# 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 0.23 percent in economic development, on average. The detrimental effects are observed for up to three years following the attack. Areas that are within a 50-kilometer radius of the incident location are affected. The attacks targeted at 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. Findings survive a battery of robustness tests.

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

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# 1 Introduction

Terrorism is a persistent threat to societies worldwide, causing widespread destruction and 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, 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. 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 pathways through which terrorism affects economic activity.

[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).

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 0.23 percent in NL activity. We conduct a couple 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, 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] Terrorism has a strong negative effect on economic activity, subject to both exercises.

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 50 km radius of the attack location. However, we find no impact when performing our analysis at a state level (first-level administrative units). 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 (with a radius of up to 50km). On the other hand, it shows that by considering state-level data, one could easily underestimate or even completely miss the impact of terrorism.

[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.

Terrorism may have heterogeneous impacts based on the target type, 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.

We perform further heterogeneity analyses. Based on the type of attack, armed attacks and bombings reduce economic activity the most. The OECD and non-OECD groups of countries are affected in terms of economic development. Geographically, the Middle East and North African countries (MENA), South Asian countries (SA), and sub-Saharan African (SSA) countries are the most affected regions.

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 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.[4] 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. 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.

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, we cluster the standard errors at the state rather than the district level. In addition, we conduct various other sensitivity exercises, such as 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 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

[4] 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) note that domestic and transnational terrorist attacks are more concentrated among middle-income countries; thereby, the 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 Pakistan.[5] 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.[6] For this reason, following the recent literature[7], 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.[8] 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

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

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

[7] 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.

[8] Not only is NL data often the only available source of economic activity, due to 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), NL data can be considered as to be more accurate as well.

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.[9]

Table 1: Terrorism and Economic Development - Summary Statistics

| Variable | Mean | Standard Deviation | Source |
|---|---|---|---|
| | Panel A: Variables of Interest | | |
| Log Nightlights$_{i,t}$ | 0.776 | 2.065 | 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: 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) |
| Media Frequency$_{wi,t}$ | 0.014 | 0.118 | MICS (2022) |

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 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.

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, along with the disaster exposure and pollution levels in a district. Our measures of rainfall and temperature are from Willmott and Matsuura (2001), Version 4.01,

[9] 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.

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.[10]

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. 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.

# 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.[11] Our treatment variable of interest is $Attack_{isct}$, which we refer to as 'attack intensity,' and the coefficient of interest is $\beta_1$. 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.[12]

We include district fixed effects, $\lambda_i$, and time fixed effects, $\lambda_t$, 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, and whether the district has experienced

[10] 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).

[11] A potential concern is that the NL intensity data from DMSP is top-coded at 63; hence, we exclude the top one percentile of data in terms of NL intensity as robustness, to which the findings remain unchanged.

[12] We use alternative forms for the explanatory variable as a robustness exercise. A detailed discussion is provided in Section 5.5.

any natural disaster. The error term $\varepsilon_{isct}$ includes the time-varying unobservable shocks to the outcome variable.

Our primary coefficient of interest is $\beta_1$. 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. As a further exercise, we include only the district-years that experienced an attack, thereby reducing any further selection bias due to terrorists non-randomly choosing a district or year.

# 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. Based on the estimated coefficient, one additional fatality per attack leads to a drop of 0.0023 percentage points (pp) in the outcome variable, i.e., a 0.23 percentage drop in NL activity.[13]

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 in column 3; however, it remains significant at the 1% level. Subject to the conditional specification in column (4) (the baseline specification), the coefficient of AI increases slightly and remains significant.

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

[13] The percentage change in NL for one unit increase in attack intensity is calculated using the standard formula: $[e^{\beta} - 1] * 100$, i.e., $[e^{0.0023} - 1] * 100$, equal to 0.23%. Refer to column (1), Table 2 for the estimated coefficient $\beta$.

