which specific interventions are treated as dummy variables. Methodologically these approaches can be quite problematic[39], and there are statistical issues in assessing these results when some countries experience no terrorism due to other factors, such as the socio-political environment, and opportunities[22]. Nevertheless, these studies can still be informative. In reviewing the results, indiscriminate policies, like widescale crackdowns, generally have no effect on terrorism, or produce backlash effects, increasing terrorism. Conversely, policies conceptualized as representing 'soft' approaches are regularly associated with decreases in the risk of terrorism[11, 55-57].

There are few studies testing the likelihood of arrest in a way that is comparable to general deterrence research. These studies partially overcome some of the statistical issues that exist when there is an absence of terrorism due to background characteristics, since there is at least time variation on the independent variables[22]. The first such study, examined how a small number of annual arrests (between 11 and 17) of Palestinian Liberation Organization (PLO) terrorists impacted the number of attacks carried out by the group outside of Israel (international attacks). The study did find evidence that higher arrest rates (number of arrests per incident) displayed a small deterrent effect[58]. In another study focused on Israel, it was found that increased arrests reduced the likelihood of suicide bombings[59]. It should be noted however, that for both studies, data for arrests was derived from open-sources and their dependent variables were both limited to very specific types of terrorism activity. The only known study which used counts of arrests, as derived from official sources, was a thesis study which found that increased terrorism related arrests in Pakistan were associated with lower terrorism[60].

One observation that can be made from the above noted literature is that whether measuring deterrence through dummy variables representing specific counter-terrorism actions, or through more traditional measures such as the numbers of arrests, different types of terrorism in different contexts may respond differently[61]. What the overall effects may be also remains unknown, as reflected by the ongoing debate as to whether terrorism can be deterred by the criminal justice system. As above, some have argued that since terrorists are willing to die for their cause or group, deterrence is not a relevant factor. However, others reject this proposition as representing a narrow understanding of terrorism, and such notions may be limited to the now relatively rare case of suicide bombings[62]. Much of the 'new terrorism' experienced in the Europe involves actors engaging in extensive planning for survival, even if they are prepared to die. Many terrorists, including Osama bin Laden, sought to evade capture and punishment[63]. Moreover, the willingness to die for a cause is not unique to terrorists. Many ordinary offenders may prefer to 'get away with it' whilst at the same time being prepared to accept the possibility capture or death[64]. As such, differences in motivations and objectives do not necessarily lead to differences in the theorized impact of deterrence.

While most deterrence research has focused on high-volume crimes such as assault and property crime, most cross-national research has focused on homicide[34-36]. Terrorism is more similar to homicide in that it is a low base-rate crime, and a relatively small proportion of the population are ever at risk of offending[65, 66]. Whilst police resources can become overwhelmed by high-volume crime, reducing likelihood of capture and punishment[32], extensive resources are dedicated for dealing with homicide and terrorism, which also small non-reporting rates[67].

There are additional issues with how the criminal justice systems in Western countries treat terrorism that could lead to differential deterrent effects. For example, compared to ordinary crime, the rate of release without charge may be quite high. According to UK's Home Office, some years have seen more than 50% of those arrested under the Terrorism Act (2000) released without charge[68]. Our own review of these statistics shows that this rate increases commensurate with the volume of arrests. Similarly, in the US, while arrests for terrorism have increased, and have been viewed as having led to a decrease in successful attacks, the rate of declination, in which charges are dropped, has increased, possibly indicating that authorities are identifying terrorism threats early enough to prevent them, but too early to gather sufficient evidence for successful prosecution[69]. Additionally, conviction rates may be lower than for ordinary crime, although they have increased in recent years as terrorism cases have increasingly been tried as criminal-cases[70, 71].

In the absence of any rigorous tests of the deterrence theory model with respect to terrorism, it is still only possible to theorize about how it may respond to the criminal justice system. There are both theoretical and empirical reasons to assume that it will respond in ways similar to ordinary crime, as well as reasons to suggest that it may respond differently. While a direct test comparing terrorism and crime would be idyllic, as described above, there is a lack of cross-national data for deterrence variables as they relate to crime, As such, the current study tested whether the criminal justice system has a deterrent effect on terrorism and whether the effects follow similar patterns to what extent literature has found in the case of ordinary crime. Our study draws on data from EUROPOL's annual Terrorism Situation and Trends reports (TE-SAT) from 2006-2021, testing how arrests, charges, convictions, and sentence length for terrorism offences impact gross terrorism offending. Our analytic strategy employs a dynamic panel-data framework in which we treat the data according to different modelling specifications, namely as offending rates (as is common in the criminological literature), and counts (as is common in the terrorism literature). All models include multiple fixed-effects and theoretically relevant control variables. Extensive robustness checks were also performed to test the impact of model specification and measurement bias, and the influence of alternative explanatory variables.

Results

The results of the primary GMM analysis are displayed below in Table 2. The first two models, Model Ia (without controls) and Model IIa (with controls), present the results in which arrests are treated as exogenous. The two models demonstrate great consistency in their results. Between both models, the size of the coefficients remains relatively similar. Relying on Model II, the largest effect is for the lagged terrorism incident rate, with a one unit increase in the incident rate in a prior year associated with more than a 9% increase in attacks the subsequent year. In terms of deterrent effects, a one unit increase in the arrest rate is associated with a 0.2% reduction in the terrorism rate. With respect to the conviction rate, a one-unit increase is associated with a 12% reduction in the terrorism offending rate. Two deterrent variables are associated with an increase in terrorism. An additional one unit increase in the rate of charged individuals is associated with a 0.16% increase in the terrorism rate, and an additional one unit increase in the average sentence length with a 0.14% increase. In Model IIIa, arrests are treated as endogenous. The main differences between model II and model III are that the coefficients are smaller for all factors, with the exception of the factor measuring the charge rate. That is, the reductions in the terrorism incident rate for both arrest and conviction rates are about half the size as in model II, whereas there is a slight increase in the size of the coefficient for the charge rate. Additionally, in this model, the coefficient for sentence length remained below the conventional 90% level of statistical significance. Drawing on Model IIa, these effects can be further illustrated by the plots presented in Figure 4. The plots present the predicted margins with 95 percent confidence intervals for each of the primary predictor variables. The plots vary in their scales as they relate to the effects from the minimum to maximum values of each of the variables.

These models were replicated using count models, where raw counts of terrorism events served as the dependent variable. In model I, all independent variables were also measured as counts (e.g., number of arrests, number of charges, number of convicted individuals), with the exception of sentence length, which was the raw average number of years. Here, the estimates for all of the main predictors follow the same direction as the effects observed in the GMM models. The exception to this pattern is for the number of arrests, which follows the same direction but was well below the level of statistical significance (p=.292). In model II, the number of convictions was replaced with the conviction rate. The results followed those of model I, including with respect to the non-significant effects of arrests, however the effects for conviction were considerably larger. Models III and IV replicated models I and II but absorbed the dummy variables for non-events in the current and preceding years as a fixed effect. These two models follow the results of models I and II except that the effects for arrests become statistically significant. Model V used the arrest rate (arrests/events) and charge rate (charges/arrests) together with the conviction rate, with zeros filled in, whereas Model VI used the IHS transformed variables used in the GMM models above.

