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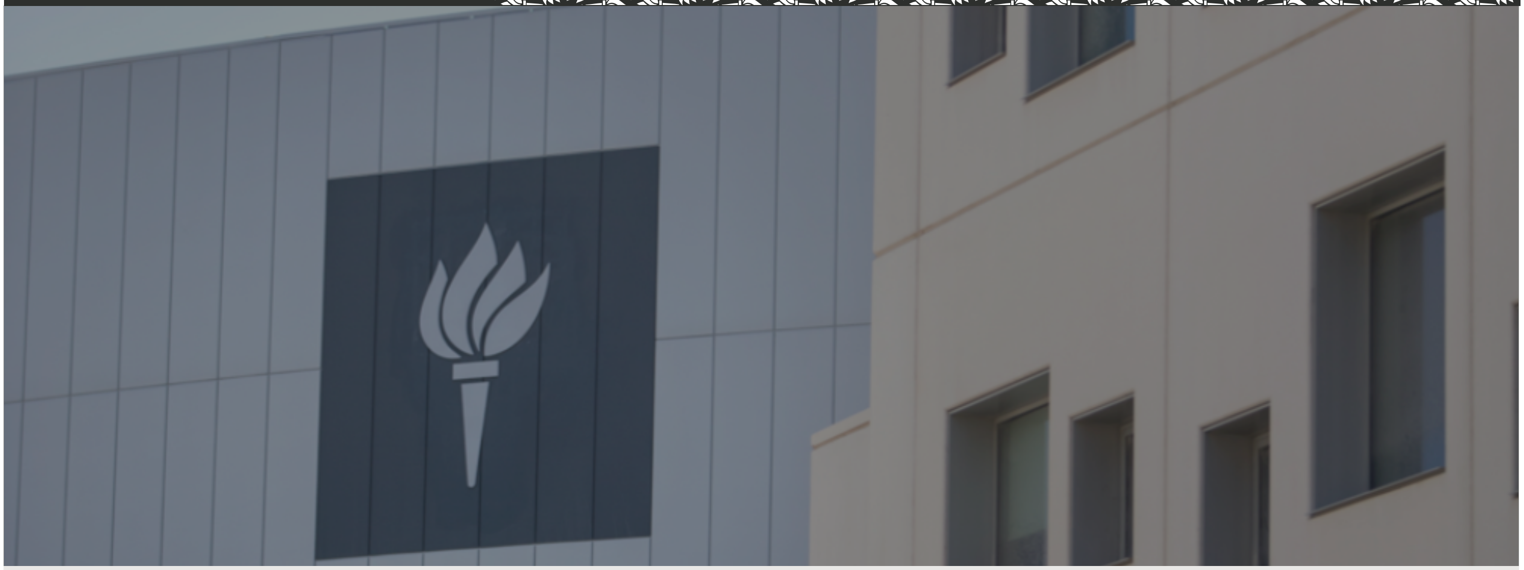

# Is it the Rags or the Riches? The Impact of Income on Domestic Terrorism


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# Is it the rags or the riches?

# The impact of income on domestic terrorism

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April 24, 2023

**Abstract**

Despite the popular rhetoric around poverty being the root cause of terrorism and the resulting alliance between the war on terror and the war on poverty, the literature remains divided on this issue. From finding either a positive or a negative association between income and terrorism as well as a lack of any association between the two, the literature now stresses the non-linear association between income and terrorism. The present study begins by theoretically formalizing the nonlinear relationship between income and domestic terrorism by considering the profit maximization of a representative agent. Next, using a novel instrument of natural disasters in related countries to isolate causality, I show that empirical evidence indeed supports a nonlinear relationship between income and terrorism. Further, with the bias-corrected estimates, the concavity of the relationship decreases keeping the impact of income on terrorism decreasing but positive throughout the observable income levels in the sample.

JEL Classification: D74, O11
Keywords: Domestic terrorism, instrumental variable, income, natural disasters, two-stage Poisson estimation

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"Those of us who fight global poverty share a guilty secret: our cause got more attention and resources after September 11, 2001. It soon became clear that there would be an alliance between the *War on Poverty* and the *War on Terror*." Easterly (2016)

# 1 Introduction

On March 22, 2002, the then-Pakistani President Pervez Musharraf launched Gwadar deep-sea port project in the most under-developed province, Balochistan, in Pakistan (Shahid, 2002). The project was envisioned to drive industrial growth, generate multiple work opportunities, and drive economic development in the region.[1] However, the province saw a heightened terrorist activity as soon as the economic activity gained momentum in the region (Grare, 2006; see Panel A, Figure 1). Domestic terror attacks which averaged around four attacks per year from 1990 to 2002, jumped up to 183 attacks as the port was being built from 2003 to 2007, increasing to an average of 282 attacks per year afterward (START, 2021). A similar phenomenon later occurred in another part of the continent in the Philippines, where the 'Nickel rush' in response to the 2006-08 sudden international price hike in nickel left a long-lasting effect on the mineral's extraction rates; nickel continues to be the largest (by weight and value) metallic mineral extracted in the Philippines (Moon, 2022). Panel B of Figure 1 shows the trends in domestic terrorism in the major nickel extraction regions; domestic terrorism closely follows the trends in the production of nickel.

While these hand-picked examples obviously do not provide evidence for a general trend, they defy to an extent the popular narrative where better economic opportunities or increasing income levels are presented as a panacea for global terrorism threat. Moreover, this proposed recipe for counter-terrorism through poverty alleviation comes with certain obvious implications. On one hand, the alleged association of low-income countries and nations with terrorism, especially after the 9/11 incident (Al Gore, 2002; Bush, 2002; Wolfensohn, 2002) increased funding for poverty alleviation, but on the other hand, the marriage between the war on terror and war on poverty resulted in negative stereotyping of people from the low-income world, contributing subsequently to aggravating xenophobia and anti-immigration views (Easterly, 2016).

[1] See Anwar (2010) for more on the Gwadar Port project and the associated plans for Balochistan's development.

Panel A: Launch of the Gwadar Port Project and terror attacks in Balochistan, Pakistan

Panel B: Nickel extraction and terror attacks in regions with Nickel mines, Philippines

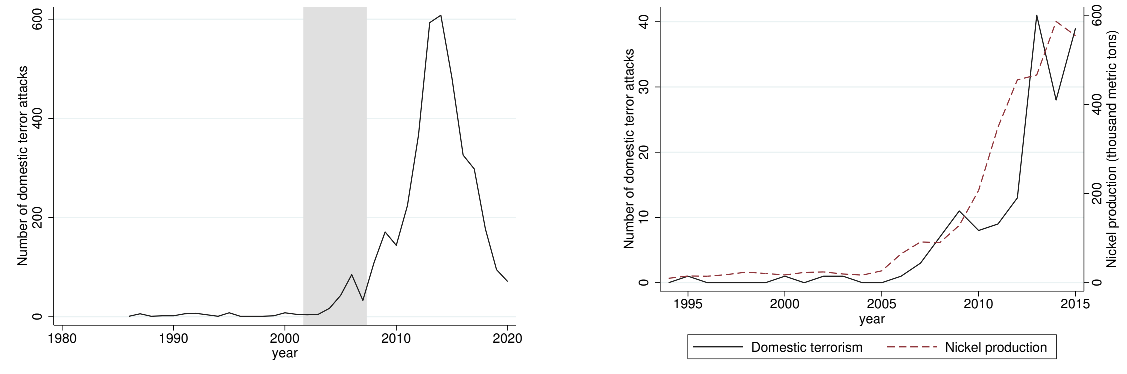



**Figure 1:** Panel A shows the number of domestic terror attacks in Balochistan while the shaded region shows the years from the ground-breaking ceremony of the Gwadar port to the project's completion. Panel B shows nickel production levels (dashed line) in the Philippines (obtained from USGS, 2021) and the number of domestic terror attacks (solid line) in the major nickel-producing regions (namely, Surigao del Sur, Surigao del Norte, Tawi Tawi, Agusan del Norte, and Palawan).

Despite such huge economic, social and political consequences, there is no empirical support for the narrative linking low income levels to terrorism. For example, some studies find a positive association between income and terrorism (Eyerman, 1998 and Kurrild-Klitgaard et al., 2006), some find a negative association (Azam and Delacroix, 2006; Azam and Thelen, 2008, and Li, 2005), others suggest the relationship is non-linear (Freytag et al., 2011; De la Calle and Sánchez-Cuenca, 2012; Enders and Hoover, 2012; and Enders et al., 2016) , while still others do not find any association between income and terrorism (Abadie, 2006; Basuchoudhary and Shughart, 2010; Berman and Laitin, 2008).[2] Additionally, from the reverse impact of terrorism on income (Gaibulloev and Sandler, 2008; Gaibulloev and Sandler, 2011) to a range of factors such as regime properties (Piazza, 2008; Wilson and Piazza, 2013), education (Krueger and Malečková, 2003; Korotayev et al., 2021), communications technology (Mahmood and Jetter, 2020), foreign direct investment (Bandyopadhyay et al., 2014), etc. that can potentially impact both terrorism and income levels, correlational estimates remain susceptible to bias - a fact that may partially explain inconclusive empirical findings.

