

TERRORISM FINANCING, RECRUITMENT, AND ATTACKS

NICOLA LIMODIO

Department of Finance, BAFFI CAREFIN and IGIER, Bocconi University and CEPR

This paper investigates the effect of terrorism financing and recruitment on attacks. I exploit a Sharia-compliant institution in Pakistan, which induces unintended and quasi-experimental variation in the funding of terrorist groups through their religious affiliation. The results indicate that higher terrorism financing, in a given location and period, generate more attacks in the same location and period. Financing exhibits a complementarity in producing attacks with terrorist recruitment, measured through data from Jihadist-friendly online fora and machine learning. A higher supply of terror is responsible for the increase in attacks and is identified by studying groups with different affiliations operating in multiple cities. These findings are consistent with terrorist organizations facing financial frictions to their internal capital market.

KEYWORDS: Terrorism, finance, National Security.

1. INTRODUCTION

THIS PAPER INVESTIGATES THE ROLE OF TERRORISM financing and recruitment in promoting terrorist attacks. A critical question grounded in economic theory is central to this research: does the timing and location of terrorism financing affect the timing and location of terrorist attacks? The answer is negative if terrorist organizations can costlessly store or transfer funds. However, if there are financial frictions to their internal capital market (e.g., cost of moving funds over time and across locations), they may deploy local attacks. Consequently, a correlation can emerge between the timing and location of financing and attacks and, therefore, the availability of recruits can be a central source of heterogeneity in the local conditions affecting an attack's success.

The empirical identification of the financial frictions of terrorists is challenging because it requires changes in the funding available to these groups that are exogenous to their conditions. As a result, it is necessary to detect a source of quasi-experimental variation affecting the supply of terrorist attacks due to extremist organizations, without influencing the local economy through the demand of terrorist attacks (e.g., changes in policing, radicalization). To address this, I combine a natural experiment produced by a Sharia-compliant institution in Pakistan with a novel method to isolate the supply of attacks. This quasi-experimental variation affects a specific form of terrorism financing—charitable donations—and treats terrorist groups heterogeneously through its institutional design. To dissect the demand and supply of terrorist attacks, I follow multiple terrorist groups

Nicola Limodio: nicola.limodio@unibocconi.it

I would like to express my gratitude for their useful suggestions to the Editor, Alessandro Lizzeri, four anonymous referees and Matteo Benetton, Eli Berman, Ethan Bueno de Mesquita, Mirko Draca, Oeindrila Dube, Ruben Durante, Thiemo Fetzer, Alessandro Gavazza, Hani Mansour, Gerard Padró i Miquel, Daniele Paserman, Jacopo Perego, Nicola Persico, Pablo Querubín, Shanker Satyanath, Jacob N. Shapiro, Maria Micaela Sviatschi, Mathias Thoenig, Juan Vargas, Alessandra Voena, Eric Weese, Austin Wright, Luigi Zingales and seminar participants at several conferences, seminars, and workshops. I thank Matthew S. Gerber, the AI Lab at the University of Arizona for data and support. Serena De Lorenzi, Daniele Goffi, Federico Lenzi, Edoardo Marchesi, and Lorenzo Schirato provided excellent research assistance and Antonn Park offered useful editorial service. I am grateful for the financial support of Bocconi University, EIEF, the PEDL/CEPR initiative, and the Stigler Center at the University of Chicago, Booth School of Business. I am responsible for all errors.

© 2022 The Author. *Econometrica* published by John Wiley & Sons Ltd on behalf of The Econometric Society. Nicola Limodio is the corresponding author on this paper. This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial-NoDerivs](https://creativecommons.org/licenses/by-nc-nd/4.0/) License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

operating in various cities over time. As a result, I study the variation occurring within a group and within a city, and how terrorist groups exposed to this financing react relative to unexposed groups in the same city and time. This setting advances the work of [Dube and Vargas \(2013\)](#), offering a novel method to isolate the effect of shocks on violent groups and conflict.

I study two aspects of the relationship between terrorism financing and attacks: (1) the correlation between the timing of financing and attacks; (2) the relation between financing and recruitment in generating attacks. To investigate the first point, I follow 1750 cities over 588 months between 1970 and 2018 containing the universe of terrorist attacks (e.g., more than 14,000 events). I also build a panel with 29 terrorist groups operating in the same number of cities and the same period. To study the second point, I combine data from multiple online fora active in Pakistan disseminating Jihadist-friendly material with the work of two judges and a machine-learning algorithm, leveraging novel techniques from the computer science literature.