Robustness checks

Several robustness checks were performed. First, we estimated an alternative specification of our equations in which we used contemporaneous values of control variables. This specification addresses the fact that economic variables could potentially affect crime differentially between lagged and contemporaneous effects. Here, there were no substantive differences in the effects of the main explanatory variables. Additionally, none of the control variables demonstrated statistically significant effects. Second, we also carried out a series of robustness checks in which we assessed the potential for omitted variable bias as an issue in the analysis of deterrence, as it has been found to be an issue in criminological research (Bun et al., 2020). These tests revealed a good degree of stability in the effects of the explanatory variables, including statistical significance. However, we note that when arrest rates are assessed on their own, the estimate falls below the level of statistical significance. This is not surprising however as one of the criticisms of deterrence research mentioned above is the risk of type II errors in the context of examining deterrence variables in isolation[32]. Third, we added additional, time-varying control variables of theoretical relevance, namely: GDP, population density, urbanity, violent crime rate, the number of asylum seekers, and rule of law (a composite measure that captures confidence in and abidance of the law, quality of law enforcement measures, property rights, police and judicial quality and efficiency, and the likelihood of crime and violence). All data were derived from official sources such as the World Bank. For all of these tests, the jackknife estimation method was employed to identify whether the estimates of the explanatory factors were also sensitive to the iterative exclusion of panels. Except for the first set of tests in which the impact of contemporaneous measures of control variables was tested, lags of the control variables were used in order that the models would be more closely related to the specification of the main models (Tables 2 & 3).

Across all of these analyses, results not only remained robust but remained fairly consistent (See supplementary materials). There were, however, some differences. First, in the model using contemporaneous factors, sentence length had a small, statistically significant effect in a negative direction. In the model using conviction rate, it was not statistically significant. In the model using the IHS transformed variables, the effect for arrests was quite large, conviction rate was positive, and sentence length was negative. For the model specification checks, whilst conviction rate and charges continue to point in the same direction, arrests have a positive relationship and sentence length a negative relationship. This points to the potential for specification bias if we would not have modelled all the factors in a single model. With respect to robustness against additional control variables, while the results across models remained substantively consistent, there were some differences. When regressing the violent crime rate, the effects for arrests fall below statistical significance, whereas sentence severity shows a marginally significant negative effect. When including rule of law, all factors follow the direction and magnitude of the effects in the main model, except for sentence severity, which again shows a small but statistically significant effect (p=.000) of -.012.

As an additional robustness check, we conducted a series of Zero-Inflated Poisson (ZIP) models. Across these models, the effects for convictions and charges were consistent with the main models, whilst the effects for arrest were only statistically significant when measured as a rate but not as a count. The estimates for sentence length demonstrated a statistically significant negative relationship across all models.

Discussion

The objective of this work was to test the deterrence model in the case of terrorism, an especially important line of inquiry given the central and consistent role of the criminal justice system in dealing with the phenomenon. Whereas most prior research has been limited to testing the effects of specific counter-terrorism policies or actions, usually modelled using dummy variables, our goals was to test the effects of arrests, charges, convictions, and sentencing. Our study relied on official data reported to EUROPOL by 28 EU member states over a 16 year period. To summarize the major findings, increased convictions have the most consistent and salient relationship with terrorism offending. Whereas increased arrests also have a consistent negative relationship, the relationship is smaller, although this is to be expected as arrests are more frequent than convictions. Conversely, charges almost always have a significant positive relationship. The results for sentence length are less clear, with the GMM models demonstrating positive (backlash) relationships and the count models producing negative (deterrence) relationships. The robustness checks indicate that for the count models, the addition of certain control variables can change the sign of the effects, although in such cases it is not statistically significant. The consistent findings for arrests, charges and convictions are noteworthy given that the effects for many factors may differ when terrorism is measured variously as rates or counts[72]. This can also explain the divergent findings for sentence length.

The results regarding arrest are consistent with those few studies that have found that increased arrests are associated with reductions in terrorism. However, like much of the criminological literature, these studies focussed on single contexts[58-60]. Despite the fact that the broader deterrence literature widely discusses whether potential offenders are aware of the risk of apprehension, the case of terrorism may be somewhat unique. Terrorism events are rare, their outcomes are highly publicized, and at least within ideological milieus, there is a high degree of information sharing. This could increase the potential ability for the criminal justice system to exert a general deterrent effect against terrorism, at least in comparison to ordinary crime.

Our results also broadly overlap with findings pertaining to ordinary crime, and particularly homicide, as demonstrated by the results of a meta-analysis in which certainty of punishment was found to have a pooled estimate of r=-.15. On the other hand, the pooled estimate of r=-.032 for sentence length was not statistically significant[29]. Drawing on our GMM models, our results for both likelihood of arrest and charge would be equivalent to correlations of r=-.13, and conviction rate, r=-.10. With regard to sentence severity, the results would be equivalent to .03, and combined with our divergent results from the count models would provide a similar, non-significant pooled result. Here, the degree of overlap even in the relative magnitude of the estimates is quite striking.

Beyond the more substantive findings, these results point to possible policy implications. In this regard, counter-terrorism tactics, like police methods against gang violence, often involve large scale crackdowns in which there may be extensive arrests but many arrestees are eventually released without charge. As noted above, some research indicates that these types of crackdowns can have backlash effects. In synthesizing our own results with those of these prior studies, we are able to perhaps offer some insights into those findings that widescale crackdowns can have potential backlash effects. In our study, we found that increased arrests are associated with a deterrent effect. However, the evidence also points to a potential backlash effect when there is a larger number of arrests that do not lead to charges. Policy makers and law enforcement should consider the chances of charge and conviction when making arrests if they want to reduce the potential for iatrogenic effects.

Whilst we have endeavored to conduct a study using the most robust data and methods available, and our analytic approach and models follow the contemporary approaches in both the deterrence and terrorism research fields, caution is still warranted in how the results are interpreted and there are also several limitations of note. One issue, for example, is the potential impact of unobserved confounders. While we endeavored to include theoretically relevant controls, we were limited in the number of controls that could be included given that for methodological reasons, as the number of instruments could not exceed the number of panels. Further, some of our controls were imperfect. For example, the dummy variable representing the years in which there were changes to counter-terrorism laws cannot capture the nature or extent of these changes, and elements of deterrence they affected (i.e., certainty or severity of punishment). Additionally, a key component of the deterrence model that we were unable to address at a high level of specificity in the current study is celerity, or the swiftness of punishment. We were able to include a general measure of celerity, yet it did not relate specifically to only the terrorism cases included in the data, as such a measure was not available. Ideally, future research will be able to identify appropriate data for assessing the role of celerity in deterrence research on terrorism. This may be particularly important as it has previously been argued that the small effects observed for likelihood of punishment and punishment severity on crime, may be related to the swiftness—or lack thereof—of punishment.