[2] Enders et al. (2016) nicely summarizes the evolution of related literature while Gaibulloev and Sandler (2022) call the alleged link between income and terrorism "a common myth."

The present study analyzes the impact of income levels in a country on domestic terrorism. It is important to differentiate between domestic and transnational terrorism because the mechanisms governing the relationship of the two with income levels are different (Enders et al. (2016)). While a majority (69 percent) of documented terror attacks lack transnational elements (START, 2021), increasing domestic terrorism in a country also becomes a global security issue (Enders et al., 2011). The present study begins by formalizing the theoretical expectations about the relationship between income and domestic terrorism.[3] As the income of a society increases, on one hand, the bounty or rents that terrorists may capture increase (Lai, 2007; Enders et al., 2016), while on the other hand, increasing resources may further enhance terrorists' ability to win allies and recruits (Lai, 2007) making terrorism more attractive. At the same time, however, increasing income lets governments invest in counter-terrorism measures (Enders and Hoover, 2012) lowering the probability of success for terrorists, and thus, decreasing their expected benefits from terrorism. Also, better general income levels in society increase prospective income from the formal labor market (Frey and Luechinger, 2003; Anderton and Carter, 2006), raising the opportunity cost of investing time in terrorism.[4] I show that a representative agent at the margin of choosing between terrorism and formal labor activities factors in these costs and benefits while deciding on the optimal time they invest in terrorism in order to maximize profits. The theoretical model shows how increasing income increases terrorism but at a decreasing rate. I further show that the income associated with the peak of terrorism changes in response to the confounding factors, impacting the observed relationship between income and terrorism. The theoretical exposition, therefore, stresses the need to carefully address the problem of omitted variable bias in empirical analysis for understanding the income-terrorism nexus.

In order to empirically analyze the relationship between income and domestic terrorism, I use global data from 1990 to 2019 derived from the Global Terrorism Database (START, 2021) for terrorism and the Penn World Table (Feenstra et al., 2015) for real GDP per capita.[5] In order to isolate causality, the study exploits the variation in GDP per capita of a country induced

[3]The formalization presented here differs from Blomberg et al. (2004) in that (among other things) the latter does not make explicit the role of income in affecting counter-terrorism operation of the government.

[4]Kindly note that the 'formal' part of the formal labor market delineates it from the terrorism-related labor activities and should not be confounded with the formal vs informal/underground economic activities.

[5]Although Global Terrorism Database records events since 1970, the data on another key variable, the migration matrix, is consistently available since 1990 (see details in section 4).

by natural disasters in related countries. I define related countries in terms of the share of migrants: The larger the number of migrants of a country in a destination, the higher will be the impact on the country if the destination gets hit by natural disasters. A host of evidence suggests natural disasters in migrant destinations affect remittances the migrants send back home (UN-Migration, 2011; Guadagno, 2015; a detailed discussion on this follows in section 3). Admittedly, there are other potential channels that may affect the income of the source country when migrant destination countries are hit by natural disasters. As long as those channels exogenously affect the income levels of the country but not the other determinants of terrorism, the identification strategy remains valid. I show that natural disasters in migrant destinations of a country have a statistically significant and economically meaningful relationship with income levels in the country, but are uncorrelated with the other determinants of terrorism in the country. Potential threats to identification arise from the possible relationship between (*i*) natural disasters in migrants' destinations and source countries, (*ii*) endogeneity of migrant shares to terrorism, (*iii*) the impact of natural disasters in migrants' destinations on employment levels in the country, and (*iv*) the correlation between natural disasters in migrant destinations of a country and the other determinants of terrorism. I conduct a battery of tests and none of these channels appeared at work strengthening confidence in the identification. Additionally, recentering the instrument using the method proposed in Borusyak and Hull (2020) produces consistent results, placating concerns about endogeneity arising from the predetermined migrant shares.

Using the Two-Stage Poisson regression suitable for analyzing count data (Hausman et al., 1984; Cameron and Trivedi, 2013), the causal estimates point towards a non-linear relationship between income and domestic terrorism, in line with the literature that presents evidence for an inverted-u shape relationship between the two (Freytag et al., 2011; De la Calle and Sánchez-Cuenca, 2012; Enders and Hoover, 2012; and Enders et al., 2016). The main point of departure, however, is that when we remove bias from our estimates, the mechanism reducing terrorism with an increase in income appears weak, keeping the impact of income on terrorism decreasing but positive throughout the observable income levels in the sample. These results hold across (*i*) alternative definitions of the outcome and endogenous variable, and the instrumental variable (*ii*) accounting for a range of potential confounders, and (*iii*) controlling for past terrorism.

Falsification tests show that the instrument works for future income (and terrorism) but not past income (and terrorism). Further, using placebo instrument of natural disaster shock from countries not closely related to a country (i.e., with zero migrants from the country) produces null results. Nonetheless, I stress that the estimates show a Local Average Treatment Effect (LATE) incorporating the impact of the income shock operating through migrants, with the compliers to this setting likely concentrated in the developing countries.

Overall, the study makes two contributions. First, it provides a formal theoretical framework for studying the relationship between income and terrorism. Although the literature proposes several channels through which income may influence terrorism (Li, 2005; Lai, 2007; Enders et al., 2016), a theoretical formalization incorporating the suggested channels helps understand the dynamics of the relationship better. It lays bare the implicit associations between potential sources of the impact of income on domestic terrorism, as well as the sources of endogeneity that may impact or explain the observed association between income and terrorism.

Secondly, the present analysis suggests an instrumental variable that is exogenous to the problem of terrorism. The instruments for income popularly used in the literature run the risk of being associated with other determinants of terrorism. Rainfall (Miguel et al., 2004), for example, may affect income levels in the country but may directly influence terrorist activities by changing the logistical feasibility of attacks, making the instrument endogenous. Similarly, international oil prices or prices of natural resources (Brückner et al., 2012) influence income at the country level but may also affect the cost of operations for terrorists in net importers of such resources while the international prices may be endogenous to terrorism in the net exporters (Coleman, 2012). Using the novel instrument of natural disasters in other related countries, the study sets the stage for future causal analyses of the income-terrorism nexus.[6]

I begin by presenting the theoretical formalization in section 2.2 followed by details on data and instrument in sections 4 and section 5. Section 3 discusses the empirical strategy while Section 6 presents the findings. Section 7 concludes.

[6] Abadie (2006) uses the instrument of landlockedness to predict income of a country in cross-sectional data but this time-invariant instrument is not applicable to panel data.

# 2 Theoretical Framework

## 2.1 Background

The potential linkages between income and terrorism can operate through various channels, affecting either the costs or the benefits of engaging in terrorism. First and more directly, terrorists need funds to undertake their activities be it propaganda and recruitment, buying weapons, or planning and executing attacks. Putting it in perspective, the estimated cost of the September 11 attacks in the US reach around USD 500,000 (National Commission Committee, 2004) while Hamas claims they spent around USD 50,000 on their 2002 bombing of the Hebrew University (Prober, 2005). Common sources of funds for terrorist organizations include donations, profits from businesses and charities, and illegal activities such as kidnapping, smuggling, and extortion (Raphaeli, 2003; Freeman, 2011; UNODC, 2023). All of these sources tend to have a direct association with general income levels in a country; keeping other things constant higher per capita income means higher levels of donations, more profits from business income as the economy is thriving and greater sums in ransom, for example. In other words, comparing two economies that are exactly same in all dimensions (e.g. education, ideological orientation, counter terrorism efforts, etc.) except income levels, the potential of raising funds for terrorism in the richer economy is greater than that in the poorer economy.

Also, in case the terrorists eventually succeed in getting a hold on the resources of a country, bigger size of the economy translates into more resources captured by the terrorists. The case of ISIS becoming one of the richest terrorist organization by capturing oil fields in Syria and Iraq and subsequently producing and selling oil from those fields (Al-Khatteeb and Gordts, 2014; CGSRS, 2015) is a recent example of this phenomenon. In short, as the pie grows bigger terrorists can not only get a bigger slice (even when their share remain the same) but can also have the bigger pie all to themselves if they succeed in acquiring it. Another channel operates through quality of recruits. Following the argument in De Mesquita (2005) that terrorists look for skilled recruits, countries with very low incomes tend to offer recruits that are not as productive and skilled as countries with relatively higher incomes (Lai, 2007). Therefore, ceteris paribus, increasing income levels in a society increases potential benefits from terrorism by making more resources available for terrorist activities as well as by increasing the bounty.