The natural experiment affects a specific form of charitable donation and terrorism financing through an Islamic institution: the Zakat. During Ramadan, Muslim individuals offer this Sharia-compliant contribution to philanthropic causes. While the amount is a personal choice, the Pakistani government collects a mandatory payment through a levy on bank deposits applied immediately before Ramadan.¹ When the tax hits fewer people due to its unique design, there is an increase in donations. This expansion in charitable donations boosts the probability that funds reach terrorist organizations due to multiple extremist groups having a legal charity branch.² This unintended channel through which the design of the Zakat levy promotes terrorism financing has also been acknowledged by Pakistani government officials in the past.³

Three features of the Zakat levy induce a quasi-experimental variation in charitable donations and terrorism financing. First, there exists a deposit threshold, which generates a notch. Individuals with fewer deposits than the announced threshold enjoy a zero levy, while those above the threshold pay 2.5% on the overall deposited amount. Second, the deposit threshold corresponds to the monetary value of 612.32 grams of silver and is announced only a couple of days before the collection. As a result, the threshold increases when silver prices are high; hence, some individuals escape the 2.5% notch, are no longer taxed, and offer more charitable donations. Third, another institutional characteristic of the Zakat levy generates cross-sectional variation in the effect of silver prices: religious affiliation. Pakistan is a Sunni Islamic Republic, with the Sunni school of Islam being closer to the religious interpretation prominent in Saudi Arabia. For this reason, such tax only applies to Sunni Muslims, while other religious groups are exempt (including the Shia school of Islam).

Given these institutional characteristics, I exploit the international price of silver to verify how individual contributions and attacks evolve. Using a representative data set

¹Such funds are then directly appropriated by the government and spent on the vulnerable population soon after Ramadan (e.g., the poor, blind, disabled). See the government of Khyber's website for an overview of Zakat programmes: https://swkpk.gov.pk/?page_id=1382.

²A typical example is the case of Lashkar-e-Taiba, one of the largest terrorist groups in Pakistan. Hafiz Saeed, one of the founders of this organization, was also the head of a charitable foundation in Pakistan until February 2018. See Reuters: <https://www.reuters.com/article/us-pakistan-militants-financing/pakistan-bans-charities-linked-to-founder-of-militant-group-idUSKCN1FY1SN>.

³In 2015, the former Minister of Information, Pervaiz Rashid 'ha[d], advised people to pay Zakat and charity to institutions, which save lives and not to those producing suicide bombers, as reported by the newspaper *Dawn*. See the following article: <https://www.dawn.com/news/1194098>.

on individual charitable donations, I show that donations increase with silver prices by individuals in divisions with a higher share of Sunni (divisions are second-order administrative units, like counties in the United States). Furthermore, individuals in the middle of the income distribution are responsible for this result, as they tend to be hit or missed by the threshold. As a result, changes in the international price of silver affect donations heterogeneously for Sunni (treated) or non-Sunni (control) cities and the financing of Sunni terrorist organizations (treated) and non-Sunni ones (control). A religious map of Pakistan and intelligence and news reports lead me to classify, respectively, cities and organizations based on their religious affiliation.

These empirical findings are aligned with a model in which financial frictions dictate the timing and location of terrorist attacks. Sunni-majority cities experience more terrorist attacks (higher probability, number, and casualties) only when silver prices are high and exclusively during the month marking the beginning of Ramadan and the following one. This violent escalation occurs only for highly capital intensive activities (e.g., bombs, heavily armed assaults). On the contrary, events characterized by low capital-intensity activities are unresponsive to changes in terrorism financing (e.g., stabbings, kidnappings).

Given the role of some charitable organizations in transforming donations in terrorism financing, I then study whether and how the characteristics of charities matter during the period of Zakat donations. I find that cities with a high share of charities using cash as a means of payment display a severe amplification of terrorist attacks due to the Zakat levy (between three and six times the average effect).⁴ To isolate changes in the supply of attacks due to better-funded terrorist organizations, I study variation at the city-organization time level to complement the previous city-time analysis. This novel setting offers a critical insight into the higher number of attacks due to the Zakat levy: the vast majority of the increase in terror in Sunni-majority cities is due to Sunni terrorist groups being more active than to non-Sunni ones.

