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Terrorism and Local Economic Development*

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Abstract

We study the local economic effects of terror incidents at a sub-national level for a global set of developed and developing countries. Using night lights as a proxy for local economic activity, we identify that one additional fatality per attack results in a drop of 0.14 percent in economic development, on average. The effects are observed for up to a 15-kilometer radius from the incident location. The attacks targeted at business infrastructure and the police/military bases have the most detrimental effects. The group of countries from the Middle-Eastern and Northern African region, South Asia, and Sub-Saharan African regions suffer the most. Using individual-level data from four countries as a case study, we show that terrorism affects individual well-being and lowers the desire to have additional children among women. It is also evident that terrorism is detrimental to child health in the treated districts. Findings survive a battery of robustness tests.

Keywords: Terrorism; Economic Development; Spatial Analysis
JEL Classification: F52, H56, J13, O10

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1 Introduction

Terrorism is a persistent threat to societies worldwide, causing widespread destruction, loss of life, and impacting the economy of the affected regions.[1] Between 1992 and 2019, the Global Terrorism Database reported over 150,000 terrorist incidents worldwide, resulting in more than 365,000 fatalities. The economic effects of terrorism are equally severe, with terrorism costing the world economy a staggering 855 billion USD between 2000 and 2018 (Bardwell and Iqbal, 2020).

The impacts of terrorism on economic development can be two-faceted. In the aftermath of a terrorist incident, governments may allocate additional resources to rebuild critical infrastructure and bolster security in the affected areas, fostering economic activity through a process similar to creative destruction (Hsiang and Jina, 2014). On the other hand, terrorism can instill fear among the public and investors (Becker et al., 2004), potentially driving investments away from affected regions and inflicting adverse effects on economic activity. While both forces might be at play together, determining which one tends to dominate remains an empirical question. The existing literature, which largely relies on cross-country data or isolated incidents, has found the effects of terrorism to be detrimental to economic growth. However, analysis at a micro-level using granular data on the evidence of terrorism on local economic development is still missing in the literature. An analysis at the sub-national level that leverages the exact incident location can provide insights into the local and spatial extent of terrorism's impact on economic activity. The scarcity of such evidence can be attributed to the lack of reliable measures of economic development at the sub-national level till recent years.

Addressing these critical gaps in the literature, this study makes three major contributions. First, it provides causal evidence of the economic impact of terrorism at a sub-national level (second-level administrative units) across approximately 41,000 districts, encompassing both developed and developing countries. To address the scarcity of economic activity data at the sub-national level in developing countries, we apply night lights (henceforth, NL) data as a reliable proxy for local economic development (Henderson et al., 2012). The use of NL data also helps us side-step from the potential issue of measurement errors present in official GDP measures (Deaton and Heston 2010; Johnson et al. 2013), especially in authoritarian regimes (Martinez, 2022)).[2] Second, we explore the spatial extent of the effects of terrorism by examining how far they extend from the attack location, providing insights into the geographical reach of terrorism's impact. Third, we investigate the behavioral effects of terror attacks on individuals in the affected regions – specifically, whether there is a drop in well-being or an increase in pessimism following terror incidents, as these factors can serve as potential path-

[1] See Enders et al. (1992); Eckstein and Tsiddon (2004); Gordon et al. (2007); Abadie and Gardeazabal (2008); Straetmans et al. (2008).

[2] While the democratic countries have experienced a total of 473 incidents and 882 fatalities due to terrorism between 1992–2013, on average, autocratic regimes have faced around 973 incidents and 2840 casualties in the same period. Source: Authors' calculations based on GTD (2022).

ways through which terrorism affects economic activity. Additionally, we present evidence on the impact of terrorism on child health, demonstrating that the implications of terrorism extend beyond economic development.

We examine the impact of terrorism on NL activity by using a difference-in-differences (DID) framework. Using night light data (luminosity) available in a raster format from the NOAA (2022) and the sub-national boundary maps from the Global Administrative Areas Database (GADM), we extract luminosity data for 41,491 districts from 1992 to 2013. Information on terrorism incidents, such as the geographical location of attacks, the resulting number of fatalities, the nature of the incident (success/failure), and the type of target, are sourced from the Global Terrorism Database (GTD) for the period 1992–2013. Our treatment variable is the attack intensity, measured as the ratio of the number of deaths to the number of incidents that occurred in a district in a given year. In line with Grossman et al. (2019), we treat the attack intensity (henceforth, AI) as quasi-random; though terrorists might have a specific target in mind, the successful elusion of security and execution of the attack has a quasi-random nature.

Baseline results in which we control for district and year-fixed effects suggest that one unit increase in the contemporaneous AI, i.e., one additional fatality per attack, results in a drop of 0.0014 percentage points (pp.) in NL activity. Compared with the mean outcomes, it is equivalent to a decline of 0.58% in NL. Results remain robust to controlling for various potential confounders such as rainfall, temperature, population, pollution, inequality measured at a state level (first-level administrative units), and exposure to natural disasters.

We conduct an extensive set of exercises to establish the causality of our findings. First, we include only the districts that experienced at least one attack in the sample period. This approach, commonly referred to as Timing DID, only requires the timing of the attack to be random and not the location (Camacho 2008; Deshpande and Li 2019). Second, we relax the assumption of parallel trends and allow for differential pretrends following the estimation procedure from Rambachan and Roth (2023). Third, in a similar approach to Brodeur (2018) and Amarasinghe (2023), we restrict our control group to the districts that experience an attack without casualties, i.e., failed attacks. This approach helps us address endogeneity concerns further, ensuring that the baseline findings are not driven by terrorists targeting certain regions based on their levels of economic activity.[3] Fourth, to address the negative weighting concerns in two-way fixed effects specifications, we follow de Chaisemartin and D'Haultfoeuille (2020) (henceforth, CH) and apply an alternative estimator that is robust to negative weights. Terrorism has a strong negative effect on economic activity subject to all the exercises employed.

[3] Along with the information on the geolocation of an attack, and the number of casualties associated with it, GTD also provides information on the nature of the attack, i.e., whether an attack is a success or failure. However, we are unable to compare successful attacks with failed ones following the GTD definition as nearly 94% of the units are treated, and only 6% of the observations are controls for the years with a terror incident. Therefore, we employ our own slightly modified version of failed attacks in this part of the analysis by comparing attacks with casualties (treated) to attacks without casualties (controls) to establish causal evidence.

Next, we analyze the spatial extent of the impact of terrorism. We investigate how far the effects of terrorism are observed, by using the exact geographical location of attacks available from the GTD database and extracting NL activity within circles of varying radii around the centroid of the attack location. Our results suggest that the effects of terrorism are significant up to a 15 km radius of the attack location. However, when performing our analysis at a state level (first-level administrative units), we find no effects. The results remain robust to accounting for potential spatial correlation in errors (see Conley 1999; Colella et al. 2019). This finding is relevant for two sets of reasons. On the one hand, it illustrates that the effects of terrorist attacks extend, on average, over very large areas, up to roughly 700 km^2.[4] On the other hand, it shows that by considering state-level data, one could easily underestimate, or even completely miss, the impact of terrorism.

Terrorism may have heterogeneous impacts based on the type of target, i.e., whether the business infrastructure, government buildings, or military/police bases are targeted. For example, an attack on military or police bases can create more fear among the public and investors, which can drive investments away from the affected regions on a larger magnitude. If there is a mismatch in the outflow of funds (from investors and the public) and the inflow of funds (from the government), then it can cause some heterogeneity in the effects of terrorism based on the nature of the attack. To shed some light on this, we measure the AI intensity by the type of target and examine their impacts on local development. Our results reveal that AI arising from attacks on military/police bases has the most detrimental effect, followed by attacks on business infrastructure. On the other hand, attacks on government buildings have a positive impact on NL.[5]

We perform further heterogeneity analysis by the development status or the geographic location of countries. Based on the levels of economic development, both OECD and a non-OECD group of countries are affected. Based on the geographical analysis, Middle-East and North African countries (MENA), South Asian countries (SA), and sub-Saharan African (SSA) countries are affected the most. [6]

Next, we examine whether terrorism affects behavioral outcomes. Terrorism can affect the mental health of individuals and increase fear or pessimism, which can act as a potential mechanism through which terrorism affects local economic development. For example, an increase

[4] As a comparison, note that this is about 4 times the size of Washington D.C.

[5] One explanation for the latter set of findings is that federal or state governments may consider the attacks on their infrastructure to be detrimental to their status, thereby providing additional funds for counter-terrorism activities or to rebuild the infrastructure. On the other hand, attacks on military bases may result in the loss of confidence in the security forces to the general public, which can result in more fear, thereby resulting in a larger outflow of investments from the affected areas.

[6] We also perform an analysis based on past exposure to terrorism, as the previous experiences can shape the current responses. We divide our sample into low/high-risk regions, depending on whether a district experienced an attack or fatality between 1992 and 2000, and then perform our analysis for the 2001–2013 sample. Our results inform us that both low and high-risk regions are affected by terrorism. However, the impacts of terrorism are most detrimental in the group of districts that have never experienced an attack in the past. Therefore, past experience may have a role to play in the current responses.

in pessimism among individuals and businesses in the treated districts can lower the investment in their enterprises or decrease the productivity of workers, which can have detrimental effects on economic activity.[7] Due to the lack of information on the mental health of individuals at a global scale, we rely on Multiple Indicator Cluster Surveys (MICS) that provide information on various behavioral aspects of around 250,000 women aged 15–49 from four countries – Bangladesh, Lesotho, Pakistan, and Sierra Leone. Our outcome variables include whether women experience a decline in life satisfaction, their expectation of the quality of life for the following year, their desire to have another child (aged 18–49), smoking intensity, and whether they follow the news daily. We find that terrorism has a strong, detrimental association with their current and expected life satisfaction, lowers the desire to have another child, and increases the likelihood of smoking.