There is, however, a competing channel at work as well. When income of a country increases, government can invest larger sums in counter terrorism efforts (Enders and Hoover, 2012). Government investment in building surveillance and policing capabilities make it harder for terrorists to coordinate and successfully execute an attack. This will directly influence the net benefits from engaging in terrorism.[7]

## 2.2 Theoretical Formalization

Let's consider an agent on the margin deciding between investing their time in terrorism and the formal labor market in order to maximize their profits. If they devote the fraction $\beta$ of their time to terrorism, $1 - \beta$ is the fraction they may devote to the formal labor market.[8] The agent decides optimal $\beta$ by factoring in the costs and benefits of devoting time to terrorism. The potential benefits from terrorism, $F(\beta, y)$, depend both on the time invested in terrorism as well as the size of the bounty or rents the terrorists seek to acquire which are proportional to the income level $y$ in the society, where $0 \leq y \leq 1$. The marginal benefits from terrorism are increasing both in $\beta$ and $y$, i.e., $\frac{\partial F}{\partial i} > 0 \ \forall i \in \{\beta, y\}$. The marginal benefits, however, increase at a decreasing rate with additional time invested in terrorism, i.e., $\frac{\partial^2 F}{\partial \beta^2} < 0$. For example, investing a larger fraction of your time in terrorism increases productivity but exhaustion also increases such that with each additional unit of time the gain is not as large as the earlier units. In contrast, as the bounty or rents grow, terrorists can increasingly take larger advantage of the resources by putting them to a variety of uses that help grow them multidimensional, from executing better and precise attacks more efficiently to investing in communications technology and propaganda that improve their appeal to potential recruits. The gain from an additional unit of income, thus, grows larger with an increase in income, i.e, $\frac{\partial^2 F}{\partial y^2} > 0$.

On the other hand, income levels in society also change the probability of apprehension of terrorists as the society can invest greater amounts in counter-terrorism operations as the income level goes up. Let $p$ be the probability of getting caught such that $p = p(\tau, y)$ where $\tau > 0$ denotes exogenous factors that change the productivity of investments in counter-terrorism.

[7] One can argue that as average income increases, the possibility of terrorists ditching counterterrorism also decreases. For example, they may employ means to frequently change locations or employ ways to avoid being tracked online or offline. This is a valid argument and one should see government's improvement in counter terrorism net of terrorist' improvement in avoiding counter-terrorism measures.

[8] Imagine $\beta$ as a fraction of work time only as the model does not consider leisure for the sake of simplicity.

For the sake of exposition, first, imagine $\tau > 1$ as a technology that improves the chances of apprehension by improving the surveillance and detection capabilities of security forces.[9] Conversely, $\tau$ may decrease the productivity of counter-terrorism funds, i.e., $0 < \tau < 1$, for example, when increasing incomes, say through foreign investments, introduce cultural shocks to society.

Finally, the formal labor market provides an alternative where the agent can earn wages, $G(y)$, which increase linearly with income with $\frac{\partial G}{\partial y} > 0$ and $\frac{\partial^2 G}{\partial y^2} = 0$.[10]

Formally, the agent has the following profit function they are trying to maximize.

$$\pi(\beta) \;=\; (1 - p(\tau, y))\; F(\beta, y) + \;(1 - \beta)G(y) \tag{1}$$

Next, I use simple functional forms for $p(.)$, $F(.)$, and $G(.)$ to explore how changing income level $y$ affects time devoted to terrorism $\beta$. Consider the following profit function.

$$\pi_i \;=\; (1 - \lambda\tau y)\; \beta^{\alpha} y^{\gamma} \;+\; (1 - \beta)ky \tag{2}$$

where $0 \le \lambda \le 1$ such that $0 \le \lambda\tau y \le 1$ shows the probability of apprehension of terrorists. $0 < \alpha < 1$ and $\gamma > 1$ in accordance with the first- and second-order conditions explained above and $k > 0$.[11] Maximization of profits along $\beta$ gives the optimal investment of $\beta$ as:

$$\beta^* \;=\left[\frac{\alpha y^{\gamma-1}(1 - \lambda\tau y)}{k}\right]^{\frac{1}{1-\alpha}} \tag{3}$$

Equation 3 shows that $\beta^*$ is naturally bound between 0 and 1 as $\alpha$, $\lambda\tau y$ and $y$ are fractions. Also, $\beta^* = 0$ if income level, $y$ is zero or if the probability of apprehension $\lambda\tau y$ is 1.

Now, coming to the impact of income on terrorism, let's find the income level, $y^*$ that

[9] Additionally, $\tau > 1$ can be thought of as the awareness in the society that decreases the odds of the society buying terrorists' propaganda decreasing support for their narrative, which, in turn, makes terrorists more vulnerable to being reported. With increasing income, such awareness may go up.

[10] Frey and Luechinger (2003) and Anderton and Carter (2006) introduce this opportunity cost by decreasing the cost of other (non-terrorist) activities in terrorists' problem and I also follow, in essence, a similar approach.

[11] There is a debate on whether increasing income levels, e.g., following increased productivity do translate into increasing wages (see, OECD, 2018, for example). On can argue that the size of $k$ will depend upon how wages respond to income levels in a society, where a general trend of the two is more relevant in the context of the present study.

maximizes terrorism. Comparative statics of $\beta^*$ along $y$ shows that:

$$y^* = \left(\frac{\gamma - 1}{\gamma}\right) \frac{1}{\lambda\tau} \tag{4}$$

The income that maximizes terrorism, $y^*$, decreases when $\lambda$ increases, as higher $\lambda$ inflates the probability of apprehension of terrorists. The case of $\tau$ is interesting. Figure 2 shows the relationship between income and terrorism in two cases: $(i)$ $0 < \tau < 1$, and $(ii)$ $\tau > 1$İf $0 < \tau < 1$, the income level associated with a maximum of terrorism is higher ($y_2^*$) than if $\tau > 1$ ($y_1^*$). This is important for any empirical analysis relating income to terrorism. If the unobservable, $\tau$, is a fraction, we expect an upward bias in the correlational estimates relating income to terrorism. In contrast, if $\tau > 1$, it will introduce a downward bias in the correlational estimates.

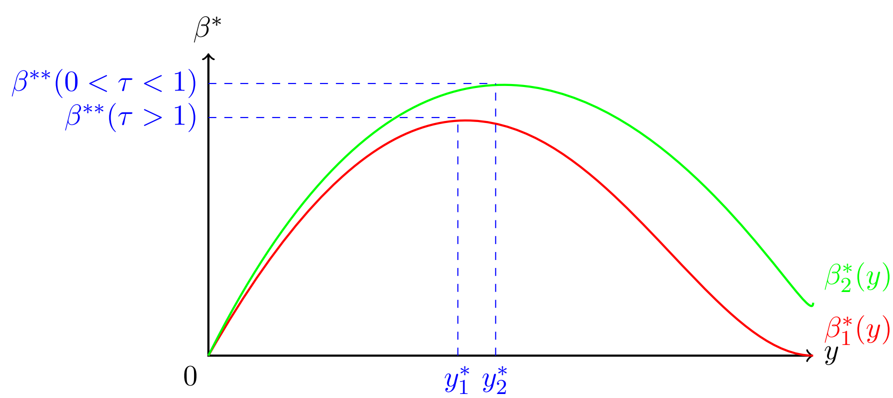



**Figure 2:** The impact of income level in society on the optimal fraction of time devoted to terrorism ($\beta^*$).

Overall, the theoretical formalization suggests that $(i)$ the relationship between income and terrorism is non-linear with increasing income causing an increase in terrorism at a decreasing rate, and $(ii)$ potential confounders complicate the observed relationship between income and terrorism by introducing bias in the estimated coefficient of interest, shifting the peak of the concave relationship. Next, I turn to measure the unbiased estimates of the impact of income on terrorism and test if the correlational estimates suffer from endogeneity, and if so, what is the direction of bias.

## 3 Empirical Strategy

Measuring the impact of income on terrorism is challenging owing to the issues of reverse causality and omitted variables. On one hand, GDP of a country may react to the level of terrorism (Gaibulloev and Sandler, 2008; Gaibulloev and Sandler, 2009) while on the other hand, a variety of socio-political changes in the country may influence both income and terrorism. Building further on the scenarios presented in section 2.2, I further explain how omitted variables can introduce bias in the observed relationship between income and terrorism. For example, consider the case of improvements in border security that can introduce downward bias in correlational estimates. On one hand, improved border security may lead to a decline in clandestine trade improving government revenues (Yürekli and Sayginsoy, 2010) while on the other hand, it may make it harder for terrorists to get arms and foreign funds (UNCCT, 2012). Similarly, investments in human capital may improve income levels in the country (Barro, 2001) while also enabling people to resist believing terrorists' propaganda (see Brockhoff et al., 2015 on the additional conditions mediating this impact). In another example, technological innovation may lead to increasing income levels in the country (David et al., 1975) while also enabling security forces to employ better surveillance, reducing terrorism (Vaseashta et al., 2012). The direction of bias may well be positive. For example, when foreign direct investment drives economic growth, local population may feel threatened by the negative environmental and socio-economic externalities increasing the incidence of violence (Mihalache-O'Keef, 2018). In order to correct the bias in the correlational estimates, I employ instrumental variable approach to arrive at the relationship between income and terrorism.