A further limitation of our study is that the external validity of our findings is limited given our use of TE-SAT data, which pertains only to EU member states. It is possible that in other regions of the world, such as the US, Canada, Australia, and elsewhere, results may be different. Such differences may be related to variations in the nature of the criminal justice system, the level of terrorist activity, and the nature/ideology of terrorist organizations, groups, and adherents in operation in different contexts (which may influence deterrent vs backlash responses). Of course, we would highly encourage additional studies in a broader set of contexts and we caution against assuming that deterrence patterns would be universal.

Relatedly, although the TE-SAT reports provide for reporting events disaggregated by ideological motivation (e.g., Islamist, right-wing, left-wing etc.), not all countries report such data. Additionally, this option does not exist for charges, convictions, and sentence length, precluding the ability to conduct analysis across and between ideological strains. Such an analysis would seem pertinent given that different types of terrorism may respond to deterrence differentially.

Our study measured the impact of the certainty and severity of punishment on terrorist activity in the next year. Future research might consider lower time frames, such as monthly ones, to dig deeper into analyzing the longevity of effects. Additionally, our study does not examine other issues relevant to deterrence, such as perceptions of the likelihood of punishment and expected punishment severity. These are areas of research that are prominent in the criminological literature and which may be applicable to terrorism as well.

Whilst acknowledging these limitations, and caution against assuming the generalizability of our findings at this stage in the development of the body of knowledge, we do believe that they should serve as encouragement for further integrating terrorism and deterrence research more generally. This line of inquiry offers significant promise for informing more evidence-based policy.

Methods

Our study follows what could be referred to as a classic deterrence framework, in which the expected deterrent effect on terrorism activity is a function of: the probability of arrest (P_A), the probability of charge conditional on arrest ($P_C|_A$), the probability of conviction conditional on being charged ($P_P|_C$) and the severity of punishment as expected prison sentence length (S). This approach follows economic models of crime deterrence, and also includes the background environment against which terrorism occurs, and the resources available to police that constrain their potential effectiveness.

Data sources

The primary data for our study comes from the annual TE-SAT reports published by EUROPOL between 2006-2022 and which collect verified information provided by member states, which it cross-references with the Eurojust system[73-88]. One advantage of this data source is that contributing countries have all adopted the European Union's counter-terrorism strategy and associated definitions. To the best of our knowledge this data has yet to be exploited by researchers.

The TE-SAT reports aggregate counts of the annual completed, failed, and foiled terror attacks in each country, which offers several advantages over other data sources. First, as Nagin[27-28]explains, deterrence is achieved through the (perceived) probability of apprehension given both completion and noncompletion of an offence. Second, while it is common to observe no terrorism in a given year for a given country, this does not mean that the country is free of terrorism. Rather, police may have simply been effective in that year in preventing or deterring terrorism, perhaps through arrest, and as such, these are not "true zeroes"[89]. As such, our data more accurately captures the “gross plot production” and not just the number of attacks that succeeded in avoiding detection[90]. While EUROPOL does not define "failed" or "foiled" plots, examples are given throughout the reports. For example, on January 16th, 2016, counter-terrorism police in Belgium conducting a raid killed two suspects and arrested a third who were suspected of preparing an immediate attack. Also, on June 19th, 2017, an offender in Paris, France died from fumes generated by explosive materials in his vehicle that failed to detonate.

Whilst these specific examples are also included in the widely used, open-sourced Global Terrorism Database (GTD), "The GTD does not include plots or conspiracies that are not enacted, or at least attempted. For an event to be included in the GTD, the attackers must be "out the door," en route to execute the attack. Planning, reconnaissance, and acquiring supplies do not meet this threshold"[91]. Additionally, many events recorded in the GTD are not recorded as terrorism by EU member states, perhaps being classified as some other form of sub-terroristic violent extremism, such as hate crime[92]. The GTD includes a filter for whether there is doubt that the incident was terrorism, however, with few exceptions, research often overlooks this option[93]. About 17% of GTD incidents for our country list from 2006-2020 (the GTD is not updated to 2021) are classified as "in doubt". Filtering out these incidents, the GTD provides 7.48 incidents per observation (SD=19.10), whereas our data has 8.97 (SD=33.75). While the differences are small ($t(419)= 1.37$, $p=.086$), they could be potentially meaningful. Additionally, whereas the GTD includes counts of offenders arrested or killed per attack, it does not include all terrorism-related arrests or post-arrest data, such as convictions.

In line with terrorism trends in the West[94], the majority of events were 'domestic', with perpetrators being residents of the target country, and there were only a small number of cases that can be defined as truly 'international', in which the offenders travelled to the country from elsewhere specifically to engage in an attack. There was however significant heterogeneity in terms of the distribution of ideologies attached to the incidents (e.g., Jihadist, right-wing, left-wing etc.), however as noted above, not all countries report disaggregated data.

Dependent variable

Terrorism studies commonly use raw counts of events as the dependent variable. However, terrorism is known to increase with population size[18, 72]. As there are justifications for modelling terrorism as either a count or a rate, and these measurement choices can significantly impact results[72], we calculated terrorism incidents as both a raw count of the number of the number of events, and as a rate per 100,000 residents, with population data retrieved from the World Bank[95]. For the incident rate, we applied the hyperbolic sin transformation (see the "Model specifications" subsection for further details).

Independent variables

Our main independent variables were 1) the probability of arrest, 2) the probability of being charged, 3) the probability of conviction, and 4) sentence severity (average number of years), representing a fully specified model. Like our approach for the dependent variable, we measure these variables both as counts and rates. For the latter, we calculated 1) the number of arrests divided by the number of terrorism events, 2) the number of charges divided by the number of arrests, and 3) the number of convictions divided by the number of charges. In line with our objectives of testing deterrent effects, the first lag of all variables was used. This also inherently reduces the risk of reverse causality.

Control variables

There is no shortage of macro-level factors that demonstrate important relationships with the occurrence of terrorism[19]. However, "the direction and nature of these relationships vary substantially across studies"[17], and the relative importance of the factors has not been determined.

In light of this, we have included a variety of control variables in our models. A key deterrence variable is swiftness of punishment. Unfortunately, neither TE-SAT nor any other identifiable data source provide such data for terrorism cases. However, the European Commission for the Efficiency of Justice (CEPEJ) Council of Europe provides data on the average disposition time for all criminal cases[96]. Whilst imperfect, we included this variable to provide at least a partial control for the variation in the overall celerity of punishment in the different included countries.

We also controlled for the Human Development Index (HDI) given its highly time variant nature. The HDI provides a composite measure of multiple, relevant socio-economic dimensions, namely: 1) life expectancy at birth, 2) education (mean of years of schooling for adults aged 25 years and more and expected years of schooling for children of school entering age), and 3) standard of living (measured by gross national income (GNI) per capita). As per the United Nations Development Programme (UNDP), from which data on HDI was retrieved, the HDI utilizes the logarithm of income to better reflect the diminishing importance of income with increasing GNI[97].