Our spatial analysis results suggest that terrorism has an effect for up to a 15 km radius. However, the effects are not identified when NL are observed at a larger geographical location, i.e., at a state level. This set of findings may imply that an outflow of investments from treated districts may be captured by other districts in the same state, which can nullify the impacts of terrorism if the analysis is done at a state level. Therefore, we perform an additional analysis to explore whether terrorism may affect the treated districts beyond the local development. Using data on neonatal (less than 28 days old), infant (aged less than one year), and child mortality (children of age 0–5 years) from Burstein et al. (2019), we examine the relationship between terrorism and child health for 100 developing countries. We find that terrorism is detrimental to child health in the treated districts – one additional fatality per attack results in an increase of 0.09% in under-5 mortality, a small but statistically significant effect. Compared with the mean under-5 child deaths, this translates to an additional 5.19 deaths per 100,000 live births.

We perform a battery of additional robustness exercises to examine the sensitivity of our findings. First, as only 1.7% of the observations in our sample have ever experienced an attack, to make sure that our baseline findings are not due to chance, we perform a permutation-type exercise in line with Conley and Taber (2011) by randomly assigning treatment to the control districts. Second, to address the calibration and top-coding issues in the NL data from NOAA (2022) (refer to Gibson et al. (2021)), we apply the harmonized NL data from Li et al. (2020), which provides integrated and consistent NL data at a global scale. In addition, we conduct various other sensitivity exercises such as clustering the standard errors at a state level instead of a district level, using country-year fixed effects, different forms of the outcome variable or explanatory variable, and excluding high-risk regions to ascertain that a select few countries do not drive our results, among various other sensitivity exercises. Our results remain robust to all the exercises employed, lending further credibility to our findings.

The rest of the paper is organized as follows. Section 2 contains a brief overview of the literature. Section 3 introduces the data used in this study. Section 4 presents the estimation

[7] Indeed, we observe adverse implications of terrorism on Foreign Direct Investment (FDI) inflows. Using cross-country data on FDI inflows, we find that the higher the attack intensity, the lower the FDI inflows.

method. Section 5 reports the results, and Section 6 concludes.

2 Literature

Economists have long been interested in understanding the impact of different forms of violence, such as civil wars and terrorism, on economic growth and development. In this section, we provide a brief review of the literature on the effects of terrorism on economic activity. One strand of this literature focuses on cross-country data. Meierrieks and Gries (2013) analyze data from 160 countries, producing evidence of the detrimental effect of terrorism on economic growth for a group of African and Islamic countries in the post-Cold War era; they show that countries with higher political instability, lower political openness, and a presence of strong terrorist activity are the ones that are affected the most. Blomberg et al. (2004) focus on annual data from 177 countries between 1968 and 2000, showing that an additional terror incident per million population results in a decline of economic growth by 0.25 percentage points. In a similar vein, Gaibulloev and Sandler (2009) consider data from 42 Asian countries, showing that one extra terror attack per million people leads to a 1.5% drop in GDP. Enders et al. (2016) argue that domestic and transnational terrorist attacks are more concentrated among middle-income countries; thereby, an existence of a non-linear relationship between real per capita gross domestic product and terrorism is evident. Llussa and Tavares (2011) find that terrorism negatively affects private consumption and investment.

Other papers focus, instead, on individual country setups or case studies. In a seminal paper, Abadie and Gardeazabal (2003) adopt the synthetic control method (SCM) and show that terrorism in the Basque country is associated with a ten percentage points decrease in GDP per capita compared to the synthetic control group that didn't experience any terrorist activity. Ocal and Yildirim (2010) analyze Truskish data, reporting that terrorism hinders economic growth, and the effects are more pronounced for Eastern and South-Eastern than Western provinces. Following the SCM approach, Bilgel and Karahasan (2017) show that the provinces exposed to terrorism by the Kurdistan Workers' Party (PKK) have experienced a 6.6% decline in per capita real GDP compared with the synthetic control group. Using the 2013 Boston marathon bombing as a case study, Clark et al. (2020) note that the attack led to an immediate reduction in individual well-being, compared with the 2012 Boston marathon as a counterfactual. Using data from the Palestinian Labour Force Survey, Benmelech et al. (2010) indicate that successful suicide attacks led to an increase in unemployment rates and a higher likelihood of a fall in district wages. In a study on the economic effects of violence, Rozo (2018) argues that those firms that experienced violent crimes in Colombia were forced to reduce production and, in some cases, even exit the market due to lower output prices.

Abadie and Gardeazabal (2008) explore the potential mechanisms through which terrorism impacts economic activity, showing that the risk linked with terrorism causes an outflow of foreign direct investment equal to roughly 5% of the country's GDP. This drainage can be attributed to the uncertainty of the returns to investment produced by the threat of terrorism, while the mobility of productive capital can explain the differences between the direct and equilibrium effects of terrorism. Terrorism is also bad for business. Tingbani et al. (2019) show that terror attacks are positively associated with business failures, especially in developing countries in South Asia and Sub-Saharan Africa. By employing survey data from Africa, Guo and An (2022) document that terrorist attacks increase pessimism among people, thereby hindering their optimal decision-making and well-being.

Nemeth et al. (2014) analyze the determinants of terrorism, relying on sub-national level data. They provide evidence that various attributes such as the proximity to the state capital, mountainous terrain, population density, the number of ethnic groups in a country, and the presence of poor economic conditions have a positive effect on the likelihood of terrorism. Montalvo and Reynal-Querol (2019) show that past occurrence of earthquakes leads to a higher likelihood of terrorism. Using rainfall as an instrument for agricultural income, Aman-Rana (2014) find that higher rainfall is associated with a higher probability of terrorist attacks in rural Pakistan.[8] In a recent work using cross-national data from roughly 160 countries, Curtis et al. (2021) shows that higher temperature is associated with the number of terrorist attacks, as well as terrorism-induced deaths. For this reason, geographic features, local economic conditions, and weather conditions are potential determinants of terrorism, which we account for in this study.

3 Data

We begin by noting that economic activity data at sub-national levels are generally unavailable, especially for developing countries (Henderson et al., 2012), where even country-level GDP is typically not accurately measured.[9] For this reason, following the recent literature[10], we rely on night lights measured from space as our outcome variable of interest, i.e., a proxy for economic activity at the district level.[11] Data on NL are sourced from the National Oceanic and Atmospheric Administration (NOAA) database, available in a raster format for the period 1992–2013 from NOAA (2022). The United States Air Force Defense Meteorological Satellite Program (DMSP) satellites have been measuring the Earth-based light with their Operational Linescan System (OLS) sensors since the 1970s, with a digital archive being made available

[8] Refer to Burke et al. (2015) for a detailed review of the literature on the link between climate change and conflict.

[9] Martinez (2022) show that official GDP figures are prone to government manipulations in more authoritarian regimes.

[10] See, for instance, Henderson et al. (2012), Hodler and Raschky (2014), Alesina et al. (2016) and Khalil et al. (2021). Refer to Henderson et al. (2012) and Khalil et al. (2021) for a detailed description of NL data.

[11] Not only is NL often the only available source, but is also considered more accurate given the uncertainty in many of the income estimates used for international comparisons (Deaton and Heston, 2010) and the inherent measurement error in some of the most commonly used economic growth data such as Penn World Tables (Johnson et al., 2013).

from 1992 onward (Henderson et al., 2012). Using sub-national boundary maps available from the Global Administrative Areas Database (GADM, 2021) and employing the ArcGIS software, we extract luminosity data for 41,491 districts between 1992 and 2013.

Data on terrorism is sourced from the Global Terrorism Database, GTD (2022), maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) for the US Department of Homeland Security. The Global Terrorism Database provides information on terrorist incidents across the world from 1970 onward, reporting the location, date, casualties, and nature of the attack. Using the coordinates of terrorist attacks, we geocode through the ArcGIS software all incidents that occurred in the period 1992–2013, linking them to the district in which they took place. Based on the summary statistics in Table 1, we see that 1.7% of the sample experienced terrorist activity. The mean attack intensity, defined as the ratio of the number of fatalities to the number of attacks, is 0.053, and the average number of casualties in the districts in our sample is 0.172. These values increase to 3.091 and 10.123, respectively, for the districts that experienced a terror incident in a particular year.[12]

As we explained in Section 2, variables such as rainfall, temperature, and population affect economic development and are also related to terrorist activity. Therefore, we control for these potential confounders, the disaster exposure and pollution in a district, and inequality levels. Our measures of rainfall and temperature are from Willmott and Matsuura (2001), Version 4.01, which provides gridded precipitation data at a global level until 2014. Monthly rainfall data (in millimeters) and temperature data (in degrees Celsius) are extracted at the district level by matching weather stations to the centroids of district boundaries for the period 1992–2013 to identify the average yearly rainfall and temperature for a given district.[13]

The district-level population data are retrieved from CIESIN (2018), which provides gridded population data for five-year intervals from 1990 onward and extracted using ArcGIS software. We interpolate population data for the missing periods and control for it in the specifications. Data on pollutant concentration (PM2.5 particulates) is from Global Modeling and Assimilation Office (2015), which provides information on ground-level fine particulate matter. As exposure to natural disasters or the level of inequality can affect both terrorism and economic activity, we also control for both of these variables. Data on natural disasters is available from Rosvold and Buhaug (2021), which provides the geo-coded location of disasters (floods, droughts, storms, earthquakes, heat waves, landslides, or volcanic eruptions), which is then matched to the districts in our sample. We follow Alesina et al. (2016) to construct inequality indicators at the state level using NL data measured at the district level. Table 1 provides summary statistics for these variables.

[12] A potential limitation of the GTD dataset is that, for most incidents, it does not report whether the origin of an attack is domestic or transnational terrorism. However, Enders et al. (2011) note that most attacks are typically domestic.

[13] Average monthly rainfall temperature levels are extracted using the ArcGIS software by linking weather station data to the sub-national level boundaries shapefile from GADM (2021).