Let us begin by describing the relationship of interest in the equation below.

$$Terror\ attacks_{i,t+1,..,t+5} = \alpha_1\ Ln(GDP\ per\ capita)_{i,t} + \alpha_2\ Ln(GDP\ per\ capita)^2_{i,t} + X_{i,t}\,\Gamma + \gamma_i v_i + \delta_t w_t + \epsilon_{i,t} \quad (5)$$

The index $i$ in equation 5 refers to countries while $t$ denotes time periods. The data consists of a panel of 179 countries from 1990 to 2019. The main outcome is aggregated over a period of five years, i.e., the number of domestic terror attacks in the period $t+1$ to $t+5$ (see section 6.1 and Table A3 for various time frames). The endogenous variable of interest is $Ln(GDP\ per\ capita)_{i,t}$ measuring logged GDP per capita in country $i$ in year $t$ which enters in both linear and quadratic form to account for potential non-linearities (De la Calle and Sánchez-Cuenca, 2012; Jetter et al., 2021). $X_{i,t}$ is a vector of country-year controls based on the existing literature that will be motivated and discussed while presenting the results. $\gamma_i v_i$ denotes country fixed effects to control for time-invariant, country-specific features that determine the vulnerability of a country to violence. These may include geography and terrain (Collier and Hoeffler, 2004; Abadie, 2006), colonial background, historical cultural values (Jetter et al., 2022), and climatic factors (Burke et al., 2015), for example. $\delta_t w_t$ introduces year-fixed effects to account for changes in global factors that contribute to determining overall trends in terrorism over time. Examples include the periods of global recession (ans, 2020), changes in traditional and social media (Mahmood and Jetter, 2020), post-Cold War or 9/11 changes in global scenario (Li, 2005; Gaibulloev et al., 2017), to name a few. $\epsilon_{i,t}$ denotes the error term. Because the main outcome is measured as count data, I employ Poisson regression for estimating equation 5.

Because endogeneity can bias the coefficients of interest, $\alpha_1$ and $\alpha_2$, in equation 5, I instrument GDP per capita with the natural disaster shock in closely related countries to estimate the first stage. The migration matrix is used as a proxy for the proximity of a country with other countries. When a natural disaster hits a migrant-destination country, the migrant-source country may get affected by a number of channels operating through the migrants. Consider remittances as an example: An established body of literature suggests that remittances respond to host countries' macroeconomic conditions (Katseli and Glytsos, 1989; Higgins et al., 2004; Vargas-Silva and Huang, 2006). It is expected that natural disasters and its accompanying economic effect in the migrant destinations (Noy, 2009; Strobl, 2011; Loayza et al., 2012) will introduce variation in the flow of remittances which will introduce exogenous variation in income of the migrant-source country (Giuliano and Ruiz-Arranz, 2009; Yang, 2011). In addition, migrants in natural disaster hit areas are affected disproportionately more compared to local population owing to a host of factors that make them more vulnerable in the event of a disaster.

Bernales et al. (2019), for example, document how migrants in Chile emotionally suffer more than native Chileans during and after a disaster because of knowledge barriers and limits on coping abilities. Peacock et al. (1997) suggest that in the aftermath of Hurricane Andrew in the US, migrants were reluctant to approach rehabilitation workers for the fear of deportation. There have been episodes where public officials announced to check citizenship status of storm evacuees leading to deportation of illegal migrants (Brezosky, 2008; Donner and Rodríguez, 2008) making them more vulnerable to post-disaster economic and physical trauma. According to a report by UN migration, in the aftermath of crises migrant workers' income flow becomes susceptible to disruptions, adversely affecting their abilities to remit income to their families (UN-Migration, 2011). The disasters, thus, affect not only the migrants but also the countries where the migrants originate from (Guadagno, 2015).

Against this backdrop, I propose that natural disasters in countries of migrant destinations are sources of exogenous shocks to the local economy. In the present study, the scale of impact of natural disasters in migrant destinations on migrant source country is measured as a weighted average of disaster victims in the destination countries using the number of migrants to those countries as weights. This means that if a country A has a greater number of migrants in country B as compared to the number of her migrants in country C, then in the event of a disaster in B, A gets affected more than she would be if a similar event happened in C.[12] The main identifying assumptions in this framework are that $(i)$ the timing and extent of natural disasters in migrant destinations of a country are exogenous to income levels in the country, and $(ii)$ the countries affected by the natural disaster shock in their migrants destinations do not differentially get affected by shocks or trends in other determinants of terrorism.

Precisely, I estimate the following equation in the first stage.

$$Ln(GDP\ per\ capita)_{i,t} \ = \ \beta\ Natural\ disaster\ shock_{i,t} \ + \ X_{i,t}\,\Lambda \ + \ \pi_i v_i \ + \ \psi_t w_t \ + \ \phi_{i,t} \quad (6)$$

The variable $Natural\ disaster\ shock_{i,t}$ denotes the natural disaster shock in other countries

[12]A possible, and somewhat more intuitive, alternative is to use weighted GDP of closely related countries. However, this suffers from omitted variable bias as shocks to GDP in one country are less likely to be exogenous to GDP of another country and may be related in ways more complex than what a global trend would capture. Natural disasters, on the other hand, are not predictable exactly at the yearly level and present an exogenous shock to the local economy that can then have ramifications for other related countries.

impacting country $i$ through her migrants in those countries. Following Wooldridge (2015) and Lin and Wooldridge (2019), I calculate residual from least square estimation of equation 6 and plug it in equation 5 as a control function to get the bias-corrected estimates in equation 7.

$$Terror\ attacks_{i,t+1,..,t+5} = \alpha_1 * Ln(GDP\ per\ capita)_{i,t} + \alpha_2 * Ln(GDP\ per\ capita)^2_{i,t} + \hat{\phi} + X_{i,t}\,\Gamma * + \gamma *_i v_i + \delta *_t w_t + \epsilon *_{i,t} \quad (7)$$

where $\hat{\phi}$ is the residual estimated from equation 6 and $\alpha_1 *$ and $\alpha_2 *$ are the bias-corrected estimates measuring the impact of income on terrorism.

## 4 Data

The present study uses the number of terror attacks from the Global Terrorism Database (*GTD*; START, 2021) as the main dependent variable.[13] As I focus on domestic terrorism, I filter out the incidents involving any transnational element.[14] Alternative indicators, for example, deaths from terror attacks and terror attacks per capita, produce consistent results (see section 6.5).

The main explanatory variable, real GDP per capita, is calculated using the Penn World Table (*PWT* version 10.0; Feenstra et al., 2015) dividing the real GDP (at chained Purchasing Power Parity) of a country by its population. The results remain consistent while using an alternative measure of real GDP. Following the literature studying income and terrorism I used the logged GDP per capita as the main independent variable (see, for example, Enders and Hoover, 2012 and Enders et al., 2016) Table 1 presents the summary statistics and data sources for the main variables. It is worth noting that over the period of analysis, there are countries

[13]The *GTD* is considered the standard data source for terrorism in the relevant literature (see, for example, Gaibulloev and Sandler, 2011; Berrebi and Ostwald, 2013; Piazza, 2013; Krieger and Meierrieks, 2019 among many others). The *GTD* follows a rigorous methodology to filter information from more than a million daily publications of media articles across the globe to document information on terror attacks. Broadly, in order to be classified as a terror attack the incident *must* be intentional, involve actual or threatened use of violence, and be carried out by a non-state actor. Additionally, the *GTD* considers three criteria for inclusion: the incident (*i*) aims at achieving a social, political, religious, or economic goal, (*ii*) intends to coerce or convey a message to a broader audience, and (*iii*) does not classify as a legitimate act of warfare. The *GTD* documents which of these three additional criteria an incident satisfied to become eligible for inclusion in the database, and at least two out of the three must be met in order to call an incident a terror attack.

[14]Specifically, I exclude those incidents where $INT\_ANY = 1$ in the *GTD* (see START, 2021 for further explanation).This excludes 31 percent of total incidents listed in the *GTD* from our sample.

who have not experienced *any* attacks in the five-yearly period while there have been as many as 10 thousand attacks in other countries.