Furthermore, we control for security expenditure as a proportion of GDP, which should reflect constraints of counter-terrorism resources[89]. Criminological studies have used measures of police resources as proxies for deterrence, finding that they significantly impact arrest rates[98, 99]. Data for this factor was retrieved from the International Monetary Fund (IMF)[100]. Additionally, we included a dummy variable for years in which new counter-terrorism policies were enacted as reported in the TE-SAT reports, capturing the effects of the types of factors that have been examined in deterrence in terrorism research to date.

Table 1 displays the descriptive statistics for the above noted factors.

Analytic strategy

Several methodological considerations should be considered when developing an appropriate analytic strategy for identifying deterrent effects on crime, and many of these are relevant for terrorism as well.

First, one of the most significant predictors of crime is crime in a previous period[101-103]. In many approaches, the reliance on aggregated data gives rise to an issue of a *lack of exogeneity*, rendering it difficult to identify causal effects for law enforcement efforts. Additionally, an exogenous increase in crime may come to outweigh police resources, which are finite. This leads to a reduction in the likelihood of arrest, or the number of arrests per event, which is itself meant to be a regressor on the crime rate. This can give rise to issues of *reverse causality* or simultaneity[32]. The first issue is also true for terrorism[4, 104], however, with respect to the second issue, terrorism offending will unlikely come to outweigh police resources to the degree that it negatively impacts the arrest rate in such a way. As in the case of ordinary homicides, resources dedicated to counter-terrorism are known to be quite substantial. Compared to high-volume crimes such as general violence, there are more prevented terrorism incidents than successful ones. This however introduces an issue of ratio bias, in which there is a negative correlation between the arrest rate and the offending rate[105-106], and like homicide, terrorism is known to be a low base-rate problem[65].

Another issue relates to measurement error, which is known to be present in aggregated crime data, which do not capture actual offending rates, and which may suffer from temporal alignment issues. For example, if offenders' decisions are theorized to be impacted by the likelihood of punishment but punishment for crimes in a given time period are for crimes that occurred some time ago, then it may be difficult to capture the deterrent effects, if they exist. However, in the case of terrorism, the dark figure is exceptionally small[107]. And unlike other forms of crime, the detection of terrorism offences are not sensitive to victim reporting. Additionally, official data sources—such as TE-SAT—suffer from lower levels of bias than open-source datasets[108-109]. Temporal alignment is also less of an issue in annualized data[32], such as in the current study.

Lastly, like other types of crime, there are unobserved, time invariant characteristics of different geographical units. It has previously been said that differences between countries' legal and political culture, institutional arrangements, and constitutional traditions and values shape both crime and punishment in ways that no one has yet figured out how to quantify[110-112]. With this being the case, country-specific fixed effects serve to account for unobserved heterogeneity and enable more accurate estimation of the time-varying factors of core interest.

Model specifications

Given the aforementioned issues we implemented two types of panel regression models with fixed effects.

GMM models

We first implement a General Method of Moments Dynamic Panel Model[113], widely considered to be the gold standard practice in deterrence research[32, 38, 114, 115], and particularly in cross-national research on crime rates[116-120]. In first-differenced GMM, the dependent variable is the terrorism incident rate, which is calculated as the number of incidents in a given country (*i*) at time *t* (labelled as $Terr_{it}$) divided by the country's population (pop) size by 100,000 residents for each year (pop_{it}). The terrorism incident rate is modelled as a function of the probability of arrest, the probability of charge given arrest, the probability of conviction given charge, and the length of prison sentence given conviction, giving rise to the following model specification:

Equation 1.

$$\frac{Terr_{it}}{Pop_{it}} = \alpha\left(\frac{Terr_{it}}{Pop_{it}}\right) + \beta_1\left(\frac{Arr_{it}}{Terr_{it}}\right) + \beta_2\left(\frac{Char_{it}}{Arr_{it}}\right) + \beta_3\left(\frac{Conv_{it}}{Char_{it}}\right) + \beta_4 Length_{it} + \beta_5 HDI_{it} + \beta_6 Exp_{it} + \beta_7 Policy_{it} + n_i + \lambda_t + \varepsilon_t \tag{1}$$

The error term in (1) allows for country-specific fixed effects (η_i), which could potentially be correlated with the main explanatory factors, as well as time (yearly) fixed effects (λ_t) which are specified in order to capture common variations in the terrorism incident rate across countries. Following previous works, a time trend variable was also included [32, 121]. The coefficient for the lagged value of the terrorism incident rate (α) is specified to measure the combined effects of both the short-run dynamics and omitted, time-varying factors that may be hidden within the endogenous, lagged terrorism incident rates. Regarding the probability of arrest, we also estimated a model in which it was specified as strictly exogenous as arrest rates can be assumed to be dependent on the number of offences[32]. Conversely, charge and conviction rates, as well as sentence lengths, are unlikely to be endogenous to incident rates, and even arrest rates. The same holds true for police expenditure. Whilst time invariant characteristics of the countries which may impact the likelihood of terrorism are modelled by the fixed effects components, time-varying social and socio-economic conditions may impact the attractiveness of terrorism offending. As noted above, we included the HDI and security expenditure to model the background opportunity structure against which offending decisions are made.

Due to the dependent and main independent variables including observations with zeroes, for the calculation of the event rate we used the inverse hyperbolic sine transformation (IHS), which is common in economics in situations where the presence of zeroes prohibits the calculation of the logarithm of the variable. It has previously been demonstrated that the IHS is conceptually and statistically comparable to the log and superior to other approaches such as *log(y+1),* more closely maintaining the original properties of the data[122-124], including in the case of terrorism data[61, 89]. Figures 1 and 2 display the raw number of incidents and transformed incident rates (normalized to population size). A visual examination of the plots demonstrates that the original properties of the data are preserved following normalization and transformation. To provide an additional level of appreciation of the variation in incidents, Figure 3 provides a heatmap of the number of incidents per country over the whole observation period.

We assess the validity of the estimated model specification with Hansen's J test of overidentifying restrictions and its associated p value[124]. Additionally, we implemented a two-step model with robust standard errors, using Windmeijer's finite-sample correction for the two-step covariance matrix[125]. All analyses were conducted in Stata 17 using the XTABOND2 command[126].

Count models

As noted above, we also considered it important to also adopt the standard approach in the terrorism literature, which has been to rely on count models[127-130], or at least conduct them for comparison with linear models[128], in part due to the relatively small number of cases and skewed distributions. Some claim that terrorism event data characteristically suffers from an issue of 'two types of zeroes', as some countries never experience terrorism, whilst others experience some years with no events either following or prior to years with >1 events. Some suggest that this is the outcome of different underlying processes, and as such, these zeros are 'structural'[131-132]. However, others hold that the zeroes are not necessarily structural but 'random' in that they are being generated by deterrence or police efficiency[89].