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$_{i,t}$ | -0.0023*** | -0.0023*** | -0.0016*** | -0.0024*** | -0.0022*** | -0.0023*** |
| | (0.0007) | (0.0007) | (0.0005) | (0.0007) | (0.0007) | (0.0007) |
| Log Nightlights$_{i,t-1}$ | | | 0.4834*** | | | |
| | | | (0.0031) | | | |
| District-Specific Trend | No | Yes | Yes | Yes | Yes | Yes |
| Controls | No | No | No | Yes | No | Yes |
| Adjusted R-Squared | 0.2739 | 0.2741 | 0.4235 | 0.2665 | 0.2992 | 0.3000 |
| Observations | 776224 | 776224 | 728512 | 709405 | 91414 | 86633 |

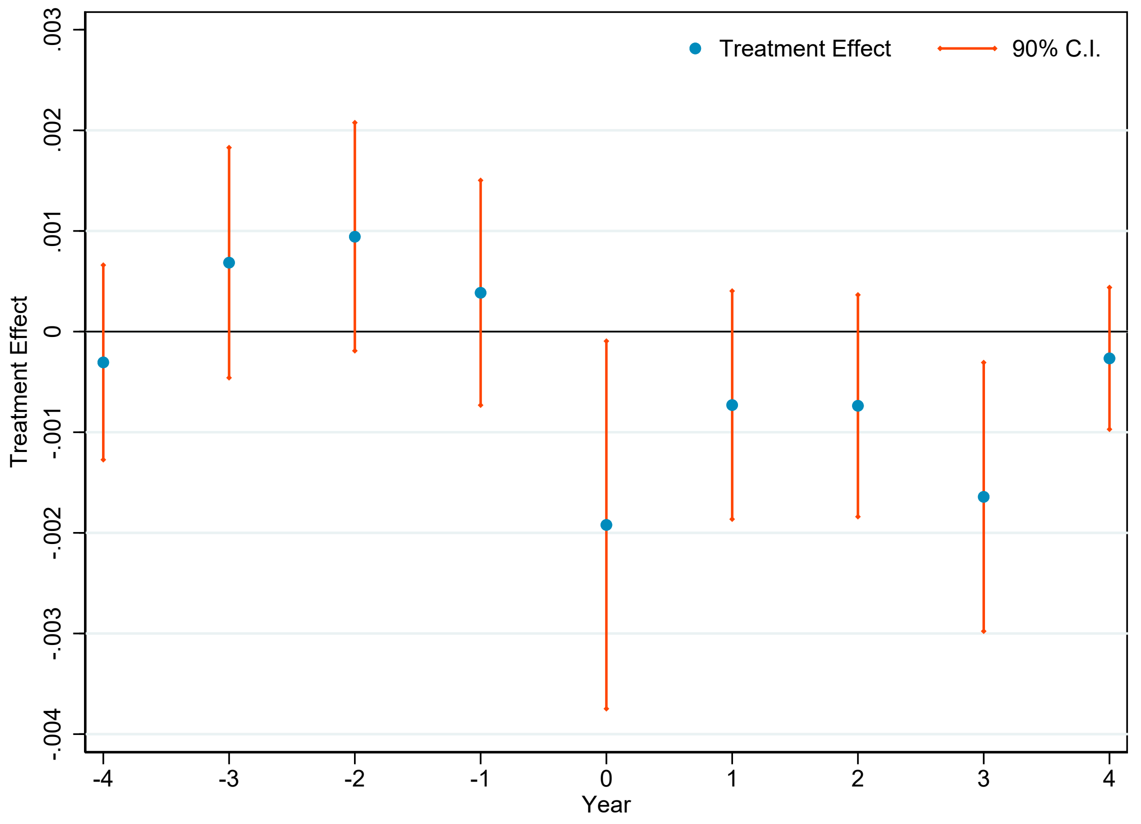
Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. The dependent variable is the log of NL. All the columns control for district-fixed effects and year-fixed effects. In the last two columns, only the districts that have experienced an attack in the sample period are included.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

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 similar to column (4) and remain significant, providing further credibility to our baseline finding.