Table 1: Terrorism and Economic Development - Summary Statistics

Variable	Mean	Standard Deviation	Source
	Panel A: Variables of Interest		
Log Nightlights$_{i,t}$	0.223	2.448	DMSP-OLS
Incident$_{i,t}$	0.017	0.129	GTD
Attack Intensity$_{i,t}$	0.053	1.809	GTD
Number of Kills$_{i,t}$	0.172	6.953	GTD
	Panel B: Explanatory Variables		
Rainfall$_{i,t}$(in mm)	94.078	65.977	Matsuura (2022)
Temperature$_{i,t}$(in degree celcius)	17.099	8.196	Matsuura (2022)
Population$_{i,t}$(in 1000's)	146.728	600.936	SEDAC (2020)
Pollution Concentration$_{i,t}$	0.058	0.122	MERRA (2023)
Disaster$_{i,t}$	0.017	0.128	EM-DAT (2021)
Protest$_{i,t}$	0.042	0.199	SCAD (2017)
	Panel C: Other Outcome Variables		
Decline in Life Satisfaction$_{wi,t}$	0.076	0.265	MICS (2022)
Expectation of Life Satisfaction$_{wi,t}$	0.010	0.101	MICS (2022)
Want Another Child$_{wi,t}$	0.436	0.495	MICS (2022)
Smoking$_{wi,t}$	0.517	0.499	MICS (2022)
Reads Newspaper Daily$_{wi,t}$	0.014	0.118	MICS (2022)
Under-5 mortality (per 100,000 births)	5777.42	4579.70	Burstein et al. (2019)
Infant mortality (per 100,000 births)	4015.17	2594.28	Burstein et al. (2019)
Neonatal mortality (per 100,000 births)	2175.78	1181.49	Burstein et al. (2019)

The table reports summary statistics for the variables used. Panel A provides information on the main outcome variable i.e. night lights activity, and terrorism variables; Panel B on the explanatory variables used, and Panel C on the other outcome variables of interest. Log NL$_{i,t}$ in Panel A refers to the log of NL activity in district i for the time period t, whereas the variable Reads Newspaper Daily$_{wi,t}$ refers to whether a woman w, residing in district i during time t reads newspaper/magazine daily.

4 Estimation Method

We follow a difference-in-differences (DID) approach to estimate the impact of terrorism on local economic development. Specifically, we estimate the following model:

$$Y_{isct} = \beta_0 + \beta_1 Attack_{isct} + \lambda_i + \lambda_t + \theta_i \times t + \delta X'_{isct} + \varepsilon_{isct} \quad (1)$$

where Y_{isct} refers to the average NL intensity in district i (second-level administrative units) within state s (first-level administrative units), in country c, and in year t, measured in log form.[14] Our treatment variable of interest is $Attack_{isct}$, which we refer to as 'attack intensity,'

[14] In line with the literature, we add 0.01 to the dependent variable to deal with observed luminosities of zero. As a robustness check, we use the log of NL instead of the log (NL + 0.01), and the findings remain unchanged. Another potential concern is that the NL intensity data from DMSP is top-coded at 63; hence, we exclude the top

and the coefficient of interest is β_1. We follow Grossman et al. (2019) and construct $Attack_{isct}$ as the ratio of the number of terrorism-related fatalities to the number of terror attacks in a district. The attack intensity variable takes a value of zero if there are no terror-related casualties in a particular year and is above zero if there are fatalities. Therefore, $Attack_{isct}$ is strictly above zero for treated units and zero for the control units.[15]

We include district fixed effects, λ_i, and time fixed effects, λ_t, to control, respectively, for unobservable differences in NL among districts due to different geographical characteristics and for any potential shock that might affect all of the sample's districts in a particular year. We also include district-specific linear trends, $\theta_i \times t$, to control for trends that districts may follow because of district-specific development policies. Finally, we control for a set of potential confounders captured by X'_{isct}, including the amount of rainfall, temperature, and pollutant concentration in a district, district-level population, whether the district has experienced any natural disaster or not, and inequality (measured at the state-level). The error term ε_{isct} includes the time-varying unobservable shocks to the outcome variable.

Our primary coefficient of interest is β_1. Following Grossman et al. (2019), we interpret the estimate as causal for the following reasons. Our measure of terrorism is attack intensity, which is directly related to the number of fatalities caused by a terrorist attack. Perpetrators might target a location based on some unobservable characteristics, which can induce a selection issue at an extensive margin. However, their chances of succeeding and being able to cause fatalities depend upon a multiplicity of factors that are hard to predict ex-ante, such as whether they are able to bypass the security to carry out the attack, the day of the attack, and its exact location. Hence, the attack intensity variable (intensive margin), which we use to measure terrorism, is quasi-random in itself. We relax the assumption that the location of the attack is random by including only the districts that have ever experienced an attack in the sample, in line with Camacho (2008), Fadlon and Nielsen (2019) and Deshpande and Li (2019). This exercise, henceforth referred to as Timing DID, requires only the timing of the attack to be random and not the location itself. We further conduct various other exercises to establish causality and to test the sensitivity of our estimates as explained in the following section.

5 Results

5.1 Baseline Results

We begin by establishing the effects of terrorism on local economic development at a sub-national level, subject to the specification in Equation 1. Table 2 provides the baseline results. In column (1), we present results for the specification with only district and year-fixed effects.

one percentile of data in terms of NL intensity, and the findings remain robust.

[15] We use alternative forms for the explanatory variable as a robustness exercise. A detailed discussion is provided in Section 5.6.

Based on the estimated coefficient, one additional fatality per attack leads to a drop of 0.0014 percentage points (pp) in the outcome variable, i.e., a 0.14 percentage drop in NL activity.[16] The 0.0014 pp drop is equivalent to 0.58% of the mean outcome variable, as reported in the third row at the bottom of the table.

Table 2: Terrorism and Economic Development - Baseline Results

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
Attack Intensity$_{i,t}$	-0.0014***	-0.0014***	-0.0012***	-0.0011***	-0.0015***	-0.0013***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Log Nightlights$_{i,t-1}$			0.4004***			
			(0.0037)			
District-Specific Trend	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	No	Yes
Mean Dependent Variable	0.242	0.242	0.283	0.358	0.173	0.310
Adjusted R-Squared	0.2617	0.2618	0.3673	0.3465	0.2917	0.3877
Observations	871290	871290	829800	771404	103320	94986

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. The dependent variable is the log of NL. All the columns control for district-fixed effects and year-fixed effects. In the last two columns, only the districts that have experienced an attack in the sample period are included. In columns 4 and 6, we include the following controls: rainfall, temperature, population, disaster exposure, pollution concentration, and state-level inequality; the missing values for pollution are replaced with a value of 99, and an indicator variable that represents the missing values are controlled for in the specifications. Standard errors clustered at the district level are reported in parentheses.

In column (2), we control for district-specific time trends, and in column (3), we include the previous year's NL activity as the past year's economic activity may have an effect on the current levels. The estimated coefficient of attack intensity is unchanged in column (2) and drops slightly in column 3; however, it remains significant at the 1% level. So far, we used unconditional specifications. In the rest of the columns, we include a set of relevant controls. Country size (Sandler and Enders 2008; Krieger and Meierrieks 2011; Nemeth et al. 2014), weather patterns (Aman-Rana 2014; Curtis et al. 2021), and natural disasters (Montalvo and Reynal-Querol, 2019) are found to be potential predictors of terrorism, which can also affect our outcome. Therefore, we control for population density, rainfall, temperature, and natural disaster incidences, along with the level of inequality and pollution in our specifications.[17] Subject to the conditional specification in column (4), the coefficient of AI drops slightly but remains significant.

In our specifications so far, the timing and the location of the attacks are assumed to be

[16] The percentage change in NL for one unit increase in attack intensity is calculated using the standard formula: $[e^{\beta} - 1] * 100$, i.e., $[e^{0.0014} - 1] * 100$, equal to 0.14%. Refer to column (1), Table 2 for the estimated coefficient β.

[17] The level of inequality in a given society may be accompanied by discriminatory public policies and the diversion of public resources from specific regions, which can result in discontent in neglected areas and thereby increase terrorist activity and affect economic development. We also add the pollutant concentration, which can act as a proxy for local industrial development.

quasi-random; indeed, though terrorists might have specific targets in mind, for their attacks to be successful and result in fatalities, randomness plays a role. Now, we relax this assumption slightly by including only the districts that ever experienced an attack in our sample period. The empirical strategy in this part (henceforth, timing DID or, in short, TDID) follows a timing difference-in-differences design that compares the changes in NL activity in places right after a terrorist attack (in this case, AI) to places that experience a terrorist event but at a different period. This type of DID approach uses the variation in the timing of events instead of the variation in the occurrence of events (Guryan 2004; Fadlon and Nielsen 2019; Deshpande and Li 2019; Fadlon and Nielsen 2021; Chen et al. 2022). The results subject to the TDID approach are provided in the last two columns. In column (5), we estimate the treatment effects subject to an unconditional specification, whereas in column (6), we include a set of controls. The estimated effects in both columns are slightly higher compared to column (4) and remain significant, providing further credibility to our baseline finding.[18]

We apply a different form of the explanatory variable next. So far, we have used the attack intensity as our primary explanatory variable of interest, measured as the ratio of fatalities to the number of attacks. This helped us treat our terrorism variable as quasi-random. Now, we use the number of casualties instead. We find that the greater the number of fatalities, the lower the level of economic activity in a district. Results are provided in Table A1 in the online appendix in the interest of space.

5.1.1 Control Group Contamination and Nature of the Attack

In this section we perform a couple of exercises. First, we address a potential control group contamination problem – along with the districts that never experienced an attack, our control group includes those that experienced terrorism without suffering fatalities. To examine whether this can be an issue, we exclude from the sample those districts that faced a terrorist attack without casualties. The results are provided in Table 3. Columns 1–3 contain results for unconditional specifications, whereas, the last three columns provide results for conditional specifications. Columns (1) and (4) reproduce the baseline estimates for ease of comparison. Columns (2) and (5) contain the specifications for addressing the control group contamination issue. From the results, findings remain unchanged to excluding the contaminated regions.

Another method used by some of the recent literature to establish causality is estimating the treatment effect based on the nature of the treatment itself (Brodeur 2018; Amarasinghe 2023). For example, Brodeur (2018) has noted that successful terror attacks reduce the number of jobs and total earnings in targeted countries compared to the failed terror attacks, and the

[18] We perform a temporal analysis by controlling for up to four lags of the AI. Based on the results in Table A5 in the online appendix, the first lag of AI has significant effects when controlled for individually or together with the contemporaneous AI; refer to columns (2) and (3) of Table A5. Once all four lags are controlled for together, only the current AI has significant effects, whereas the coefficient of the first lag is negative, albeit insignificant at conventional levels; see column (6). Therefore, the effects of terrorism on economic activity are short-run, based on the temporal analysis.

estimates are causal due to the inherent randomness in the success or failure of terror attacks. Amarasinghe (2023) finds that public discontent rises following a successful attack as opposed to failed attacks, in a recent study on the link between terrorism and public sentiment. Next, we perform an exercise akin to Brodeur (2018) and Amarasinghe (2023) by including only the district-year observations which experienced terrorism. Here, the treated units are those districts that experienced a fatality, and the control units are those that experienced an incident without a fatality.