Additionally, there is a debate about the utility of using the 'clearance rate', or the number of arrests divided by the number of crime events. One key criticism is that crime ends up serving as both the numerator of the dependent variable and the denominator of the independent variable, leading to negative correlations being statistical artifacts[133-135]. However, others have demonstrated that even when 'over controlling' for the potential partial correlation, there are no substantive differences in the correlations and thus the measure remains appropriate[136-140]. At least in the case of terrorism data, which has relatively few arrests, charges, and convictions, this issue may extend to the charge and conviction rate. As such, we use both the counts of these main predictors, as well as their likelihoods.

We follow Wooldridge[141-142], estimating Poisson pseudo-maximum likelihood (PPML) models with multiple fixed effects[143-145]. While some scholars have suggested the utility of a zero-inflated model, others hold that such models may not offer any significant benefits in the context of panel models in which zeros are not structural[146-147], and it is difficult to claim that countries with no events have zero likelihood of experiencing an event[130, 148]. Moreover, even if we assume that the zeroes are not entirely random, the heterogeneity is at least partially accounted for by the country-level fixed effects, as in recent studies from both criminology[149], and terrorism research[150] implementing similar procedures. Furthermore, to deal with the two-zeroes issue, this approach allows us to include the no-event dummy as an additional fixed effect at the level of countries that have never experienced an event[151]. In addition to the fixed effects, we employ clustered standard errors to account for heteroskedasticity and serial correlation.

As in the GMM models, the first-differenced lag of the dependent variable is entered into the model as a regressor, further accounting for the 'two zeroes' issue[118], with our model being expressed as:

$$\begin{aligned} Terror_{it} = \alpha(Terror_{it}) + Arr_{it} + \beta Char_{it} + \beta Con_{it} + \beta Sent_{it} + \boldsymbol{\sigma E}_{it} \\ + \delta Country + \theta Country - t + \varepsilon_{ct} \end{aligned}$$

2( )

In equation 2, $Terror_{ct}$ is the number of terrorism events in countries (i) in year (t). Arr_{ct}, $Char_{ct}$, Con_{ct}, and $\beta Sent_{ct}$ are the arrests, charges, convictions, and sentence lengths respectively, whereas $\boldsymbol{\sigma E}_{ct}$ is an indicator variable that=1 when there was >1 events in it and =0 if otherwise. $\delta Country$ is the country level fixed-effects component whereas $\theta Country - t$ is the country-year fixed effects component and ε_{ct} the idiosyncratic error term. As it is virtually impossible to interpret the coefficients for these dummy variables, and there is little utility in doing so, we suppress them from the tables displayed in the results section[152].

Data availability statement

The datasets generated during and/or analyzed during the current study will be made open access following publication.

Code availability

The syntax used to produce the analysis during the current study will be made open access following publication.

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Author contributions

MW and PG developed the concept and design of the studies. AS contributed to data collection, processing, and performing initial analyses. MW and GMC carried out the analyses, produced all tables and figures, and prepared the manuscript. The development and editing of the manuscript was overseen by PG.

Competing interests

The authors declare no competing interests.

Table 1: Descriptive statistics

Factor	N Obs	Mean (SD)	Min	Max
Incidents	448	8.44 (32.74)	0	294
Arrests	448	28.52 (69.73)	0	456
Charged	448	15.65 (36.70)	0	231
Conviction (%)	448	.38 (.45)	0	1
Sentence length	448	2.98 (5.13)	0	40
Years with CT laws (%)	448	24% (.43)	-	-
Security expenditure	448	1.77 (.44)	.9	2.8
HDI	448	.881 (.04)	.77	.95
Population (100,00)	448	181.40 (230.18)	4.05	843.39

Table 2: GMM Dynamic Panel Data analysis on terrorism rate

Factor	Ia	IIa	IIIa
Terror rate	.929	.909	.843
	[.789, 1.069]	[.706, 1.111]	[.617, 1.069]
	p=.000	p=.000	p=.000
Arrests	-.018	-.017	-.011
	[-.030, -.006]	[-.029, -.006]	[-.020, -.001]
	p=.002	p=.004	p=.028
Charges[a]	.016	.016	.019
	[.006, .026]	[.006, .026]	[.007, .030]
	p=.001	p=.001	p=.002
Convictions	-.113	-.095	-.057
	[-.201, -.025]	[-.168, -.023]	[-.092, -.021]
	p=.012	p=.010	p=.002
Sentence	.012	.012	.005
	[.002, .022]	[.005, .019]	[-.004, .014]
	p=.016	p=.001	p=.246
Controls	NO[a]	YES	YES
Hansen test	.442	.333	.125
N	420	420	420

Note: Coefficients with 95% confidence intervals reported from robust standard errors.
[a]Time and no-event dummies were included in all models, including model I.

Table 3: Count models

	Ib	**IIb**	**IIIb**
Attacks	.004	.004	.005
	[.003, .004]	[.003, .004]	[.005, .006]
	p=.000	*p*=.000	*p*=.000
Arrests	-.002	-.002	-.010
	[-.002, -001]	[-.002, -.001]	[-.014, -.005]
	p=.000	*p*=.000	*p*=.000
Charges	.017	.004	.086
	[.014, .020]	[.004, .004]	[.071, .100]
	p=.000	*p*=.000	*p*=.000
Convictions	-.016	-.990	-.940
	[-.019, -.013]	[-1.207, -.772]	[-1.220, -.659]
	p=.000	*p*=.000	*p*=.000
Sentence	-.036	-.024	-.023
	[-.051, -.021]	[-.033, -.015]	[-.038, -.007]
	p=.000	*p*=.000	*p*=.000

Note: All models include the full set of control variables and clustered standard errors.
*Models I uses counts of arrests, charges, and convictions as independent variables.
*Models II uses counts of arrests and charges and the conviction rate as independent variables.
*Models II uses rates of arrests and charges as independent variables.

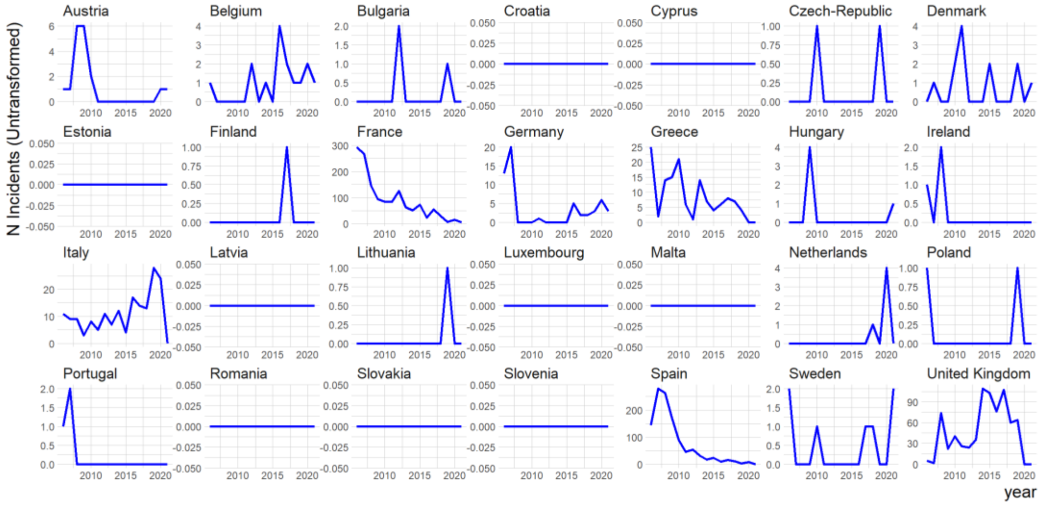

Figure 1: Raw number of incidents per country (2007-2021). The highest peaks of attacks are France in 2006 (N=294), Spain in 2007 (N=279), France in 2007 (N=267) and Spain in 2008 (263). Both countries, which are among the ones with the highest prevalence of incidents in the dataset, experienced substantial decrease after heightened levels of terrorism in the early years of the analysis. The only countries that experienced terrorist increases in more recent years are Belgium, Italy and United Kingdom, although all three report decreasing trends during the Covid-19 pandemic.