### 5.1.1 Examining Pretrends

The main identification assumption of the DID approach is that the treated and control units evolve similarly in the outcome before the treatment, i.e., parallel trends. In this section, we examine the presence of pretrends subject to the baseline specification, i.e., column (4) of Table 2. Along with the contemporaneous treatment effect, we estimate the effects of up to four leads and four lags of AI and produce the results in a graphical format in Figure 1. The point estimates reflect the differences in nightlight activity across treatment and control districts in the lead-up to an attack in the future. Based on the figures, we do not observe any significant differences in the NL activity between the treated and control regions for all four leads. This provides evidence in support of the parallel trends assumption, i.e., the economic activity was trending similarly in the treated and control regions prior to the attack, thereby making the DID results reliable. However, the contemporaneous AI and the third lag of the attack intensity are negative and significant. Therefore, the detrimental effects of nightlights are observed for up to three years following the attack. A potential reason for not observing significant effects for the first and the second lag of terrorism can be due to the inflow of funds from the government or extra security being provided following the incident. Once these resources run out, detrimental effects are clearly visible.[14]

Figure 1: Terrorism and Economic Development: Pretrends Analysis




Note: Figure provide a plot of the impact of current, lagged and future terrorism on night lights. Plots also include 90% 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.

### 5.1.2 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

[14] Skidmore and Toya (2002) and Ponnusamy (2022) observe a similar set of effects in their studies on the impacts of natural disasters. While the contemporaneous and farther lags of disasters affect outcomes, the intermediate years show null effects due to the extra resources being provided. Once the resources run out, detrimental effects become visible.

attack without casualties. The results are provided in Table 3. Column (1) reproduces the baseline estimates for ease of comparison. Column (2) contains the results in which we address the control group contamination issue. The findings remain unchanged, while 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 counties compared to failed terror attacks, and the 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 that experienced terrorism. Conditional on a district being targeted by terrorism, the nature of the attack can be considered to be plausibly exogenous (Brodeur, 2018). By restricting the analysis only to those district-years that experienced terrorist activity, we are able to mitigate further any selection bias arising due to terrorists non-randomly selecting a district or year, thereby estimating the causal effects. Here, the treated units are those districts that experienced a fatality, and the control units experienced an incident without a fatality.

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

| Dependent Variable | Log NL | Log NL | Log NL |
|---|---|---|---|
| | (1) | (2) | (3) |
| Attack Intensity$_{i,t}$ | -0.0024*** | -0.0023*** | -0.0026*** |
| | (0.0007) | (0.0007) | (0.0010) |
| Controls | Yes | Yes | Yes |
| Excluding Contaminated Regions | No | Yes | No |
| Only the Affected District-Year Observations | No | No | Yes |
| Mean Dependent Variable | 0.358 | 0.353 | 0.480 |
| Observations | 709405 | 704670 | 12692 |

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.

According to GTD's definition, an attack is considered successful if it takes place, regardless of whether it produces the damage the perpetrators wanted to achieve (with the exception of individual assassinations, in which case the attack is considered successful only if the target is killed). For instance, if a bomb explodes in a building, the attack is considered successful, even if it does not manage to bring the building down. According to this definition, 94% of the attacks in our sample are successful, and only 6% of the attacks are failures, based on mutually exclusive district-year observations.[15] Therefore, restricting the analysis to only the incident years and comparing successful attacks with failed ones would not yield reliable estimates.[16] Hence, we apply a different definition of success. 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 column (3) of Table 3. The coefficient of AI is similar in size compared with column (1) and remains significant at 1%. This exercise helps us address endogeneity concerns further, ensuring that the baseline findings are not driven by terrorists targeting certain regions or years based on their levels of economic activity and that the estimated relationship is causal.

## 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.

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

[15] 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, i.e., 838 unique failed attacks out of 14,831 total attacks.

[16] 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.

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$_{i,t}$ | -0.0024*** | -0.0029*** | -0.0023*** | -0.0017*** | -0.0010** | -0.0003 | 0.0001 |
| | (0.0007) | (0.0008) | (0.0005) | (0.0006) | (0.0005) | (0.0004) | (0.0006) |
| | [0.002] | [0.001] | [0.002] | [0.003] | [0.065] | [0.198] | - |
| Observations | 709405 | 277100 | 263867 | 256622 | 238124 | 225654 | 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 and disaster exposure; 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 100 km radius of the incident location. The effect diminishes and loses significance when we move beyond that distance to include larger areas. A caveat of this spatial analysis is that larger circles, especially in columns (5) and (6), can overlap with each other. Therefore, we take a conservative approach and conclude that circles with a radius of up to 50 km are affected by terrorism.[17]

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 i.e. 150-km radius or at a state-level, 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, while investments in the affected

[17] 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 5.5.4 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.

districts may drop, investors may shift to nearby districts, averaging out any adverse effects at the state level.