Table 3: Terrorism and Economic Development - Addressing Control Group Contamination

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
Attack Intensity$_{i,t}$	-0.0014***	-0.0014***	-0.0025***	-0.0011***	-0.0011***	-0.0021***
	(0.0003)	(0.0003)	(0.0007)	(0.0002)	(0.0002)	(0.0007)
Controls	No	No	No	Yes	Yes	Yes
Excluding Contaminated Regions	No	Yes	No	No	Yes	No
Only the Affected Districts	No	No	Yes	No	No	Yes
Mean Dependent Variable	0.242	0.238	0.412	0.358	0.353	0.480
Observations	871290	865997	14831	771404	766435	13813

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. Columns 1–3 provide results for unconditional specifications, whereas the last three columns include district-fixed effects, year-fixed effects, district-specific linear trends, and a set of controls. In columns 2 and 5, we exclude the regions which experienced a terror attack but wihtout a fatality. In columns 3 and 6, we include only the district-year observations that experienced terrorism. Standard errors clustered at the district level are reported in parentheses.

GTD provides its own definition of whether an incident is successful or not. However, we do not apply GTD's definition of the nature of attack for two reasons. First, we are unable to employ their definition as around 94% of the attacks are successful and only 6% of the attacks are failures, based on mutually exclusive district-year observations.[19] Therefore, restricting the analysis to only the incident years and comparing successful attacks with failed ones will not yield reliable estimates. Second, the definition of an attack as success or failure by GTD is imperfect in itself. For instance, GTD categorizes an assassination attempt as a failure if the intended target survives, even if the incident results in multiple casualties.[20] Due to these reasons, we apply our own definition for characterizing the nature of an attack. Specifically, we categorize an attack as a success if it results in a fatality, and as a failure if it does not lead to any terrorism-related deaths.

The results are provided in columns (3) and (6) of Table 3. The coefficient of AI almost doubles in size compared with column (1) and remains significant at 1%. This exercise helps

[19] Within our sample, 14,831 district-year observations have recorded at least one attack. Among these, 13,973 observations include at least one successful attack, while 2,775 district-year observations document failed attacks. Notably, out of these 2,775 observations with failed attacks, 1,937 also feature a successful attack. Consequently, only 6% of the mutually exclusive district-year events exclusively entail a failed attack.

[20] In our case, out of the 838 mutually exclusive district-year events with failed attacks, 122 observations have experienced at least one fatality. Additionally, among the 2,775 observations associated with failed attacks, 1,649 have experienced at least one death related to terrorism.

us address endogeneity concerns further, ensuring that the baseline findings are not driven by terrorists targeting certain regions based on their levels of economic activity and that the estimated relationship is causal.

5.1.2 Allowing for Differential Pretrends

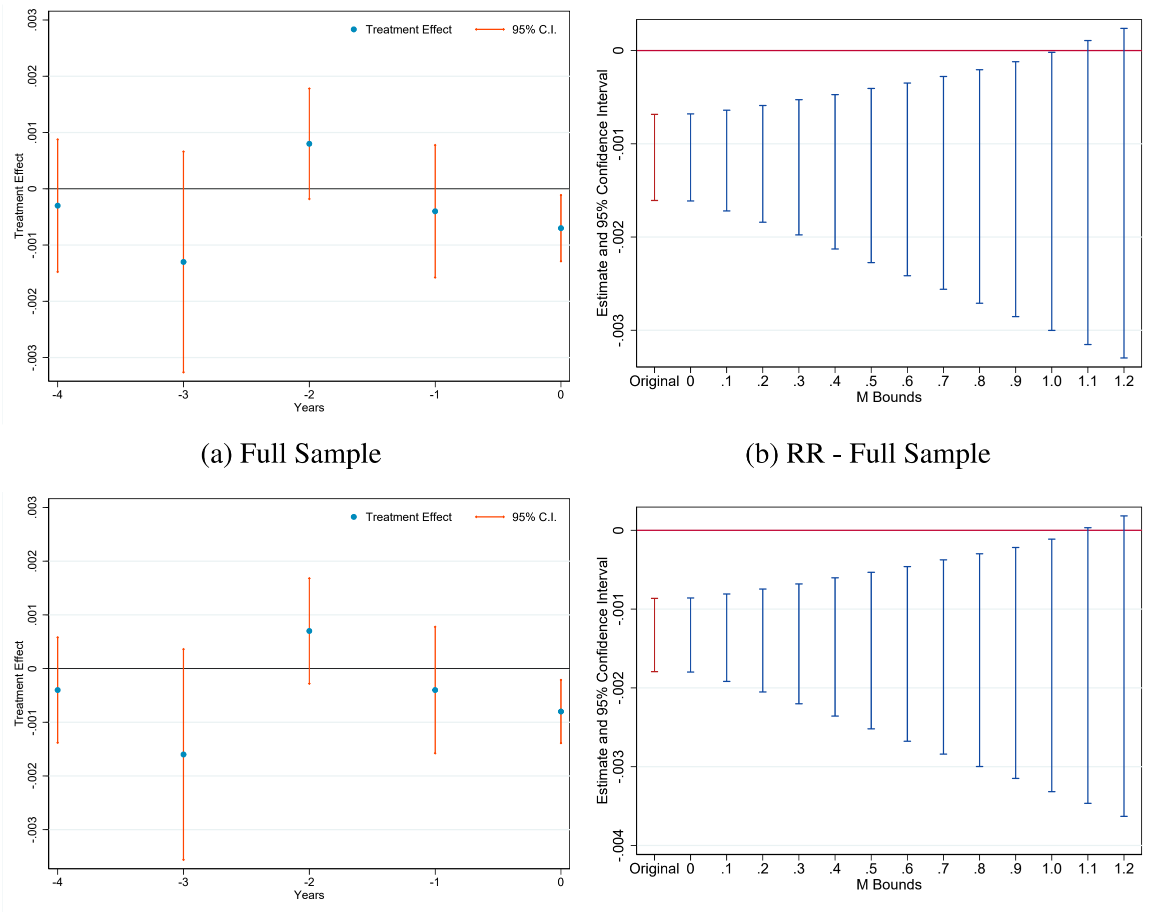
The main identification assumption of DID approach is that the treated and control units evolve similarly in the outcome prior to the treatment, i.e., parallel trends. In this section, we examine the presence of pretrends subject to the specifications in columns (4) and (6) of Table 2. Along with the contemporaneous treatment effect, we estimate the effects of up to four leads of AI and produce the results in a graphical format in Figure 1. Figure 1a and 1c provide results for the full sample and the timing DID, respectively. Based on the figures, we do not observe a clear pattern in the lead coefficients, while the contemporaneous AI remains significant. However, a potential concern here is that the coefficient of the third lead is large and negative, albeit insignificant.

To address this concern, we employ a recent estimation procedure from Rambachan and Roth (2023) (henceforth, RR), which provides credible estimates of the treatment effect under potential violation of the parallel trends assumption. Using the *honestdid* Stata package developed by RR, we allow the parallel trends assumption to be violated and estimate robust confidence intervals. We estimate the treatment effects under various bound values M, i.e., the magnitude of the post-treatment violation of parallel trends relative to the observed maximum pre-treatment violation, which can result in the treatment effects becoming inconsistent (Di Iasio and Wahba, 2023). The results are provided in Figure 1b and 1d for the full sample and timing DID, respectively. In red, we provide the 95% confidence interval (CI) estimated while allowing for linear violation of pretrends, whereas, in blue, we provide the 95% CIs while allowing for the differential trends, subject to various bound values. Based on the figures, the estimated treatment effects are robust to reasonable violations of the parallel trends assumption.

5.2 Spatial Analysis

Existing studies on the effects of terrorism on development either rely on cross-country data or focus on individual regions or countries. For this reason, evidence on the spatial extent of the impact of terrorist attacks is still missing. One advantage of using sub-national data to examine the effects of terrorism is that it allows us to explore this spatial extent for a global set of countries. In this section, we perform spatial analysis to understand how far the effects extend from the attack location. We follow an approach similar to Feyrer et al. (2017), which provides an intuitive way of examining the spillover effects when treatment is assigned to a particular geographic area. In their examination of the fracking boom in the US, they investigate the local spillover effects extending beyond the treated county by drawing expanding circles centered on the treated county's centroid.

Figure 1: Terrorism and Economic Development: Parallel Trends



(a) Full Sample

(b) RR - Full Sample

(c) Timing DID

(d) RR - Timing DID

Note: Panels A and C provide a plot of the impact of current and future terrorism on night lights. Plots also include 95% confidence interval bounds. The specifications control for district and year-fixed effects, district-specific linear trends, and a set of controls. Standard errors are clustered at a district level. Panels B and D show the sensitivity of the 95% confidence interval for the impact of terrorism on economic activity to potential violations of the parallel trends assumption. In red, we plot the original confidence interval of the contemporaneous attack intensity variable, assuming parallel trends. In blue, we plot alternative 95% confidence intervals proposed by Rambachan and Roth (2022), which relaxes the assumption of parallel trends and allows for differential trends. X-axis shows the parameter M, the maximal bound on the amount by which the underlying time trend can vary between consecutive periods. M = 0 corresponds to allowing a linear differential trend. M > 0 allows for increasingly more varied nonlinear trends.

In a similar vein, we begin by considering a narrow geographic area with a 15-kilometer (km) radius around the centroid of each attack and extract luminosity data within these circles for our sample period. We further extend this radius and focus on a 35 km, 50 km, 100 km, and 150 km radius from each attack location. Our dependent variable in this analysis is the average NL activity (measured in log form) in each circular area, whereas our treatment variable is the attack intensity within these circles. The empirical strategy in this part compares the changes in economic activity in places following a terror attack (i.e., AI) to circles that experience an attack but at a different period. This approach is similar to Timing DID conducted in the last two columns of Table 2. We also include a set of controls measured at a district level by matching the centroid of attack to the districts.