In order to construct the instrumental variable of natural disaster shock, I use data on natural

**Table 1:** Summary Statistics for main variables

| **Variable** | **N** | **Mean (Std. Dev.)** | **Min. (Max.)** | Description | **Source** |
|---|---|---|---|---|---|
| *Panel A: Dependent variables* | | | | | |
| Terror attacks$_{t+1,..,t+5}$ | 4,818 | 108.27 (609.18) | 0 (10,640) | # of domestic terror attacks in a country in $t+1,..,t+5$ | START (2021) |
| *Panel B: Income and control variables* | | | | | |
| Ln(GDP/capita)$_t$ | 5,163 | 9.10 (1.23) | 5.51 (12.62) | Logged real GDP per capita in $t$ | Feenstra et al. (2015) |
| Ln(Disaster shock)$_t$ | 6,420 | 7.45 (2.02) | 0 (12.94) | Standardized # of disaster victims in destination countries weighed by the # of migrants from the source country | Author's calculation using CRED (2021) & UN (2019) |
| Ln(Population)$_t$ | 5,163 | 1.77 (2.08) | -4.41 (7.27) | Logged population (in millions) | Feenstra et al. (2015) |

disaster victims from the International Disasters Database (*EM-DAT*; CRED, 2021). Following Cavallo et al. (2013), I standardize the measure of disaster by dividing the number of people affected by disasters in a country by the population of the country in the previous year. The natural disaster shock for a country is calculated by computing the weighted average of disaster victims in all the destination countries for the country's migrants, where stock of migrants from the source country are used as weights. I get information on the stock of migrants from a source country to various destination countries from the global bilateral migration data from the United Nations (UN, 2019). The data on bilateral migration are available at five-year intervals from 1990 to 2019. I, therefore, use the data on the stock of migrants for a data-year for that year and the subsequent four years. For example, the migration matrix for 1990 is used to calculate weights for the shocks from natural disasters from 1990 to 1994. Also note that although the *GTD* records events since 1970, the availability of migration matrix since 1990 limits our analysis to the period thereafter.

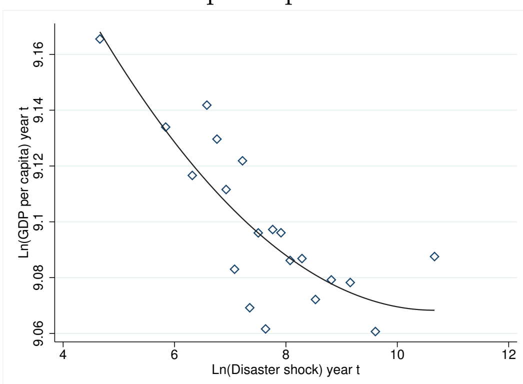
# 5 Instrument Relevance and Validity

The instrument in my analysis relies on the relationship between income of a country and natural disasters in the countries that are home to her migrants. I begin by simply plotting the relationships between the main variables of interest. Figure 3 shows the binscatterplot of the instrument - the natural disaster shock - with the GDP per capita of a country. The negative relationship highlights that as migrant-destinations of a country are hit by natural disasters, the GDP per capita of the country registers a decrease. Panel B of the figure explores the channel of remittances: Do remittances in migrant-source countries exhibit variation in response to disasters in the destination countries? Here again, the data exhibits a negative association: A higher level of natural disaster shock in migrant destinations in a year is associated with a lower level of remittances as a percentage of GDP in migrants' source countries.

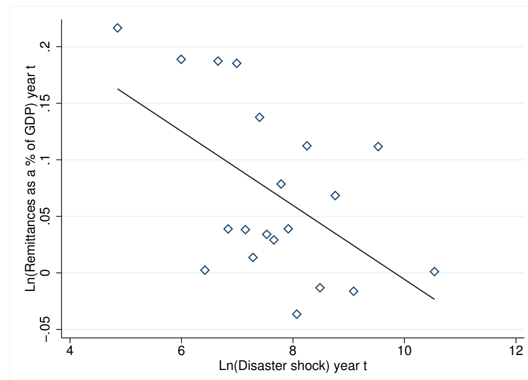
Panel C and D look at the reduced form relationships. The association between GDP per capita and domestic terror attacks appear positive but decreasing with increasing income (see Panel C). Additionally, the number of terror attacks exhibit a negative association between the instrument of natural disaster shock (Panel D). These correlation give us some confidence that the story motivating our instrument corroborates with the broad patterns observed in the data.

Table 2 shows the regression results predicting various variables of interest with the instrument of natural disaster shock. Column (1) reports a statistically significant negative association between natural disaster shock in migrant destinations of a country and GDP per capita of the country, with column (2) showing a similar relationship with inclusion of more control variables. In terms of magnitude, one standard deviation (2.15) increase in logged natural disaster shock decreases logged GDP per capita by 0.036 (2.15*0.017) units. Evaluating at mean (i.e. 9.08), this translates to a reduction of USD 2,479 in GDP per capita ($e^{9.08} - e^{9.08-9.08*0.036}$) when the natural disaster shock increases by one standard deviation. Column (3) tests the channel of remittances: Increased natural disaster shock in destination countries is associated with lower level of remittances as a percentage of GDP in source countries. The reduced form relationship between the number of domestic terror attacks of a country in period $t+1$ to $t+5$ with the natural disaster shock is shown in column (4) while column (5) shows a statistically insignificant result when the disaster shock is used to predict terror attacks in the past five years. Lastly, for testing whether migrant shares depend on past terrorism levels in the country, I regress the

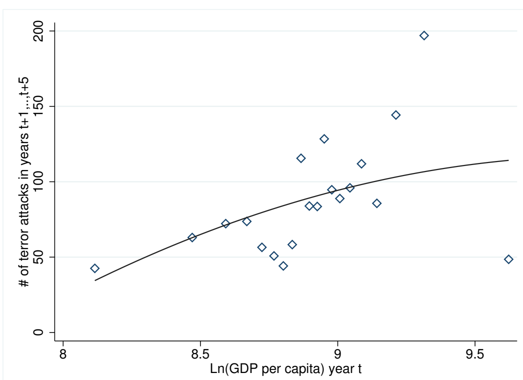
Panel A: Disaster victims in destination countries and GDP per capita in source countries




Panel B: Disaster victims in destination countries and remittances in source countries




Panel C: GDP per capita and domestic terror attacks in source countries




Panel D: Disaster victims in destination countries and domestic terror attacks in source countries

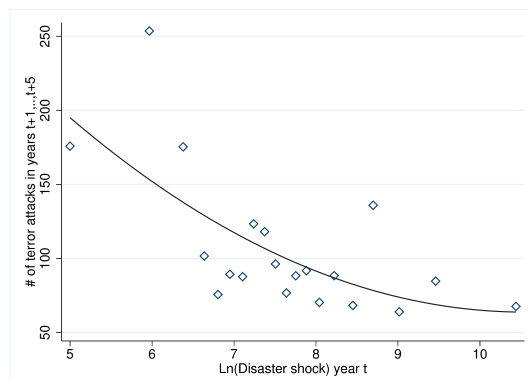



**Figure 3:** Binned scatterplots showing the association between the natural disaster shock, remittances as a percentage of GDP, GDP per capita, and domestic terror attacks. All plots control for country- and year-fixed effects,logged population, and a time trend.

instrument in the first available year, i.e., 1990 on the number of terror attacks in the previous five years. Column (6) shows that there is no meaningful statistical or economic association between the two, lending support to the independence of the disaster shock from past terror attacks.

**Table 2:** OLS Regressions exploring the association of the natural disaster shock with various indicators in source countries.

| *Dependent variable:* | Ln(GDP per capita)$_t$ | Ln(GDP per capita)$_t$ | Ln(Remit./ GDP)$_t$ | Terror attacks $t+1,..t+5$ | Terror attacks $t-1,..t-5$ | Ln(Disaster shock)$_t$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(Disaster shock)$_t$ | -0.015*** | -0.017*** | -0.035** | -23.457* | -3.501 | |
| | (0.0048) | (0.0042) | (0.0161) | (13.8952) | (3.1751) | |
| Terror attacks$_{t-1,...t-5}$ | | | | | | 0.000 |
| | | | | | | (0.0003) |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Year-FE | | ✓ | ✓ | ✓ | ✓ | |
| Ln(Population)$_t$ | | ✓ | ✓ | ✓ | ✓ | |
| $N$ | 5,163 | 5,163 | 4,305 | 3,916 | 4,278 | 177 |

*Notes:* Standard errors clustered at country level are displayed in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Although two-stage least squares (2SLS) estimation is not well-suited to the problem at hand, owing both to the non-negative count data for the outcome variable as well as using one instrument to study a non-linear endogenous variable, I present results from 2SLS in Table A1 in order to report the well-established measures of validity of the first stage (see Panel C). These results, of course, look only at the linear relationship between GDP per capita and number of terror attacks, showing in Column (3) that the placebo regression of GDP per capita on past terrorism gives null results.