### 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 100 km radius.[18]

## 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), type of attack (bombing or armed attack, for example), the countries' development status (OECD vs non-OECD), 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.

In this section, we examine heterogeneity in the treatment effects based on the target type. 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.[19] Table 5

[18] 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.

[19] Attacks on a business or corporate office and employees patronizing a business, public transportation, and utility services are combined and classified as "Business" target type in this study. Likewise, any attack on a government building, political movement, or government-sponsored institution is classified as a "Government"

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$_{i,t}$ | -0.0024*** | | | | | |
| | (0.0007) | | | | | |
| Attack Intensity (Business)$_{i,t}$ | | -0.0018* | | | | -0.0016* |
| | | (0.0009) | | | | (0.0009) |
| Attack Intensity (Government)$_{i,t}$ | | | 0.0012 | | | 0.0014 |
| | | | (0.0010) | | | (0.0010) |
| Attack Intensity (Military)$_{i,t}$ | | | | -0.0028** | | -0.0026** |
| | | | | (0.0012) | | (0.0012) |
| Attack Intensity (Other)$_{i,t}$ | | | | | -0.0024** | -0.0023** |
| | | | | | (0.0012) | (0.0012) |
| Observations | 709405 | 709405 | 709405 | 709405 | 709405 | 709405 |

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.

provides the heterogeneity analysis by target type. Row (1) reproduces the baseline findings for ease of comparison, whereas the rest 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.

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. Conversely, attacks on government targets appear to have a positive relationship with development, albeit insignificant.

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.

target. Attacks on the police force or police installations and attacks on military units, patrols, barracks, military checkpoints, and recruiting sites are combined and referred to as "Military" targets. 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.

### 5.3.2 Further Heterogeneity Analyses

We perform several heterogeneity analyses and present findings in this section. First, we explore the relationship between NL activity and the type of terror attack i.e. the primary way terrorists carried out the attack. We categorize the attacks into four types based on the definition from GTD – armed attack, bombing, infrastructure, and the other category.[20] From Table A1, armed attacks have the most detrimental effect on economic development, followed by bombings. The coefficient of the 'Other' attack type is negative but insignificant. Based on the development status, both OECD and non-OECD groups of countries are affected similarly due to terrorism. The results will be provided on request.

Next, we perform an analysis based on the geographical location of countries and provide the results in Table 6. Specifically, 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 coefficients are negative but insignificant in the ECA and LAC subgroups.

Table 6: Terrorism and Economic Development - Heterogeneity by Geographical Location

| Dependent Variable | Log NL | Log NL | Log NL | Log NL | Log NL | Log NL |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | EAP | ECA | LAC | MENA | SA | SSA |
| Attack Intensity$_{i,t}$ | 0.0018 | -0.0020 | -0.0013 | -0.0020* | -0.0029** | -0.0032* |
| | (0.0037) | (0.0018) | (0.0016) | (0.0011) | (0.0014) | (0.0018) |
| Observations | 120541 | 174975 | 189672 | 63834 | 24992 | 52258 |

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).

[20] If firearm, incendiary, or sharp instrument was used, then the attack is classified as an armed attack by the GTD. Bombing or explosion-type attacks are classified as 'Bombing' in this study. An act with the primary objective of causing damage to a non-human target, such as a building, train, or pipeline, is classified as an infrastructure attack. The rest of the attack types are classified as 'Other' attacks in this study.

## 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). Health repercussions are long-lasting (Grossman et al., 2019) and can also extend to future generations. Camacho (2008) demonstrate 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). Pesko (2014) and Pesko and Baum (2016) show that exposure to terrorism causes an increase in smoking, an indicator of stress. In this section, we explore the behavioral channel using data from Multiple Indicator Cluster Surveys (MICS). MICS Wave 6 provides information on several behavioral outcomes, along with information on the district of residence for roughly 250,000 women aged 15 to 49 from four countries: Bangladesh, Lesotho, Pakistan, and Sierra Leone.[21] The sample covers the period 2017–2020.