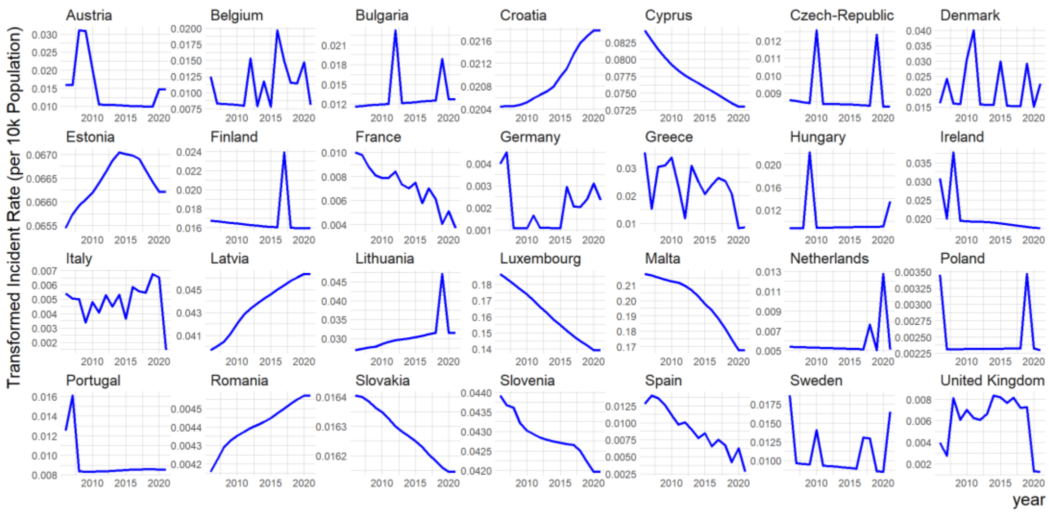

Figure 2: Inverse Hyperbolic Sine transformed variables (normalized as incident rates per 100k residents)

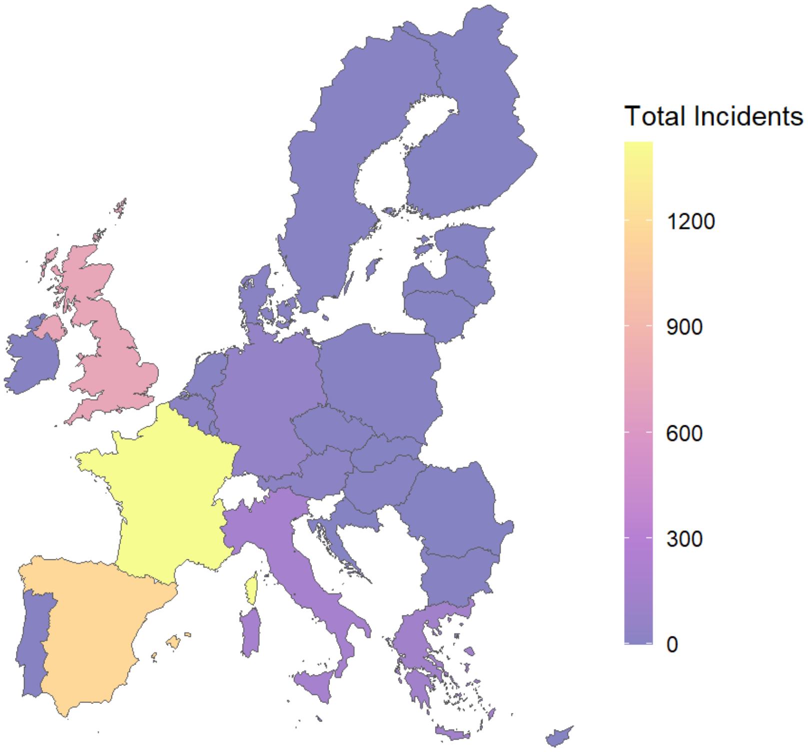

Figure 3: Heatmap of total number of incidents reported (2007-2021). France (N=1,419), Spain (N=1,175) and the United Kingdom (N=745) report the higher counts of incidents throughout the period under consideration. Conversely, nine countries report no attacks (i.e., Croatia, Cyprus, Estonia, Latvia, Luxembourg, Malta, Romania, Slovakia, Slovenia).