Finally, Table A2 shows correlations of the instrumental variable with the other potential determinants of terrorism derived from the relevant literature.[15] Polity2 measuring the level of democracy in a country has a correlation coefficient of -0.048 while executive constraints

[15]See Li (2005), Piazza (2008), Chenoweth (2013), Wilson and Piazza (2013), and Gaibulloev et al. (2017) for the impact of political systems and regime characteristics on terrorism. Mahmood and Jetter (2020) show that information flows in a society explain the level of terrorism. De Mesquita (2005) proposes that individuals with low levels of educational attainment volunteer for terrorism but terrorist organizations screen recruits for quality complicating the role of education in terrorism. I, therefore, show correlations of the instrument both with educational attainment as well as unemployment. Lastly, I show correlations for population size (Li, 2005), income inequality (Krieger and Meierrieks, 2019), and infant mortality rate as an indicator of deprivation (Bandyopadhyay and Younas, 2011).

display a correlation of -0.0517. Information flows as measured by the KOF index exhibit a negative correlation of 0.1818 while the correlation coefficients for employment, education, infant mortality rates , and population size are 0.0366, -0.2381, 0.1567, and 0.0811, respectively. Lastly and importantly, because natural disasters in a country can also influence terrorism in the country (Masera and Yousaf, 2017), I report the correlation between the instrument of disaster shock with local natural disasters and the coefficient is 0.1799. These statistics lend support to the assumption that the instrumental variable is largely unassociated with the trends in the other determinants of terrorism.

# 6 Empirical Findings

## 6.1 Main Results

I begin by running Poisson regressions predicting terror attacks in the next five years without correcting for endogeneity and Table 3 columns (1)-(3) reports the estimated coefficients. Column (1) considers only linear relationship between GDP per capita and number of domestic terror attacks and the obtained coefficient points to a positive association. Column (2) adds the squared logged GDP per capita and finds a statistically significant inverted-U shaped relationship that persists with inclusion of additional controls in column (3). Columns (4) to (6) present corresponding results from the Two-stage Poisson regressions. Panel B shows that the first stage coefficient is negative and statistically significant at one percent in all the three specifications suggesting the natural disaster shock decreases GDP per capita. Also, as shown in Panel A coefficients of the residual from the first stage are statistically significant in all specifications confirming that GDP per capita is endogenous in this setting (Wooldridge, 2015; Lin and Wooldridge, 2019). Once corrected for bias, the coefficients of GDP per capita suggest that as GDP per capita of a country increases, the number of domestic terror attacks in the next five years increases but at a decreasing rate, hinting again at the possibility of an inverted-U shaped relationship between income and terrorism. Table A3 shows that considering the next five years is not crucial for the obtained relationship. Precisely, the relationship holds for varying periods in lead (columns 6-10) but not in lags (columns 1-5) of the outcome variable.

The bias-corrected estimates reveal an interesting insight. Figure 4 visualizes the estimates

**Table 3:** Poisson regressions predicting domestic terror attacks$_{t+1,...t+5}$ with income.

| *Estimation:* | *Poisson* | | | *Two-Stage Poisson* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Dependent variable: Terror attacks$_{t+1,..,t+5}$* | | | | | | |
| Ln(GDP/capita)$_t$ | 1.787$^{***}$ | 8.254$^{***}$ | 5.674$^{***}$ | 5.083$^{***}$ | 11.931$^{***}$ | 12.373$^{***}$ |
| | (0.1979) | (2.7760) | (1.3371) | (1.1971) | (1.5394) | (2.7849) |
| Ln(GDP/capita)$^2_t$ | | -0.368$^{**}$ | -0.308$^{***}$ | | -0.381$^{***}$ | -0.317$^{***}$ |
| | | (0.1513) | (0.0729) | | (0.0663) | (0.0517) |
| Residual from the first stage | | | | -3.374$^{***}$ | -3.545$^{***}$ | -6.525$^{**}$ |
| | | | | (1.2063) | (1.1534) | (2.5978) |
| Country-FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Ln(Population)$_t$ | | | ✓ | | | ✓ |
| Year-FE & Time trend | | | ✓ | | | ✓ |
| *Panel B: First stage results with dependent variable Ln(GDP per capita)$_t$* | | | | | | |
| Ln(Disaster shock)$_t$ | | | | -0.0308$^{***}$ | -0.0308$^{***}$ | -0.0150$^{***}$ |
| | | | | 0 .0055 | 0 .0055 | 0.0037 |
| Country-FE | | | | ✓ | ✓ | ✓ |
| Ln(Population)$_t$ | | | | | | ✓ |
| Year-FE & Time trend | | | | | | ✓ |
| GDP/capita at the maximum | | 74,211 | 10,311 | | 6,055,588 | 289,945,808 |
| *N* | 3,588 | 3,588 | 3,588 | 3,588 | 3,588 | 3,588 |

*Notes:* Robust standard errors clustered on country level are displayed in parentheses for columns (1)-(3) in Panel A and columns (4)-(6) in Panel B. In columns (4)-(6) in Panel A, bootstrapped standard errors with 100 replications based on clustering on country are reported in parenthesis. $^*$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

obtained from the simple Poisson regression (column 3) in Panel A and those obtained from the two-stage Poisson regression (column 6) in Panel B. Once corrected for endogeneity, an increase in GDP per capita decreases marginal terrorism at a lower rate as compared to the biased estimates. To put the results in context, I select the domain on the x-axis of both the panels in Figure 4 up to the miximum logged GDP per capita observed in the sample. While the non-linear relationship between GDP per capita and terrorism achieves a peak in Panel A, after which further increase in GDP per capita decreases terrorism, Panel B shows a much steeper slope with no declining trends in terrorism within the observable range of income. The penultimate row in Table 3 reporting GDP per capita at the peak of terrorism also points towards similar findings.

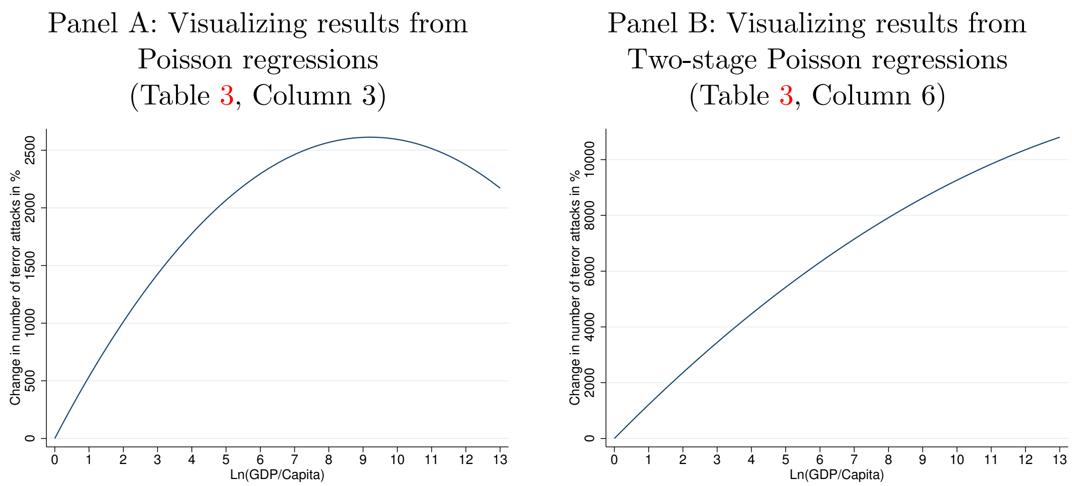



**Figure 4:** Visualizing regression results from Table 3.

### 6.2 Analyzing potential threats to the identification

This section addresses various threats to identification that can potentially bias the estimates presented in Table 2. I begin with the possible sources of omitted variable bias threatening identification in Columns (1)-(5) in Table 3. Column (1) in Table 4 presents results from including standard additional controls starting with regime characteristics (see, for example, Li (2005); Piazza (2008); Chenoweth (2013); Wilson and Piazza (2013); and Gaibulloev et al. (2017)) as captured in *polity2*, regime durability, and executive constraints from the Polity IV dataset (Marshall and Gurr, 2020), and mortality rates (Bank, 2022) as an indicator of deprivation

(Bandyopadhyay and Younas, 2011). This is important because if income changes induced by natural disasters bring in regime changes, the second-stage estimates will be capturing something more than just an income effect. Additionally, as a country's level of income inequality can relate to the level of grievances (Krieger and Meierrieks, 2019)) and may introduce bias in the estimated effect of income on terrorism, Column (2) presents results while controlling for income inequality. The sample size is reduced in this estimation but the non-linear relationship between income and terrorism remains consistent.[16] Panel B of Table 4 shows that throughout the various specifications, the first stage estimates remain statistically significant, highlighting the validity of the IV. Further, the coefficients of the residual from the first stage are statistically significant in all specifications confirming that simple correlations would produce biased coefficients (Wooldridge, 2015; Lin and Wooldridge, 2019). Column (3) controls for disaster in the source countries: If natural disasters are correlated across the migrant source and destination countries, this kicks in channels other than income in affecting terrorism (see, for example, Masera and Yousaf, 2017 on the potential impact of natural disaster on terrorism). The results, however, remain consistent to inclusion of this control.[17] Column (4) controls for employment levels in the source country because if migrant destination countries are effected by natural disasters, this may induce out-migration from those countries, increasing unemployment in the source countries. Next, column (5) addresses the concern that there may be a persisting trend in terror attacks in certain periods beyond what is captured in a linear time trend, by controlling for terror attacks in the last five years. The results remain consistent throughout these specifications.