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 about 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 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 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.[22] 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

[21] We restrict the analysis to only these four countries as the information on the district of residence is unavailable for the other countries. We repeat the baseline analysis for these four countries and find that terrorism lowers economic activity – one additional fatality per attack decreases nightlight activity by 0.15 percent, with the estimates being statistically significant at 10 percent level.

[22] 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%.

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.

effect is indiscernible.[23] 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.[24]

## 5.5 Robustness Exercises

### 5.5.1 Number of Kills

Next, we apply a different form of the explanatory variable. 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 fatalities, the lower the level of economic activity in a district. Results are provided in Table A2 in the online appendix in the interest of space.

### 5.5.2 Restricting by the Number of Incidents

A potential concern with using attack intensity as the explanatory variable is that it might not capture the full extent of attacks. For example, a district with ten deaths from ten attacks in a

[23] 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.

[24] 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 A5, 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 smaller portion of the total investment.

year has been subject to a more intense form of terrorism than a district with one death from just one attack. First of all, this is less likely to be a concern, as nearly 80% of the districts that experienced an attack in our sample have experienced fewer than three attacks. However, to address this concern, we perform an additional exercise by restricting the analysis based on the number of incidents experienced. Column 1 of Table A3 reproduces the baseline estimates, whereas, in columns 2–4, we restrict our sample subject to the number of incidents experienced. For example, in column 2, we exclude all the districts that experienced more than one incident in a particular year. As observed in column 2, districts suffer a drop in economic activity from the very first attack that results in death. And the estimates remain consistent across the last three columns.

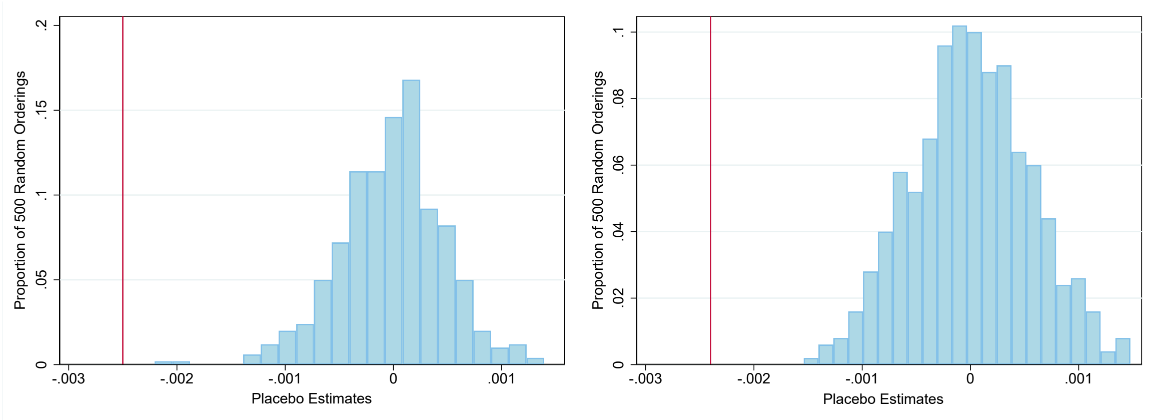
Larger attacks can have more detrimental effects. Therefore, we define variables based on the 95th and 99th percentile of the number of kills (conditioning on terror incidents), respectively. Based on the results, both variables have a negative and significant effect on the outcome – the coefficient of the top five percentile kill variable is -0.0589 (significant at 10% significance level), and the coefficient of the top one percentile kill variable is -0.1121 (significant at five percent level).

#### 5.5.3 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. 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 distribution. 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.

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 solid line shows the baseline estimate.

### 5.5.4 Negative Weights Concern

If earlier treated units are used as controls for the later treated units and if some of these treatment-control pairs carry a negative weight, there can be a bias, commonly referred to as negative weighting concern (de Chaisemartin and D'Haultfoeuille 2020, henceforth, CH; Goodman-Bacon 2018). We assess whether negative weighting poses an issue in our study. 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 incident 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 that negative weighting concern is not an issue.[25]

### 5.5.5 Further Robustness Exercises

We conclude by performing a battery of further robustness exercises to probe the sensitivity of our results. 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 remain robust to this robustness check, with a coefficient of -0.0021 and p-value remaining below 1%. Next, we implement a quadratic specification in our treatment, i.e., attack intensity.