Table 4: Terrorism and Economic Development - Spatial Spillovers

Dependent Variable	Baseline	15 Kms	35 Kms	50 Kms	100 Kms	150 Kms	State Level
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Attack Intensity$_{i,t}$	-0.0014***	-0.0021***	-0.0011*	-0.0008	-0.0000	-0.0003	0.0001
	(0.0003)	(0.0004)	(0.0006)	(0.0005)	(0.0003)	(0.0003)	(0.0006)
	[0.000]	[0.000]	[0.052]	[0.108]	[0.704]	[0.190]	-
Mean Dependent Variable	0.242	-0.634	-1.177	-1.404	-1.832	-2.062	0.299
Observations	871290	404439	407148	408114	408933	409857	72329

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for year-fixed effects. In columns 1 and 7, district fixed effects and state fixed effects are controlled for, respectively, whereas in the rest of the columns, fixed effects at the level of aggregation are used. In columns 1–6, we add a set of controls measured at the district level such as: rainfall, temperature, population, disaster exposure, pollution concentration, and state-level inequality; the missing values for controls are replaced with a value of 99 in columns 2–6, and an indicator variable that represents the missing values are controlled for in the specifications. District-specific linear trends are included in columns 1–6, whereas in the last column, we use state-specific linear trends. Standard errors clustered at the district level are reported in the parenthesis in column 1 and at the state level in column 7; in the rest of the columns, standard errors are clustered at the level of aggregation. The square brackets provide p-values from the specifications robust to spatial correlation in errors.

Column (1) of Table 4 provides the baseline results for ease of comparison across estimates, whereas columns (2–6) contain results for the specifications with circles of various increasing radii around the centroid of the attack location. The results show that the negative impact of attacks is significant up to a 15 km radius of the incident location. The effect diminishes and loses significance when we move beyond that distance to include larger areas.[21][22] Several studies have examined whether the treatment effects are observed in larger administrative regions (Hodler and Raschky 2014; Khalil et al. 2021). Therefore, in column (7), we extract NL information at the state level (first-level administrative units) and perform the analysis. Our results suggest that once we extend to a much larger geographical area, we fail to observe the effects of terrorism, whereas most of the effects are present in the areas closer to the attack location. A possible explanation for the lack of effects of terrorism when extending to a larger area is that,

[21] A caveat of this spatial analysis is that larger circles, especially in columns (5) and (6), can overlap with each other.

[22] Some of the recent literature has raised concerns regarding the negative weighting concerns in the two-way fixed effects estimator used in this study (see de Chaisemartin and D'Haultfoeuille 2020, Goodman-Bacon 2018). Refer to Section 5.6.2 for a detailed explanation. This issue may be particularly relevant in the spatial analysis conducted in this study, as some early treated units can later become controls. Therefore, we examine whether we have a negative weighting issue subject to the procedure developed by de Chaisemartin and D'Haultfoeuille (2020) and find that the percentage of treatment-control pairs receiving negative weighting is close to zero. Therefore, negative weighting does not pose a concern in our spatial analysis.

while investments in the affected districts may drop, investors may shift to nearby districts, averaging out any adverse effects at the state level. However, the absence of impact at the state level does not necessarily imply that the drop in economic activity observed at a finer level (in columns (2) to (4) of Table 4) can be neglected. As we will show in Section 5.5, treated districts also suffer an increase in child mortality due to terrorism, implying that the severity of terrorism impacts can extend beyond economic activity.

5.2.1 Spatial Correlation in Errors

The results from the main specifications in the first two rows of Table 4 assume no spatial correlation in errors among observations. However, the error structure for districts or circles that are close to each other may be correlated. Therefore, we correct standard errors for spatial correlation, following Conley (1999) and Colella et al. (2019). We apply the Stata command *acreg* developed by Colella et al. (2019) to allow for the spatial correlation in errors. The p-values from this estimation procedure are provided in square brackets in Table 4. From the p-values, it is evident that the impact of terrorism is significant for up to a 35 km radius, with the estimates for 50 km in column (4) being insignificant at conventional levels with a p-value of 0.108.[23]

5.3 Heterogeneity Analysis

In this section, we perform different types of heterogeneity analyses to shed further insights. We conduct several analyses based on the type of target (military base or government infrastructure, for example), the countries' development status, and their geographical location.

5.3.1 Heterogeneity by the Type of Target

The effects of terrorism can be twofold. On the one hand, following a terrorist attack, the government may allocate more resources to the affected areas to develop local infrastructure. In this case, terrorism can lead to higher economic development in the treated areas, which can be referred to as the creative destruction hypothesis, as outdated facilities might be replaced by advanced ones (Hsiang and Jina, 2014). On the other hand, after an attack, there may be a surge of fear among the local population and businesses (Becker et al., 2004), resulting in an outflow of investment and human capital from the treated area. This outflow can result in lower economic development in the affected district. The net effect is ambiguous and depends upon whether the government allocates enough resources to counter the outpouring of funds.

[23] We control for region and year-fixed effects and for region-level covariates in the specifications where we correct for standard errors. A radius of 100 km is used as the cut-off distance. We also perform sensitivity analysis with a 300 km radius, and the results remain robust. We do not provide adjusted p-values for column (7) as the analysis is done at the state level, a larger administrative region.

Table 5: Terrorism and Economic Development - Type of Target

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
Attack Intensity$_{i,t}$	-0.0011***					
	(0.0002)					
Attack Intensity (Business)$_{i,t}$		-0.0008**				-0.0007*
		(0.0003)				(0.0004)
Attack Intensity (Government)$_{i,t}$			0.0016			0.0017*
			(0.0010)			(0.0011)
Attack Intensity (Military)$_{i,t}$				-0.0025***		-0.0024***
				(0.0007)		(0.0007)
Attack Intensity (Other)$_{i,t}$					-0.0014	-0.0013
					(0.0009)	(0.0009)
Mean Dependent Variable	0.358	0.358	0.358	0.358	0.358	0.358
Observations	771404	771404	771404	771404	771404	771404

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for year-fixed effects, district-fixed effects, district-specific linear trends, and a set of controls. Standard errors clustered at the district level are reported in the parentheses.

In this section, we examine heterogeneity in the treatment effects based on the type of target. Along with the data on incident location and the number of fatalities, the GTD database also provides information on the target type. Using this information, we categorize the targets into four groups: business infrastructure, government facilities, military bases, and others.[24] Table 5 provides the heterogeneity analysis by target type. Row (1) reproduces the baseline findings for ease of comparison, whereas the rest of the rows provide the coefficients by target type. Each explanatory variable indicates the attack intensity arising from the attack on a specific target. For example, the variable "Attack Intensity (Business)" in Table 5 measures the attack intensity based on the attacks classified as the "Business" target type by the GTD.

Columns (2–6) of Table 5, in which we analyze the effects of terrorism by target type, help uncover some interesting findings. When we control for each target type individually in columns (2–5) or together in column (6), it is evident that the attacks on military/police targets have the most detrimental effects, followed by attacks on business targets. Conversely, attacks on government targets appear to have a positive impact on development. However, we observe no significant effects stemming from attacks on other types of targets.

[24] Attacks on a business or corporate office and employees patronizing a business are classified as a "Business" target type by the GTD. Likewise, any attack on a government building, political movement, or government institution intended to harm the government is classified as a "Government" target. Attacks on the police force or police installations are classified as a "Police" target, and attacks on military units, patrols, barracks, military checkpoints, and recruiting sites are classified as a "Military" target by the GTD. In this study, we combine both police and military targets into one and refer to them as attacks on military force. All other types of targets, such as non-military aircraft, foreign embassies, educational institutions, and the rest, are added to the "Other" category. Refer to the codebook available in GTD (2022) for a detailed definition of the target types.

The finding that a terrorist attack on military or police bases has the largest negative effect on local economic activity is consistent with the idea that such attacks can disrupt security and stability in a region, thereby spurring more fear among the investors and public, resulting in a reduction of business investment and economic activity. Likewise, attacks on businesses can discourage investment. However, the finding that an attack on a government building positively affects local economic activity is, *prima facie*, surprising and requires further exploration. One plausible explanation is that the injection of public expenditure following an attack on government targets may be greater than following an attack on military buildings, thus resulting in a greater economic stimulus. For instance, the government might allocate funds for the reconstruction of the damaged facility or enhance security measures, potentially generating jobs and fostering economic growth.

5.3.2 Heterogeneity by the Development Status/Region

We perform different heterogeneity analyses based on the development status of countries (OECD or developing) or income classification (low/middle, or high income) and based on the geographical location of countries. Panel A of Table 6 provides the results for classifying countries by their development status, whereas Panel B contains the results by their geographical location.

Table 6: Terrorism and Economic Development - Heterogeneity by Country Classification

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: By Development Status of Countries					
	Non-OECD	OECD	LICs	LMICs	UMICs	HICs
Attack Intensity$_{i,t}$	-0.0010***	-0.0029**	-0.0009***	-0.0021***	0.0077	-0.0004**
	(0.0003)	(0.0013)	(0.0003)	(0.0008)	(0.0119)	(0.0001)
Mean Dependent Variable	-0.234	1.561	-1.101	0.346	0.371	1.971
Observations	504655	224770	143454	316338	174603	132271
	Panel B: By Regional Classification					
	EAP	ECA	LAC	MENA	SA	SSA
Attack Intensity$_{i,t}$	0.0037	-0.0013	0.0021	-0.0022*	-0.0017*	-0.0012***
	(0.0040)	(0.0012)	(0.0021)	(0.0012)	(0.0009)	(0.0002)
Mean Dependent Variable	0.195	0.906	0.062	1.375	-0.278	-2.248
Observations	146819	174592	197755	65449	30436	72956

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for district-fixed effects, year-fixed effects, district-specific linear trends, and a set of controls. Standard errors clustered at the district level are reported in parentheses. In Panel A, countries are grouped based on their development status or income classification. In Panel B, countries are classified into six groups based on their region: East Asia and Pacific Countries (EAP), Eastern Europe and Central Asia (ECA), Latin America and Caribbean countries (LAC), Middle-East and North African countries (MENA), South Asian countries (SA), and Sub-Saharan African countries (SSA).