Next, I turn to the exogeneity of migrant shares. It is possible that the shares of migrants to various destinations is endogenous to terror attacks which will then violate the exogeneity of the instrumental variable - the natural disaster shock. In the main analysis, the migration matrix is updated every five years which means the instrument created from those matrices can not be influenced by changes in migrant shares for the next five years in which the outcome

[16] Inclusion of KOF index of information flows breaks down the first stage probably because of the very high correlation between KOF index and our indicator of income levels (correlation coefficient=0.802) not leaving a lot of variation to be explained by the instrument.

[17] The coefficient of logged number of disaster victims in a country is not only statistically insignificant (p-value¡ 0.10)in predicting the number of terror attacks in the next five years but is also not sizable in magnitude (coefficient=0.0002).

**Table 4:** Predicting domestic terror attacks$_{t+1,...t+5}$ with the Two-Stage Poisson regressions including additional control variables and alternative specifications.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: Dependent variable: Terror attacks$_{t+1,..,t+5}$* | | | | | | |
| Ln(GDP/capita)$_t$ | 17.207$^{***}$ | 14.904$^{***}$ | 19.122$^{***}$ | 17.222$^{***}$ | 13.110$^{***}$ | 14.780$^{***}$ |
| | (3.060) | (3.542) | (3.486) | (3.224) | (2.636) | (3.452) |
| Ln(GDP/capita)$_t^2$ | -0.459$^{***}$ | -0.519$^{***}$ | -0.537$^{***}$ | -0.395$^{***}$ | -0.443$^{***}$ | -0.447$^{***}$ |
| | (0.064) | (0.083) | (0.070) | (0.063) | (0.077) | (0.069) |
| Residual from the | -8.397$^{***}$ | -5.500$^{*}$ | -8.929$^{***}$ | -9.579$^{***}$ | -4.722$^{**}$ | -6.099$^{*}$ |
| | (2.706) | (3.332) | (3.404) | (2.872) | (2.353) | (3.161) |
| Control set A$^a$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control set B$^b$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Income inequality$_t$ | | ✓ | | | | |
| Ln(Disaster victims in source countries)$_t$ | | | ✓ | | | |
| Employment levels in source countries(%)$_t$ | | | | ✓ | | |
| Terror attacks$_t - 1, ..., t - 5$ | | | | | ✓ | |
| *Panel B: First stage results with dependent variable Ln(GDP per capita)$_t$* | | | | | | |
| Ln(Disaster shock)$_t$ | -0.0099$^{**}$ | -0.0140$^{*}$ | -0.0096$^{***}$ | -0.0089$^{**}$ | -0.0115$^{***}$ | |
| | (0.0049) | (0.0037) | (0.0050) | (0.0048) | (0.0045) | |
| Ln(Disaster shock)$_t$ fixing migrant shares at 1990 | | | | | | -0.0116$^{**}$ |
| | | | | | | (0.0045) |
| Control set A$^a$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control set B$^b$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Income inequality$_t$ | | ✓ | | | | |
| Ln(Disaster victims in source countries)$_t$ | | | ✓ | | | |
| Employment levels in source countries(%)$_t$ | | | | ✓ | | |
| Terror attacks$_t - 1, ..., t - 5$ | | | | | ✓ | |
| *N* | 3,222 | 2,890 | 3,162 | 3,222 | 2,529 | 3,199 |

*Notes:* Bootstrapped standard errors with 100 replications based on clustering on country are reported in parenthesis. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. $^a$Control set A includes country- and year-fixed effects, logged population, and a time trend. $^b$Control set B includes polity2, regime durability, executive constraints, and mortality rates.

is measured, preventing the shares to respond endogenously to terrorism. Nonetheless, as an additional constraint I restrict migrant shares at their level in 1990 to calculate disaster shock for all of the subsequent years in the analysis. Column (6) presents results from that stricter specification with migrant shares fixed at 1990 levels showing that the results remain consistent.

### 6.3 Recentering the instrument

This section addresses the concern that predetermined migration shares may introduce bias in the instrument despite the timing of natural disasters being random across various countries (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Following the solution proposed in Borusyak and Hull (2020), I recenter the instrument by calculating expected disaster shock and subtracting it from the realized shock. To be precise, I predict disaster victims by using the estimates obtained by regressing disaster victims on their ten lags. This specification explains a significant variation across countries (R-square = 0.963). Next, I calculate counterfactual expected instrument using the given shares of migrants. Removal of this expected instrument from the actual instrument produces the recentered instrument that corrects for any potential omitted variable bias arising out of potential endogeneity of predetermined shares (Borusyak and Hull, 2020). Column (1) in Table 5 shows that the main results remain consistent with using recentered instrument. This further alleviates concerns about the omitted variable bias arising from predetermined migrant shares.

### 6.4 Falsification tests

In order to further build confidence in the validity of the instrument, this section presents two sets of falsification tests in the spirit of Goldsmith-Pinkham et al. (2020). First, I recalculate the instrument by considering natural disasters in countries other than migrant destinations. If migration trends are a valid indicator of the dependence of, say Country A on Country B, then in the event of a natural disaster in Country B, the GDP of Country A will not be affected if the number of migrants from A to B are zero. Column (2) in Table 5 confirms this: there is no statistically significant association between GDP per capita of a country and natural disasters in countries where none of her migrants are situated. Column (3) further looks at the reduced form relationship of the placebo instrument with terror attacks in the country and does not find

**Table 5:** Estimates for recentered instrument, placebo instrument, and placebo outcome.

| | Terror attacks (t+1,..,t+5) | Ln(GDP/Capita)$_t$ | Terror attacks (t+1,..,t+5) | Ln(GDP/Capita)$^c_{t-2}$ | Terror attacks (t-1,..,t-5) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Reduced form and second-stage results* | | | | | |
| Ln(GDP/capita)$_t$ | 17.766$^{***}$ | | | | 6.355 |
| | (3.1744) | | | | (4.4757) |
| Ln(GDP/capita)$^2_t$ | -0.458$^{***}$ | | | | -0.158 |
| | (0.0586) | | | | (0.1130) |
| Ln(Disaster shock in destinations without migrants)$_t$ | | 0.047 | -30.003 | | |
| | | (0.0360) | (44.4107) | | |
| Ln(Disaster shock)$_t$ | | | | -0.005 | |
| | | | | (0.0039) | |
| Residual from the first stage | -8.966$^{***}$ | | | | -3.612 |
| | (3.2254) | | | | (4.3959) |
| Control set A$^a$ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control set B$^b$ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Panel B: First stage results with dependent variable Ln(GDP per capita)$_t$* | | | | | |
| Recentered instrument | -0.009$^{*}$ | | | | |
| | (0.0051) | | | | |
| Ln(Disaster shock)$_t$ | | | | | -0.0099$^{**}$ |
| | | | | | (0.0050) |
| Control set A$^a$ | ✓ | ✓ | ✓ | ✓ | |
| Control set B$^b$ | ✓ | ✓ | ✓ | ✓ | |
| $N$ | 3,216 | 4,131 | 3,273 | 4,273 | 3,410 |

*Notes:* Bootstrapped standard errors with 100 replications based on clustering on country are reported in parenthesis. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. $^a$Control set A includes country- and year-fixed effects, logged population, and a time trend. $^b$Control set B includes polity2, regime durability, executive constraints, and mortality rates. $^c$Second lag of GDP per capita is considered to avoid overlap between the calender year and fiscal year.

any statistically significant association between the two.

Further, in order to show that the association between the natural disaster shock in migrant destinations and GDP of a country is not spuriously driven by some trend, I present the first stage results predicting past GDP per capita with the instrument. Column (4) shows no statistically significant association between the two. Column (5) presents Two-stage Poisson estimates predicting past terrorism with the instrument of natural disaster showing an absence of statistically meaningful relationship in the second stage. Altogether Tables 4 and 5 lend support to the identification strategy.

### 6.5 Alternative outcomes, endogenous variables and instruments

I next turn to additional robustness checks in order to check the consistency of estimates against alternative specifications and instruments. Columns (1) and (2) of Table 6 show results for alternative measures of terrorism namely the number of people killed in terror attacks and the number of victims in terror attacks. Column (3) shows results for real GDP per capita measured in current PPP instead of constant PPP while column (4) presents estimates for expenditure-side real GDP per capita. The results show that the findings are consistent with alternative definitions of GDP per capita.