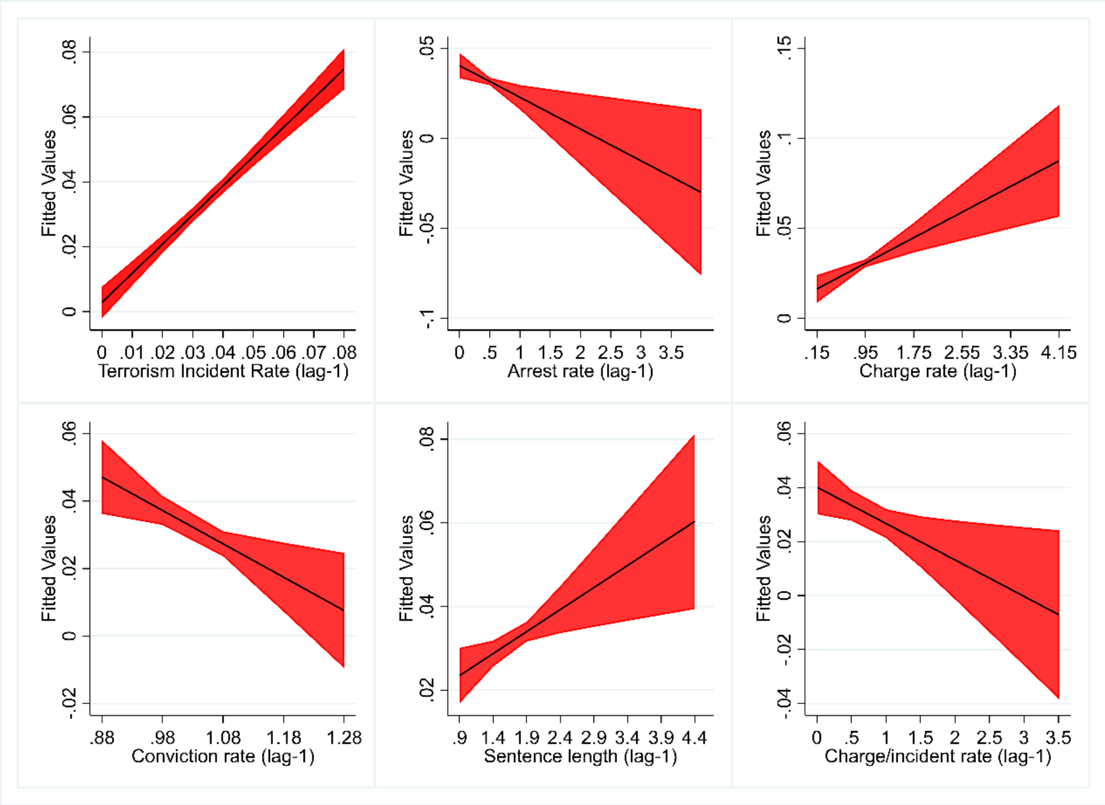

Figure 4: Predictive margins (with 95% confidence intervals) of the lagged (y-1) terrorism incident rate and the lagged (y-1) deterrence variables based on Model IIa.

Supplementary materials

S1. Descriptive statistics

S.1.1 Correlation matrix of main explanatory and control variables (non-transformed)

	Attacks	**Arrests**	**Charges**	**Convict**	**Sentence**	**Length**	**Budget**	**HDI**
Attacks	1.000							
Arrests	.697*	1.000						
Charges	.569*	.623*	1.000					
Convict	.211*	.399	.409*	1.000				
Sentence	.261*	.300*	.403*	.576*	1.000			
Length	.059	.045	.108*	-.012	.019	1.000		
Budget	.023	.011	.055	-.081	.068	-.068	1.000	
HDI	.017	.163*	.197*	.412*	.162*	.087	-.656*	1.000

Note. All statistically significant correlations are significant at the <.05 level.

S.1.2 Correlation matrix of main explanatory and control variables (transformed)

	Attacks	**Arrests**	**Charges**	**Convict**	**Sentence**	**Length**	**Budget**	**HDI**
Attacks	1.000							
Arrests	.299*	1.000						
Charges	.037	.380*	1.000					
Convict	-.317*	-.409*	.169*	1.000				
Sentence	-.302*	-.333*	.225*	.769*	1.000			
Length	.242*	.001	-.102*	-.012	.019	1.000		
Budget	-.371*	-.005	-.107*	-.081	.068	-.068	1.000	
HDI	.025	-.273*	.100*	.412*	.162*	.087	-.656*	1.000

Note. All statistically significant correlations are significant at the <.05 level.

S.1.3 Multicollinearity statistics

Factor	**VIF**	**Tolerance**
Attacks	1.98	.505
Arrests	1.74	.575
Charges	1.47	.679
Convictions	2.90	.345
Sentence length	2.75	.364
CT laws	1.10	.907
Security expenditure	2.96	.338
GDP	3.96	.253
Density	1.57	.637
Urban	2.31	.434
Mean VIF	2.27	

S.1.4 Fitted values

In Figure S.1.4 we plot the fitted values as derived from model II. As GMM models, such as those produced by XTABOND2 do not have a natural R^2 statistic, we follow others in calculating the squared correlation coefficient (*Cor*) between the actual and fitted values, which was 0.92. The considerably large statistic can be taken to mean that the variability of the underlying dependent variable is sufficiently modeled.

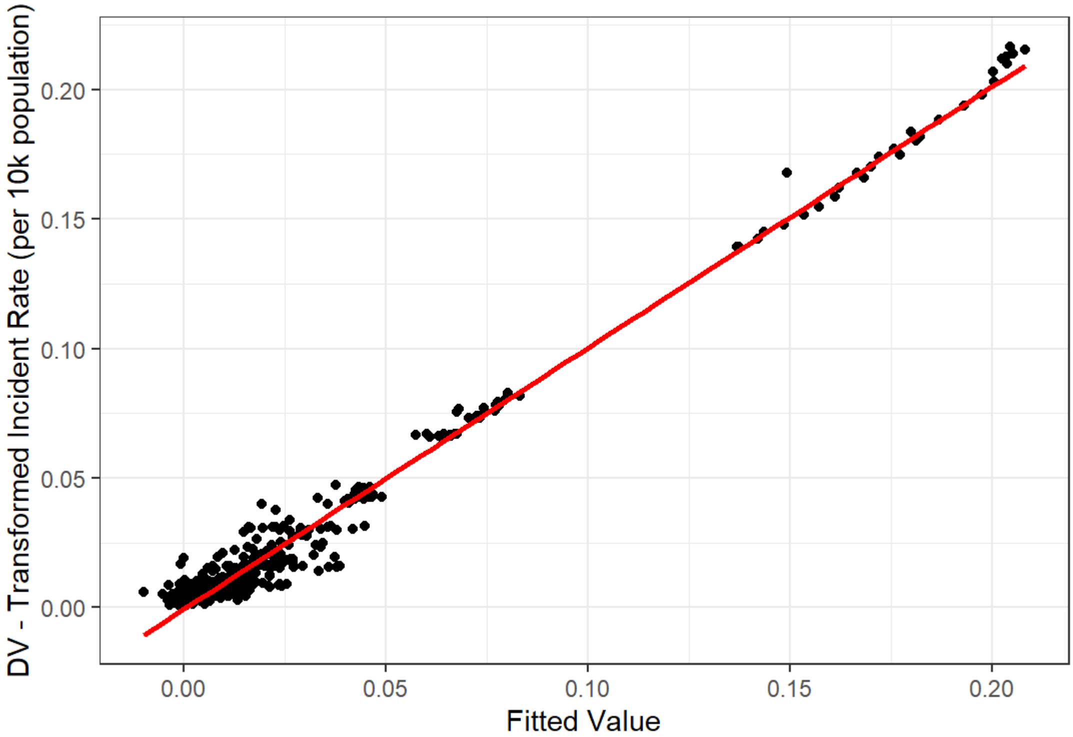

Figure S1.4: Fitted and observed values of the transformed incident rate (per 10k population) (based on model II)

S.2. Robustness checks

Table S2.1: GMM models specified with contemporaneous measures of control variables

Factor	I	II
Terror rate	.858	.876
	[.492, 1.222]	[.761, .991]
	p=.010	*p*=.001
Arrests	-.019	-.011
	[-.026, -.013]	[-.017, -.005]
	p=.006	*p*=.016
Charges	.015	.018
	[.011, .020]	[.006, .029]
	p=.005	*p*=.022
Convictions	-.119	-.060
	[-.133, -.104]	[-.111, -.010]
	p=.001	*p*=.036
Sentence	.014	.007
	[.012, .016]	[-.000, .014]
	p=.001	*p*=.050
Hansen test	.198	.101

Note: All models are run using the jackknife estimation method clustered on panels. Model I treats arrests as exogenous and Model II as endogenous

Table S2.2: Count models specified with contemporaneous measures of control variables