Based on panel A, columns (1–2), both the OECD and developing (non-OECD) countries seem negatively affected by terrorism. While the coefficients are higher in magnitude for the OECD group of countries, compared with the mean dependent variable, developing countries appear to be the most affected. In columns 3–6, we divide the countries into low-income countries (LICs), low-middle income (LMICs), upper-middle (UMICs), and high-income groups (HICs) based on the World Bank's 2010 income classification. Except for UMICs, economic development in the other three groups is negatively impacted following terrorist attacks.

In Panel B, we divide the countries into six categories based on their geographical location: East Asia and Pacific countries (EAP), Eastern Europe and Central Asia (ECA), Latin America and Caribbean countries (LAC), Middle-Eastern and North African countries (MENA), South Asian countries (SA), and Sub-Saharan African countries (SSA). Our findings suggest that terrorism has significant detrimental effects in SA, SSA, and MENA groups of countries, whereas the results are negative but insignificant in the ECA group.[25]

5.4 Terrorism and Behavioral Outcomes

Terrorism is widely known to generate feelings of insecurity, fear, and risk aversion (Becker et al., 2004). These psychological effects, in turn, are one channel through which terrorism affects economic activity (Clark et al., 2020). Pesko (2014) and Pesko and Baum (2016) show that exposure to terrorism causes an increase in smoking. Health repercussions are long-lasting (Grossman et al., 2019) and can also extend to future generations. For example, Camacho (2008) and Grossman et al. (2019) show that the intensity of random landmine explosions during a woman's first three months of pregnancy significantly reduces childbirth weight. The mass media act as a conduit through which these negative effects spread through society: repeated exposure to terrorist acts prolongs acute stress experiences and exacerbates stress-related symptoms (Marshall et al., 2007; Holman et al., 2014). In this section, we explore this channel using data from Multiple Indicator Cluster Surveys (MICS). MICS provides information on several behavioral outcomes on roughly 250,000 women aged 15–49 from four countries – Bangladesh, Lesotho, Pakistan, and Sierra Leone.

Our outcome variables of interest are: i) Decline in Life Satisfaction; ii) Decline in Expected Life Satisfaction – these two variables take a value of one if a woman has reported a decline in their current level of life satisfaction or is pessimistic for the following year, respectively; iii) whether a woman (aged 18–49) has expressed the desire to have another child; iv) whether she is currently smoking; and v) whether she reads newspaper/magazine daily. We

[25] In our final set of heterogeneity analyses, we explore the impact of terrorist attacks based on a region's past exposure to terrorism. We classify the regions into low and high-risk based on whether there have been any incidents or fatalities between 1992 and 2000, the first decade in our sample. Specifically, if there has been any incident in these nine years, the region is classified as high-risk and zero otherwise. We also perform a similar classification based on the number of fatalities. Based on the results in Table A6, online appendix, it is evident that terrorism reduces economic growth in both high and low-risk regions. However, the districts that never experienced an attack in the recent past are the ones to suffer the most.

control for several demographic characteristics of women, such as their age, marital status, education, number of children, and whether they have a mobile phone or internet access at home. We also account for district-fixed effects and month-of-survey fixed effects in the specifications.

Table 7: Terrorism and Behavioural Outcomes

Dependent Variable	Decline in Life Satisfaction	Decline in Life Expectation	Another Child	Smoking Currently	Reads Newspaper Daily
	(1)	(2)	(3)	(4)	(5)
Attack Intensity$_{i,t}$	0.0196***	0.0034*	-0.0241***	0.0497***	0.0017
	(0.0058)	(0.0019)	(0.0049)	(0.0158)	(0.0011)
Mean Dependent Variable	0.0772	0.0104	0.4245	0.5275	0.0113
Observations	192782	226016	123,967	3200	254121

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. The dependent variables in columns 1 and 2 take on one if the individual is dissatisfied with their current life and expected life next year, respectively. Analysis in column 3 is restricted to women aged 18 and above. All the specifications control for the month of the survey fixed effects and district fixed effects, along with the covariates age of women, their marital status, and secondary schooling completion, the number of children, whether the individual uses mobile or internet. Standard errors clustered at the district level are reported in parentheses.

Table 7 provides results for the relationship between terrorism and behavioral outcomes. Columns (1) and (2) report that a higher attack intensity is positively related to an increased likelihood of reporting a decline in current life satisfaction and an expected decline in future life satisfaction, respectively. To provide a quantitative interpretation, based on column (1), an additional fatality per attack results in an increase of 1.96% in the likelihood of an individual reporting a drop in well-being. Compared with the mean dependent variable, the coefficient of AI is equal to 25.39% of the mean. Based on columns (3) and (4), we find that exposure to terror-related fatalities results in a lower desire among women to have another child, as well as a higher likelihood of smoking.[26] Finally, the last column focuses on the effect on news fruition; though the coefficient is positive, the p-value is close to 0.12, and, therefore, the direction of the effect is indiscernible.[27] To summarize, results from Table 7 confirm that exposure to terrorism is strongly associated with a drop in well-being and an increase in pessimism.[28]

[26] We perform a sensitivity analysis for column 3 in which we restrict the sample to women aged 21–30. While the sample size drops to only 38,038 women, the coefficient of attack intensity is -0.0299 and statistically significant at 1%.

[27] As a robustness exercise, we restrict the sample to the years when a terrorist incident occurred. The treated units consist of those districts that experienced a fatality within 12 months before the interview date, while control units include those that experienced a terrorist incident without facing a fatality. In the results not shown, we find that attack intensity has a significant and detrimental effect on individual well-being, increases the likelihood of smoking or reading newspapers daily, and lowers the desire to have additional children. The relationship between terrorism and pessimism remains positive but becomes insignificant. Results will be provided on request.

[28] As an additional analysis, we explore the relationship between terrorism and FDI inflows. Due to the scarcity of investment data at a sub-national level, we use data on FDI inflows from World Bank (2021) available at a country level. Based on the findings from Table A7, higher attack intensity due to terrorism lowers foreign direct investment in the affected countries, subject to a set of fixed effects and controls. However, FDI only contributes to 7.1% of the gross fixed capital formation (UNCTAD, 2022); therefore, this part of the analysis captures only a

5.5 Further Implications of Terrorism

So far, our analysis has provided robust evidence in support of the detrimental effects of terrorism on local economic development. However, we also found that terrorism does not affect state-level economic activity, potentially raising the concern that the loss of any economic activity in the treated districts (which have faced at least one casualty) may be offset by other untreated districts within the same state. Therefore we perform an analysis in which we examine the effects of terrorism on health at a sub-national level. Child mortality can be a proxy for a region's overall health status. In this part of the analysis, we employ three different measures of mortality from Burstein et al. (2019): under-five mortality (probability of a child dying before turning age five, U5MR), infant mortality (probability of dying before turning age one, IMR) and neo-natal mortality (probability of dying within the first 28 days of birth for a newborn, NMR).

In a recent paper, Meierrieks and Schaub (2023) perform a similar type of analysis, though limited to a group of African countries. While health outcomes are not the primary focus of our study, we perform this exercise for around 100 developing countries to show that the effects of terrorism extend beyond economic development and are observed at a global level. Our dependent variable is the number of deaths per 100,000 births, expressed in log form. Results are provided in Table A2 to preserve space. In columns 1–3, we show results for unconditional specifications. In the last three columns, we control for potential confounders at a district level, such as rainfall, temperature, population, inequality measured at the state level, exposure to natural disasters, and pollutant concentration.

We find that the higher the attack intensity, the greater the number of child deaths. While results for U5MR and IMR remain unchanged whether a conditional or an unconditional specification is applied, findings for NMR in column (6) are rather imprecise. To provide a quantitative interpretation of the estimates, referring to column (1) of Table A2, one additional fatality per attack results in an increase of 0.09% in under-5 mortality or an additional 5.19 child deaths per 100,000 live births based on the mean U5MR.[29] We conclude that terrorism affects children's health in the treated districts.

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smaller portion of the total investment.

[29]To examine the pretrends assumption, we perform a similar set of exercises as explained in Section 5.1.2. First, we examine the presence of pretrends, and then we allow for differential trends following the estimation procedure from Rambachan and Roth (2023). The results are provided in Figure A1, online appendix to preserve space. Based on figures A1a and A1c, it is evident that some of the lead coefficients are significant. However, the coefficient of interest, i.e., the current AI, remains significant to reasonable violations of pretrends assumption, refer to Figure A1b and A1d.

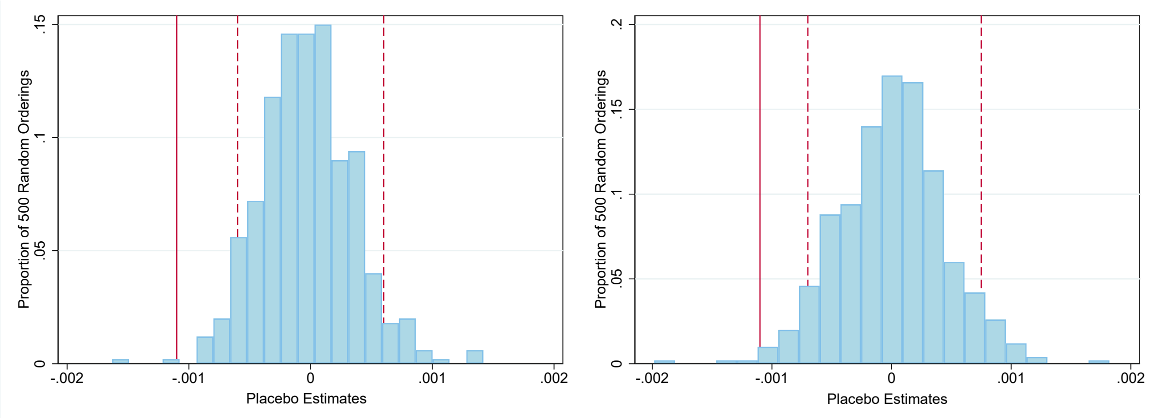
5.6 Robustness Exercises

5.6.1 Randomization Inference

Recent studies have raised concerns regarding the validity of standard errors in DID settings when there are only a few treated clusters or observations within them relative to the overall sample size (Khalil et al., 2021). This issue is particularly relevant in our case, as fewer than 2% of the districts in our sample have ever experienced a terrorist attack, and less than 1% of the districts have experienced casualties resulting from terrorism. To address potential concerns about the validity of the statistical inference procedure applied in our study, we conduct a randomization exercise following the approach outlined by Conley and Taber (2011).