Next, I present results from two different specifications of the instrumental variable. Column (5) accounts for the possibility that natural disaster in migrant destinations of a country affect income of the source country with a lag. In column (6), I use the natural disaster shock where the number of disaster victims are not adjusted for the size of population in the disaster-hit country. Panel B shows that the first stage results are not sensitive to these alternative specifications of the instrument and still produce strong association between the disaster shock in migrant destinations of a country and her GDP per capita. Considering overall, all these robustness checks strengthen my confidence in the obtained estimates allaying concerns about alternative channels and specific definitions driving the main results.

**Table 6:** Predicting domestic terror attacks$_{t+1,...t+5}$ with the Two-Stage Poisson regressions with alternative outcomes, endogenous variables, and instruments.

| | Killed in attacks$_{t+1,..,t+5}$ | Victims of attacks$_{t+1,..,t+5}$ | Terror attacks$_{t+1,..,t+5}$ | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Second-stage results* | | | | | | |
| Ln(GDP/capita)$_t$ | 18.086$^{***}$ | 16.316$^{***}$ | | | 15.957$^{***}$ | 14.100$^{***}$ |
| | (4.166) | (4.109) | | | (2.852) | (2.279) |
| Ln(GDP/capita)$^2_t$ | -0.560$^{***}$ | -0.430$^{***}$ | | | -0.448$^{***}$ | -0.453$^{***}$ |
| | (0.106) | (0.099) | | | (0.065) | (0.067) |
| Ln(GDP/capita)$_t$ Current PPP | | | 16.623$^{***}$ | | | |
| | | | (2.947) | | | |
| Ln(GDP/capita)$^2_t$ Current PPP | | | -0.458$^{***}$ | | | |
| | | | (0.066) | | | |
| Ln(GDP/capita)$_t$ Expenditure-side | | | | 12.582$^{***}$ | | |
| | | | | (3.503) | | |
| Ln(GDP/capita)$^2_t$ Expenditure-side | | | | -0.203$^{***}$ | | |
| | | | | (0.043) | | |
| Residual from the | -7.344$^{*}$ | -7.909$^{**}$ | -7.722$^{***}$ | -8.276$^{**}$ | -7.315$^{***}$ | -5.394$^{***}$ |
| | (3.867) | (3.680) | (2.611) | (3.378) | (2.502) | (1.784) |
| Control set A[a] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control set B[b] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Panel B: First stage results with dependent variable Ln(GDP per capita)$_t$* | | | | | | |
| Ln(Disaster shock)$_t$ | -0.0099$^{**}$ | -0.0099$^{**}$ | -0.0104$^{**}$ | -0.0083$^{*}$ | | |
| | (0.0050) | (0.0050) | (0.0050) | (0.0049) | | |
| Ln(Disaster shock)$_{t-1}$ | | | | | -0.0105$^{**}$ | |
| | | | | | (0.0053) | |
| Ln(Disaster shock -Non-standardized)$_t$ | | | | | | -0.0164$^{***}$ |
| | | | | | | (0.0050) |
| Control set A[a] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control set B[b] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *N* | 2,960 | 3,153 | 3,222 | 3,222 | 3,222 | 3,199 |

*Notes:* Bootstrapped standard errors with 100 replications based on clustering on country are reported in parenthesis. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. [a]Control set A includes country- and year-fixed effects, logged population, and a time trend. [b]Control set B includes polity2, regime durability, executive constraints, and mortality rates.

# 7 Conclusion

The alleged relationship between income and terrorism has been shaping global policies both around counter-terrorism and poverty alleviation at least since 9/11, but the true impact of income on terrorism is still debated. The present study formalizes the various potential channels through which income affects terrorism by considering the potential terrorists' decision making problem. Next, it employs exogenous variation in income stemming from natural disasters in closely related countries in terms of migrants, to study the relationship between income and domestic terrorism. Using data from 179 countries for around three decades, the study finds that domestic terrorism increases with income at a decreasing rate. However, unbiased estimates suggest that the peak in terrorism is nowhere seen in the observed sample of incomes suggesting a weaker downward pull of increasing income on terrorism.

Although the estimates measure a local average treatment effect (LATE), nonetheless the results suggest policymakers may observe caution in considering poverty alleviation as a panacea for terrorism. Instead of using poverty alleviation *as a* counter-terrorism strategy, they may consider using counter-terrorism strategies with poverty alleviation in order to address the heightened risk of terrorism.

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# A Appendix

## A.1 Appendix for instrument validity

**Table A1:** Results from the 2SLS regressions predicting terror attacks with GDP per capita.

| *Dependent variable:* | Terror attacks $t{+}1,..t{+}5$ | Terror attacks $t{+}1,..t{+}5$ | Terror attacks $t{-}1,..t{-}5$ |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Panel A: Second stage results* | | | |
| Ln(GDP/capita)$_t$ | 667.824*** | 1745.841*** | 296.432 |
| | (215.1881) | (651.3728) | (261.7553) |
| Country FE | ✓ | ✓ | ✓ |
| Ln(Population)$_t$ | | ✓ | ✓ |
| Year-FE & Time trend | | ✓ | ✓ |
| *Panel B: First stage results with dependent variable: Ln(GDP/capita)$_t$* | | | |
| Ln(Disaster shock)$_t$ in destination countries)$_t$ | -0.0276*** | -0.0132*** | -0.0173*** |
| | (0.0043) | (0.0041) | (0.0041) |
| Country FE | ✓ | ✓ | ✓ |
| Ln(Population)$_t$ | | ✓ | ✓ |
| Year-FE & Time trend | | ✓ | ✓ |
| *Panel C: IV Regression test statistics* | | | |
| F-Stat | 42.127*** | 12.836*** | 17.266*** |
| Underidentification test (LM-stat) | 41.892*** | 12.821*** | 16.999*** |
| Endogeneity test | 4.824** | 11.564*** | 0.808 |
| *N* | 4,093 | 4,093 | 4,455 |

*Notes:* Standard errors robust to heteroscedasticity are displayed in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table A2:** Country-level correlations between the natural disaster shock (the IV) and the other determinants of terrorism

| **Variable** | **Correlation with the natural disaster shock** |
| --- | --- |
| Polity2 | -0.0482 |
| Regime durability | 0.0072 |
| Executive constraints | -0.0517 |
| KOF index of information flows | -0.1818 |
| Number of people employed as a proportion of population | 0.0366 |
| Educational attainment (at least lower secondary) | -0.2381 |
| Population size | 0.0811 |
| Infant mortality rate | 0.1567 |
| Income inequality | 0.207 |
| Ln(Local disaster victims) | 0.1799 |

*Notes:* Pairwise correlation coefficients between the natural disaster shock in the migrant destinations of a country with the correlates of terrorism in the country are displayed in the table.

## B Changing Time frame

**Table A3:** Regression results considering various time frames for the outcome variable.

| *Dependent variable:* | Terror attacks | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (t-1,..,t-10) | (t-1,..,t-8) | (t-1,..,t-6) | (t-1,..,t-4) | (t-1,..,t-2) | (t+1,..,t+2) | (t+1,..,t+4) | (t+1,..,t+6) | (t+1,..,t+8) | (t+1,..,t+10) |
| *Panel A: Second stage results* | | | | | | | | | | |
| Ln(GDP/capita)$_t$ | 2.430 | 2.908 | 5.992 | 7.804 | 8.547 | 13.901 | 19.175*** | 13.273*** | 9.364*** | 6.462*** |
| | (22.287) | (10.649) | (5.583) | (12.958) | (6.997) | (10.238) | (3.750) | (2.743) | (1.494) | (1.822) |
| Ln(GDP/capita)$^2_t$ | 0.036 | 0.022 | -0.002 | -0.027 | -0.053 | -0.175*** | -0.260*** | -0.360*** | -0.350*** | -0.307*** |
| | (0.094) | (0.110) | (0.109) | (0.075) | (0.072) | (0.065) | (0.051) | (0.045) | (0.045) | (0.057) |
| Residual from the first stage | -3.098 | -3.230 | -5.901 | -7.285 | -7.554 | -10.672 | -14.276*** | -6.742** | -3.008** | -0.837 |
| | (22.435) | (10.700) | (5.776) | (12.932) | (6.806) | (9.967) | (3.489) | (2.623) | (1.208) | (1.573) |
| Controls[a] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Panel B: First stage results with dependent variable: Ln(GDP/capita)$_t$* | | | | | | | | | | |
| Ln(Disaster shock)$_t$ | -0.0123*** | -0.0123*** | -0.0123*** | -0.0123*** | -0.0123*** | -0.0123*** | -0.0123*** | -0.0123*** | -0.0123*** | -0.0123*** |
| | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) |
| Controls[a] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *N* | 3,260 | 3,542 | 3,864 | 4,186 | 4,508 | 4,320 | 3,744 | 3,432 | 3,120 | 2,808 |

*Notes:* Bootstrapped standard errors with 50 replications based on clustering on country are reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Controls include country- and year-fixed effects, logged population, and a time trend. Period for the first lag is selected to avoid the overlap between the calendar and the fiscal year.