	Ib	IIb	IIIb
Attacks	.005	.005	.007
	[.005, .006]	[.005, .006]	[.006, .007]
	p=.000	*p*=.000	*p*=.000
Arrests	-.001	-.002	-.006
	[-.002, -001]	[-.002, -001]	[-.009, -.004]
	p=.000	*p*=.000	*p*=.000
Charges	.017	.005	.031
	[.014, .019]	[.004, .006]	[.001, .060]
	p=.000	*p*=.000	*p*=.043
Convictions	-.014	-1.098	-1.013
	[-.017, -.012]	[-1.256, -.939]	[-1.154, -.872]
	p=.000	*p*=.000	*p*=.000
Sentence	-.012	.003	.000
	[-.021, -.003]	[-.011, .017]	[-.012, .013]
	p=.000	*p*=.640	*p*=.955

Note: All models include the full set of control variables and clustered standard errors.
*Models I uses counts of arrests, charges, and convictions as independent variables.
*Models II uses counts of arrests and charges and the conviction rate as independent variables.
*Models II uses rates of arrests and charges as independent variables.

Table S2.3: GMM models specified with exclusion of explanatory variables

Factor	Arrests	Charges	Convictions	Sentence
Terror rate	-.139 [-1.485, 1.208] *p*=.840	.641 [-.418, 1.700] *p*=.235	-.557 [-1.734, .621] *p*=.354	-.184 [-1.071, .703] *p*=.684
Arrests	-.021 [-.042, -.000] *p*=.051			-
Charges		.021 [.007, .035] *p*=.003	-	-
Convictions		-	.192 [.053, .332] *p*=.007	-
Sentence	-	-	-	.022 [.007, .037] *p*=.005
Controls	YES	YES	YES	YES
Hansen	.020	.048	.262	.220

Note: All models are run using the jackknife estimation method clustered on panels.

Table S2.4: Count models specified with exclusion of explanatory variables

Factor	Arrests	Charges	Convictions	Sentence
Terror	.003 [.002, .004] *p*=.000	.004 [.003, .004] *p*=.000	.006 [.005, .007] *p*=.000	.004 [.003, .004] *p*=.000
Arrests	.000 [.000, .000] *p*=.000			
Charges		.004 [.003, .005] *p*=.000		
Convictions			-.982 [-1.320, -.643] *p*=.000	
Sentence				-.009 [-.013, -.006] *p*=.000

Note: All models include country, year, and no-event fixed effects and clustered standard errors

Table S2.5: GMM models specified with additional control variables

Factor	GDP	Density	Asylum	Violence	Rule of law	Urban
Terror	.918	.940	.968	.937	.904	.922
	[.812, 1.205]	[.819, 1.061]	[.772, 1.163]	[.744, 1.131]	[.709, 1.100]	[.818, 1.031]
	p=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000
Arrests	-.019	-.019	-.020	-.019	-.022	-.019
	[-.035, -.004]	[-.039, -.000]	[-.034, -.006]	[-.031, -.007]	[-.041, -.003]	[-.039, .000]
	p=.025	*p*=.048	*p*=.012	*p*=.005	*p*=.032	*p*=.053
Charges	.017	.016	.018	.016	.013	.016
	[.009, .025]	[.009, .023]	[.007, .028]	[.005, .026]	[.003, .023]	[.008, .024]
	p=.004	*p*=.002	*p*=.005	*p*=.006	*p*=.026	*p*=.003
Convictions	-.120	-.123	-.126	-.127	-.151	-.120
	[-.166, -.074]	[-.178, -.068]	[-.186, -.067]	[-.197, -.056]	[-.197, -.104]	[-.182, -.058]
	p=.002	*p*=.002	*p*=.001	*p*=.002	*p*=.001	=.003
Sentence	.013	.014	.013	.015	.016	.014
	[.008, .018]	[.006, .022]	[.007, .018]	[.002, .027]	[.009, .023]	[.007, .021]
	p=.002	*p*=.006	*p*=.001	*p*=.016	*p*=.003	*p*=.003
Hansen test	.407	.357	.452	.213	.446	.345

Note: All models are run using the jackknife estimation method clustered on panels and with lagged control variables.

Table S2.6: Count models specified with additional controls

	GDP	Density	Asylum	Violence	Rule of law	Urban	All
Terror	.005	.005	.005	.004	.006	.005	.010
	[.005, .006]	[.004, .006]	[.005, .006]	[.004, .005]	[.005, .006]	[.004, .005]	[.009,.011]
	p=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000
Arrests	-.001	-.001	-.002	-.001	-.001	-.002	.001
	[-.002, -.001]	[-.002, -.001]	[-.002,-.001]	[-.001, -.000]	[-.002,-.001]	[-.002, -.002]	[.000, .001]
	p=.000	*p*=.001	*p*=.001	*p*=.006	*p*=.000	*p*=.000	*p=.003*
Charges	.005	.005	.004	.005	.005	.004	.005
	[.003, .006]	[.003, .006]	[.003, .005]	[.004, .006]	[.004, .006]	[.004, .005]	[.003, .007]
	p=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000
Convictions	-1.110	-1.125	-1.047	-.993	-1.070	-1.089	-.950
	[-1.302,-.918]	[-1.383,-.867]	[-1.33, -.761]	[-1.134, -.852]	[-1.196, -.944]	[-1.154, -1.022]	[-1.298, -.602]
	p=.000	*p*=.000	*p*=.000	*p*=.000	*p*=.000	=.000	*p*=.000
Sentence	.004	.004	.004	.010	.001	-.000	-.063
	[-.009, .018]	[-.011, .018]	[-.013, .020]	[.001, .018]	[-.014, .017]	[-.003, .003]	[-.088, -.038]
	p=.536	*p*=.640	*p*=.648	*p*=.032	*p*=.892	*p*=.828	*p*=.000

Note: All models include country, year, and no-event fixed effects and clustered standard errors.

Table S2.7: Zero-inflated Poisson regression models with fixed effects dummies

	1	**II**	**III**
Attacks	.004	.004	.005
	[.003, .005]	[.002, .005]	[.004, .006]
	p=.000	*p*=.000	*p*=.000
Arrests	-.001	-.001	-.009
	[-.002, .000]	[-.002, -000]	[-.013, -.006]
	p=.077	*p*=.112	*p*=.000
Charges	.015	.001	.080
	[.011, .019]	[.000, .003]	[.020, .141]
	p=.000	*p*=.072	*p*=.009
Convictions	-.016	-.870	-.869
	[-.021, -.012]	[-1.075, -.665]	[-1.071, -.667]
	p=.000	*p*=.000	*p*=.000
Sentence	-.032	-.023	-.020
	[-.048, -.016]	[-.039, -.007]	[-.035, -.004]
	p=.000	*p*=.006	*p*=.015

Note: All models include the full set of control variables and clustered standard errors.
*Models I uses counts of arrests, charges, and convictions as independent variables.
*Models II uses counts of arrests and charges and the conviction rate as independent variables.
*Models III uses rates of arrests and charges as independent variables.