The randomization exercise involves a straightforward procedure of randomly assigning treatment to control districts. We conduct two variations of this exercise: firstly, we randomly assign false treatment to control districts within the same country as the treated unit. Secondly, we perform another exercise in which placebo treatments are assigned to districts within the same state (first-level administrative units) as the treated unit.

Figure 2: Terrorism and Economic Development: Permutation Exercise



(a): Within Country (b): Within State

Note: Figures 1(a) and 1(b) provide the plot of a randomization inference based on 500 replications, where the treatment indicator is shuffled across districts. Figure 1(a) shuffles 'attack intensity' values within a country, whereas Figure 1(b) shuffles 'attack intensity' values across districts within a state. The dashed lines indicate the 95th percentile values of the placebo estimates, whereas the solid line shows the baseline estimate.

The results for specifications based on Equation 1, subject to 500 replications, are provided in a graphical format in Figure 2. Based on these figures, we can infer two conclusions: first, the false treatment effects are centered around the mean value of zero; second, the real treatment effect (from column (4), Table 2), indicated by the solid red line, lies to the left-hand side of the bottom fifth percentile of this distribution, indicated by the dotted red line. This exercise boosts the credibility of our finding that terrorism is detrimental to local economic development and allays any concerns regarding the validity of the inference procedure because of the low number of treated units.

5.6.2 Addressing Negative Weights Concern

Some recent studies have pointed out potential concerns when estimating specifications similar to the two-way fixed effects in Equation 1. This is known as the negative weighting concern. In the DID setting, where average treatment effects are also estimated as pairwise comparisons between earlier and later treated units, there is a potential bias in case of heterogeneity in treatment effects across time and space, as negative weights can be assigned to some of the treated/control comparison groups (de Chaisemartin and D'Haultfoeuille 2020, henceforth, CH; Goodman-Bacon 2018). As we follow a DID design, this negative weighting concern is relevant for our analysis.

First, we assess whether negative weighting poses an issue in our study by examining the presence of negative weights using the Stata command $'twowayfeweights'$, developed by de Chaisemartin and D'Haultfoeuille (2020). Following Lundborg et al. (2022), we discretize the treatment and define it on an extensive margin, taking a value of one if there is any terror-related fatality in a particular year in the district, and zero otherwise. Regardless of whether we use the entire sample or restrict it only to the ever-treated units, we find no negative weights in our main two-way fixed effects specifications.[30] Second, even though negative weights is not an issue in our study, we apply '*didmultiplegt*' package in Stata developed by de Chaisemartin and D'Haultfoeuille (2020), which provides estimates that are robust to negative weights (henceforth referred to as MDID). Subject to the MDID estimator, we find that terrorism has a significant and detrimental association with economic activity, whether we use the full sample or restrict it only to the ever-treated units. In both cases, the coefficient of terrorism (in this case, attacks that resulted in fatalities) is approximately -0.0148 and remains significant at the 5% level.

5.6.3 Further Robustness Exercises

We conclude by performing a battery of further robustness exercises to probe the sensitivity of our results.

i) In addition to the district fixed effects and year fixed effects already included in the baseline specification, we introduce country-year fixed effects, as each country may experience a different type of economic or health shock in a given year. Our estimates of attack intensity

[30]Notably, only 10 treatment-control pairs out of 8,844 receive a negative weight in the full sample, and 18 receive a negative weight when we restrict the analysis to the treated units.

remain robust to this robustness check, with a coefficient of -0.0014 and p-value remaining below 1%.

ii) We explore different forms of the outcome variable. Instead of employing log(NL + 0.01) as the outcome variable, we consider NL and per capita NL, both in log form. Additionally, instead of using average NL intensity in log form, we examine it in level form. Since the level form of the outcome variable includes zeroes, we apply the Poisson estimation technique while incorporating district and year-fixed effects. Our estimate of attack intensity remains robust when using this alternative estimator with a slightly different form of the outcome variable. Results are available upon request.

iii) As a third exercise, we implement a quadratic specification in our treatment, i.e., attack intensity. The estimate of AI remains negative and significant. However, the coefficient of the quadratic term is positive and insignificant, with a p-value of 0.87.

iv) So far, we have clustered standard errors at our level of treatment, i.e., at the district level. As districts may share similar characteristics within a state (first-level administrative units), we apply state-level clustering instead of district-level clustering. Based on the results provided in Table A3, in the online appendix, the significance of the attack intensity variable remains unchanged, i.e., AI has detrimental effects on economic activity, irrespective of the clustering employed.

v) To ensure that our treatment effects are not solely driven by high-risk areas, we conduct two exercises. First, we exclude the top one percentile of districts based on the number of casualties during our sample period. Second, we replicate this procedure but based on the number of incidents. Our results remain robust even after excluding high-risk regions, confirming that these effects are not solely attributable to a few districts or countries.“

vi) Recent studies have expressed concerns regarding blurring, top-coding, and calibration issues in the NL data from NOAA (2022), see Gibson et al. (2021) for detailed comments. Addressing these concerns, Li et al. (2020) have created a harmonized NL dataset that provides integrated and consistent night lights data at a global scale by harmonizing the inter-calibrated NL data from DMSP and the simulated DMSP-like NL data from the Visible Infrared Imaging Radiometer Suite (VIIRS) data. As the next exercise, we apply harmonized NL data to address any concerns about using the NL data from DMSP. The results are provided in Table A4. Panel A reproduces the estimates from Table 2 for ease of comparison, whereas panel B uses harmonized NL data as the outcome. Comparing across panels, a significant and negative relationship between NL and attack intensity persists. However, the coefficients of AI are larger when harmonized NL data are used (see Panel B). Therefore, our estimates in Table 2 are conservative only.

vii) We already controlled for a set of relevant confounders in our specifications. Another potential confounder that can be related to both terrorism and economic activity is the level of political unrest in a region. Next, we control for the level of political unrest in a district proxied by the number of civil protests. Data on protests, riots, strikes, and other disturbances are available from the Social Conflict Analysis Database (SCAD) for a group of African and Latin American countries. Controlling for the level of civil unrest, the coefficient of AI is -0.0011 and remains statistically significant at 1%.

viii) Another potential concern is that the NL data used is the average luminosity for the entire year, but the terrorism variable may relate to the end of a given year. For example, an incident that occurred in November or December of a year is assumed to have similar effects as that of incidents that happened at the beginning of a year. Therefore, we conduct an additional exercise by splitting the year into two halves – January to June and July to December – and creating an attack intensity variable based on the number of fatalities and incidents in a given half. Based on the findings, the coefficient of AI for the first and second half is similar, with an estimate of -0.001. However, the coefficient of attack intensity for the first half is significant at 1%, whereas the coefficient of AI for the second half is imprecisely estimated with a p-value of 0.108.

6 Conclusion

Terrorism, a form of collective violence, poses severe economic and non-economic consequences, affecting both developed and developing countries. Existing research on the impacts of terrorism on economic growth has primarily relied on cross-country data or focused on isolated events. This paper addresses a significant gap in the literature and provides causal evidence on the micro-economic impacts of terrorism on a global scale. Using night light data as a proxy for local economic development at the district level, we provide insights into how terrorism influences economic activity on a sub-national scale while also exploring the geographical extent of its effects.

Our study finds that terrorism has major detrimental effects on the local economic activity of a global set of developed and developing countries. Our difference-in-differences estimates indicate that an additional fatality per attack leads to a decrease of 0.14 percent in night light activity, on average. The results remain robust subject to various exercises, underscoring that the relationship is causal. We perform a few heterogeneity analyses to shed further insights. Based on the type of target, attacks on military/police bases and business infrastructure are the most detrimental. Based on the geographical regions, the Middle East and North African group of countries, South Asian countries, and sub-Saharan African countries suffer the most. Next, we uncover the spatial extent of terrorism impacts and find that areas within a 15-kilometer radius of the incident location experience the negative impacts of terrorism. For comparison, this spatial effect encompasses an area roughly four times the size of Washington D.C.

We then examine the behavioral responses of women to terrorism and find that exposure to terrorism affects individual well-being, increases pessimism and lowers the desire to have additional children among women. This evidence emphasize that terrorism might drive away investments from the affected regions by creating pessimism, which results in lower economic activity. As the impacts of terrorism can extend beyond economic development, we explore the relationship between terrorism and child mortality for a global set of developing countries. The results highlight that terrorism has adverse effects on child health.

In the last two decades, terrorism has emerged as a significant threat to both developed and developing nations, resulting in over 430,000 injuries and more than 315,000 fatalities. These figures represent just the direct consequences of terrorism. According to a report by ETR (2022), a staggering 58 percent of the 830 million people grappling with food insecurity reside in the 20 countries most severely affected by terrorism. Consequently, terrorism not only disrupts economic activities but can also inadvertently affect the impoverished populations in these regions who already struggle for sustenance. Our research uncovers the severe ramifications of terrorism, revealing its adverse impact on economic activity and heightened child mortality rates in the affected regions. In light of these findings, it becomes essential for governments to provide vital assistance and allocate resources to the affected districts, matching the financial outflow caused by terrorism. The spatial extent of impacts identified in this study can also help inform policy-makers on the geographical reach to focus upon.

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Online Appendix (Not for Publication)

Terrorism and Local Economic Development

Table A1: Terrorism and Economic Development - Number of Kills

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
Number of $\text{Kills}_{i,t}$	-0.0004**	-0.0004**	-0.0003**	-0.0003**	-0.0004***	-0.0003**
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Log $\text{Nightlights}_{i,t-1}$			0.4004***			
			(0.0037)			
District-Specific Trend	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	No	Yes
Mean Dependent Variable	0.242	0.242	0.283	0.358	0.173	0.310
Observations	871290	871290	829800	771404	103320	94986

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for district-fixed effects, year-fixed effects, district-specific linear trends, and a set of controls. Standard errors clustered at the district level are reported in parentheses.