[25] Notably, less than 1.2 percent of the treatment-control pairs receive a negative weight for both specifications. The results are robust to using whether there has been any terrorism-related fatality in a particular year. Here, less than one percent of the treatment-control pairs carry a negative weight.

The estimate of AI remains negative and significant. However, the coefficient of the quadratic term is close to zero and insignificant, with a p-value of 0.421.

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 A4, 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. Further, to ensure that high-risk areas do not solely drive our treatment effects, we conduct two exercises. First, we exclude the top five percentile of the countries based on the number of total casualties during our sample period. Second, we replicate this procedure 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 countries.

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, to which the coefficient of AI is closer to the baseline estimate and remains significant at one percent.[26]

# 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 0.23 percent in night light activity, on average. The results remain robust, subject to various exercises, underscoring that

[26] We try different forms of the outcome variable – first, instead of log nightlights, we try nightlights per capita in a log form; then, we use the mean nightlight activity and estimate the results subject to a Poisson specification. Finally, we add 0.01 to the mean nightlight activity and then use the log form of the variable. The coefficient of AI remains negative and significant to all three exercises employed. The results will be provided on request.

the relationship is causal. We perform a few heterogeneity analyses to shed further insights. Based on the target type, attacks on military/police bases 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 50-kilometer radius of the incident location experience the negative impacts of terrorism.

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 emphasizes that terrorism might drive away investments from the areas affected by creating pessimism, which results in lower economic activity.

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 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 - Type of Attack

| Dependent Variable | Log NL | Log NL | Log NL | Log NL | Log NL | Log NL |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Attack Intensity$_{i,t}$ | -0.0024*** | | | | | |
| | (0.0007) | | | | | |
| Attack Intensity (Armed Attack)$_{i,t}$ | | -0.0035*** | | | | -0.0035*** |
| | | (0.0011) | | | | (0.0011) |
| Attack Intensity (Bombing)$_{i,t}$ | | | -0.0014* | | | -0.0013* |
| | | | (0.0008) | | | (0.0008) |
| Attack Intensity (Infrastructure)$_{i,t}$ | | | | 0.0003 | | 0.0006 |
| | | | | (0.0020) | | (0.0021) |
| Attack Intensity (Other)$_{i,t}$ | | | | | -0.0014 | -0.0011 |
| | | | | | (0.0013) | (0.0013) |
| Observations | 709405 | 709405 | 709405 | 709405 | 709405 | 709405 |

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.

Table A2: 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 Kills$_{i,t}$ | -0.00034** | -0.00035** | -0.00022** | -0.00030*** | -0.00044** | -0.00033** |
| | (0.00015) | (0.00015) | (0.00011) | (0.00011) | (0.00017) | (0.00013) |
| Log Nightlights$_{i,t-1}$ | | | 0.31736*** | | | |
| | | | (0.00296) | | | |
| District-Specific Trend | No | Yes | Yes | Yes | Yes | Yes |
| Controls | No | No | No | Yes | No | Yes |
| Observations | 776224 | 776224 | 743279 | 709405 | 91414 | 86633 |

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 A3: Terrorism and Economic Development - Restricting by the Number of Incidents

| Dependent Variable | Baseline | One Incident and Below | Two Incidents and Below | Three Incidents and Below |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Attack Intensity$_{i,t}$ | -0.0025*** | -0.0024*** | -0.0024*** | -0.0027*** |
| | (0.0008) | (0.0009) | (0.0008) | (0.0008) |
| Observations | 698710 | 693093 | 695079 | 696010 |

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 A4: 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$_{i,t}$ | -0.0024*** | -0.0024*** | -0.0016** | -0.0025*** | -0.0023*** | -0.0023*** |
| | (0.0008) | (0.0008) | (0.0007) | (0.0008) | (0.0008) | (0.0008) |
| Log Nightlights$_{i,t-1}$ | | | 0.3203*** | | | |
| | | | (0.0097) | | | |
| District-Specific Trend | No | Yes | Yes | Yes | Yes | Yes |
| Controls | No | No | No | Yes | No | Yes |
| Observations | 787200 | 787200 | 753762 | 708045 | 91387 | 86063 |

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 A5: 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.