Table A2: Terrorism and Health

Dependent Variable	Log U5MR	Log IMR	Log NMR	Log U5MR	Log IMR	Log NMR
	(1)	(2)	(3)	(4)	(5)	(6)
Attack Intensity$_{i,t}$	0.0009***	0.0005***	0.0004**	0.0008***	0.0003*	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Controls	No	No	No	Yes	Yes	Yes
Mean Dependent Variable	8.376	8.082	7.525	8.358	8.063	7.509
Observations	172760	172760	172760	159175	159175	159175

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. The dependent variable is the log of mortality, expressed as the number of under-five deaths per 100,000 births. U5MR refers to under-5 mortality, IMR refers to Infant mortality, and NMR refers to Neonatal mortality rates. All the columns control for district-fixed effects, year-fixed effects, and district-specific linear trends. Columns 1–3 provide results for unconditional specifications, whereas the last three columns include a set of controls. Standard errors clustered at the district level are reported in parentheses.

Table A3: Terrorism and Economic Development - Clustering at State Level

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
Attack Intensity$_{i,t}$	-0.0014***	-0.0014***	-0.0012***	-0.0011***	-0.0015***	-0.0013***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log Nightlights$_{i,t-1}$			0.4004***			
			(0.0098)			
District-Specific Trend	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	No	Yes
Mean Dependent Variable	0.242	0.242	0.283	0.358	0.173	0.310
Observations	871290	871290	829800	771404	103320	94986

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for district-fixed effects, year-fixed effects, district-specific linear trends, and a set of controls. Standard errors clustered at the state level are reported in parentheses.

Table A4: Terrorism and Economic Development - Alternate Sources of Night lights Data

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: DMSP NL Data					
Attack Intensity$_{i,t}$	-0.0014***	-0.0014***	-0.0012***	-0.0011***	-0.0015***	-0.0013***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Log Nightlights$_{i,t-1}$			0.4004***			
			(0.0037)			
District-Specific Trend	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	No	Yes
Mean Dependent Variable	0.242	0.242	0.283	0.358	0.173	0.310
Observations	871290	871290	829800	771404	103320	94986
	Panel B: Harmonized NL Data					
Attack Intensity$_{i,t}$	-0.0018***	-0.0018***	-0.0015***	-0.0015***	-0.0018***	-0.0016***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Log Nightlights$_{i,t-1}$			0.4005***			
			(0.0039)			
District-Specific Trend	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	No	Yes
Mean Dependent Variable	0.275	0.275	0.320	0.391	0.188	0.325
Observations	858561	858561	817679	760959	103110	94797

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for district-fixed effects, year-fixed effects, district-specific linear trends, and a set of controls. Standard errors clustered at the district level are reported in parentheses.

Table A5: Terrorism and Economic Development - Temporal Analysis

Dependent Variable	Log NL	Log NL	Log NL	Log NL	Log NL	Log NL
	(1)	(2)	(3)	(4)	(5)	(6)
Attack Intensity$_{i,t}$	-0.0011***		-0.0009*	-0.0011*	-0.0013**	-0.0014**
	(0.0002)		(0.0005)	(0.0006)	(0.0006)	(0.0006)
Attack Intensity$_{i,t-1}$		-0.0014***	-0.0014***	-0.0011	-0.0011	-0.0016
		(0.0004)	(0.0004)	(0.0009)	(0.0009)	(0.0010)
Attack Intensity$_{i,t-2}$				-0.0003	-0.0003	-0.0002
				(0.0004)	(0.0004)	(0.0004)
Attack Intensity$_{i,t-3}$					0.0001	-0.0002
					(0.0003)	(0.0004)
Attack Intensity$_{i,t-4}$						-0.0003
						(0.0003)
Mean Dependent Variable	0.358	0.426	0.426	0.438	0.451	0.476
Observations	771404	703358	703358	668665	634185	599486

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for district-fixed effects, year-fixed effects, district-specific linear trends, and a set of controls. Standard errors clustered at the district level are reported in parentheses.

Table A6: Terrorism and Economic Development - Heterogeneity by Terror Exposure

Dependent Variable	Low Risk (By Incidents)	Low Risk (By Kills)	High Risk (By Incidents)	High Risk (By Kills)
	(1)	(2)	(3)	(4)
Attack Intensity$_{i,t}$	-0.0025***	-0.0023***	-0.0013***	-0.0012***
	(0.0009)	(0.0009)	(0.0002)	(0.0002)
Mean Dependent Variable	0.322	0.349	0.817	0.522
Observations	715642	733963	55762	37441

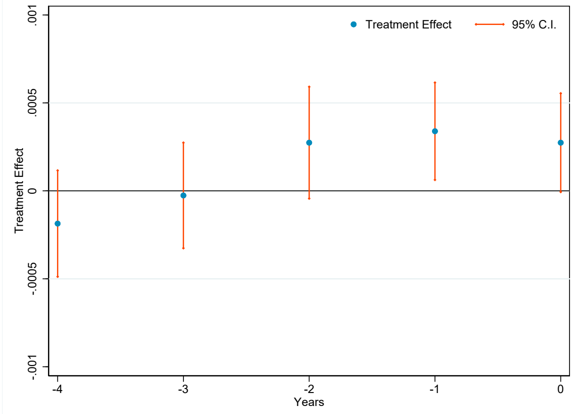
Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the columns control for district-fixed effects, year-fixed effects, district-specific linear trends, and a set of controls. Regions are defined as low/high risk based on the number of incidents or casualties that occurred between 1992 and 2000. For example, Low Risk (By Incidents) in Column 1 refers to the sample that never experienced a terror attack between 1992 and 2000, whereas 'High Risk(By Incidents)' refers to the sample that experienced at least one attack between 1992 and 2000. Standard errors clustered at the district level are reported in parentheses.

Table A7: Terrorism and Foreign Direct Investment - Cross-Country Analysis

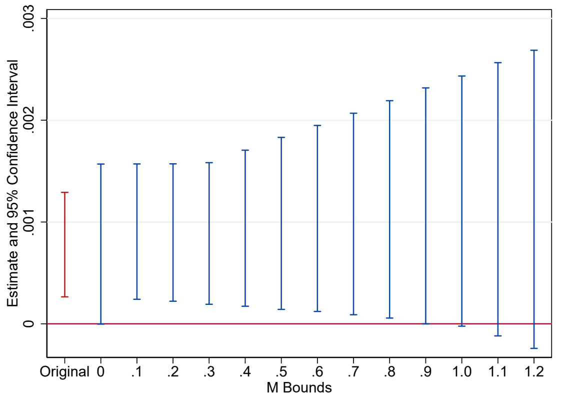
Dependent Variable	FDI	FDI	FDI	FDI	FDI
	(1)	(2)	(3)	(4)	(5)
Attack Intensity$_{i,t}$	-0.0478***	-0.0461***	-0.0327***	-0.0326***	-0.0244***
	(0.0109)	(0.0102)	(0.0084)	(0.0084)	(0.0081)
Year Fixed Effects	No	Yes	Yes	Yes	Yes
Region Fixed Effects	No	No	Yes	Yes	Yes
Country-specfic Trend	No	No	No	Yes	Yes
Controls	No	No	No	No	Yes
Mean Dependent Variable	0.676	0.676	0.652	0.652	0.657
Observations	2981	2981	2838	2838	2809

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. The dependent variable is the foreign direct investment (in the log form) of a country. Standard errors clustered at the country level are reported in parentheses. Countries are classified into one of the following seven regions: East Asia and Pacific Countries (EAP), Eastern Europe and Central Asia (ECA), Latin America and Caribbean countries (LAC), Middle-East and North African countries (MENA), Central Asian countries (SA), Sub-Saharan African countries (SSA) and Western European countries (WE). In the last column, we control for the GDP and population of a country in log terms.

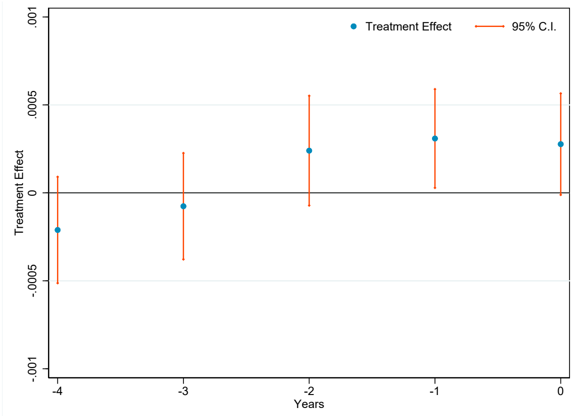
Figure A1: Terrorism and Child Health: Parallel Trends



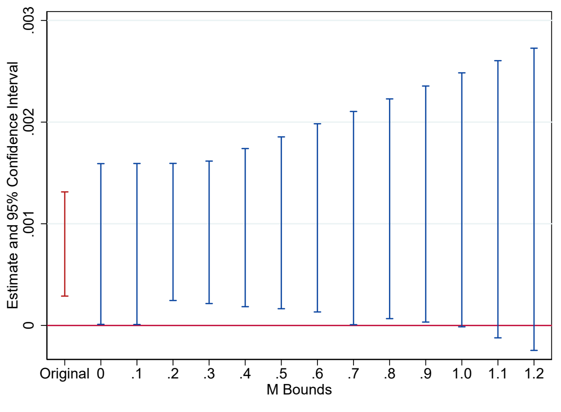
(a) Full Sample



(b) RR - Full Sample



(c) Timing DID



(d) RR - Timing DID

Note: Panels A and C provide a plot of the impact of current and future terrorism on under-five mortality rates. Plots also include 95% confidence interval bounds. The specifications control for district and year-fixed effects, district-specific linear trends, and a set of controls. Standard errors are clustered at a district level. Panels B and D show the sensitivity of the 95% confidence interval for the impact of terrorism on child mortality to potential violations of the parallel trends assumption. In red, we plot the original confidence interval of the contemporaneous attack intensity variable, assuming parallel trends. In blue, we plot alternative 95% confidence intervals proposed by Rambachan and Roth (2022), which relaxes the assumption of parallel trends and allows for differential trends. X-axis shows the parameter M, the maximal bound on the amount by which the underlying time trend can vary between consecutive periods. M = 0 corresponds to allowing a linear differential trend. M > 0 allows for increasingly more varied nonlinear trends.