The presence of financial frictions points toward terrorism financing being particularly effective in producing attacks upon a high recruit availability. To test this implication, I construct a measure of terrorist recruitment by analyzing more than four million messages from six fora operating in Pakistan between 2003 and 2012, which contained Jihadist-friendly material. I build an algorithm based on Scanlon and Gerber (2014) in computer science, and conceptually in line with Mueller and Rauh (2018), that analyzes this data and identifies all conversations containing recruitment materials through supervised learning and natural language processing. This method relies on the initial work of two judges, who evaluated a sample of random messages, and manually and independently highlighted those containing an intent to recruit violent extremists to some group or movement. After training the algorithm on this initial sample, I apply this evaluation to all other messages, de facto replicating the work of several judges marking each post.

By combining this data set with the Zakat setting, I find two critical results. First, there is no immediate and direct effect of an increase in terrorism financing on recruitment, which is consistent with the access to a pool of recruits not being a binding constraint to extremist groups. Second, in line with the theoretical work of Bueno de Mesquita (2005b), the effect of terrorism financing on attacks increases strongly and significantly in recruitment. This result is consistent with a complementarity between capital (finance) and labor (recruits) in producing terrorist events.

⁴The relation between terrorism financing and the use of cash as a predominant mode of payment has been recently targeted by the National Counter Terrorism Authority in Pakistan through various initiatives. Refer to the following link: <https://nacta.gov.pk/counter-financing-of-terrorism/>.

To address possible confounders, I explore multiple additional tests. For example, I replicate my empirical design and focus on a second Islamic holiday, Eid Adha, which is characterized by charitable donations unrelated to silver and cannot reject a zero effect. In addition to this placebo, I find that the 2 months following the Zakat donations are a period of increased alert on terrorism financing, through a data set on sanctions related to terrorism and terrorism financing administered by the United States, the European Union, and the United Nations. An additional section explores the robustness of the results to alternative specifications (exploiting the boundaries of the religious map, analyzing the heterogeneity in silver prices and verifying that mines do not affect the paper's estimates). More evidence is made available on the disaggregated capital intensity of attacks, organization time variation, the effect of cash use by charities in relation to terrorism financing and alternative methods. It is important to note that these results are specific to Pakistan and to this unique empirical design. For this reason, the frictions and constraints of terrorist groups may depend on their organizational and financial structure (e.g., international versus local, financially-diversified versus specialization, etc.).

This paper complements and contributes to the literature on the organizational economics of terrorist and violent groups, by providing empirical evidence that terrorist groups face financial frictions and this affects their attacks. [Berman \(2003\)](#), [Berman \(2011\)](#), and [Shapiro \(2013\)](#) pioneered this field, showing that terrorist organizations are sophisticated in their reward structure, including monetary incentives and delegation problems.

The role of finance and its relation to terrorism is introduced by [Shapiro \(2007\)](#), [Shapiro and Siegel \(2007\)](#), and [Shapiro \(2013\)](#), who note that while large-scale organizations enjoy significant funding, their local level operatives are cash-constrained because of agency problems (e.g., monitoring funds). This argument is consistent with my results since a funding shock to local operatives may complement centralized funding and promote attacks. My results are in line with [Berman, Shapiro, and Felter \(2011\)](#), [Fetzer \(2014\)](#), [Croft, Felter et al. \(2016\)](#), [Wright \(2016\)](#), [Beath, Christia, and Enikolopov \(2017\)](#), and [Fetzer, Souza, Vanden Eynde, and Wright \(2021\)](#), who show how conflict and tactics change with financing, as highlighted by [Bueno de Mesquita \(2013\)](#). Recent work by [Battiston, Daniele, Le Moglie, and Pinotti \(2022\)](#) find that drug cartels respond to the war on drugs in Mexico by diversifying their financing away from drugs toward large-scale oil thefts and this changes the competitive landscape between groups. Relatedly, [Bueno de Mesquita \(2005a,b, 2007\)](#) argue the importance of financial counterterrorism compared to alternative strategies, and my empirical evidence shows the existence of the financial frictions reinforcing this hypothesis.⁵

This paper is also connected to the literature on crime and conflict in developing countries. [Dube and Vargas \(2013\)](#) advanced this literature by exploiting shocks to commodities of different labour intensity to identify the demand and supply of conflict. My method

⁵The existence of a relation between the donations, terrorism financing, and attacks has been noted in different settings since 9/11. [Basile \(2004\)](#) notes the link between Zakat donations, their misuse by charities and attacks through a qualitative study. [Levi \(2010\)](#) discusses how such specific donations are hard to tackle given the current antimoney laundering initiatives. [Milton-Edwards \(2017\)](#) shows how stricter oversight of the Palestinian Zakat committees by Israel and the Palestinian Authority became a powerful device of counterterrorism. [Aman-Rana \(2014\)](#) and [Aman-Rana \(2017\)](#) explore the economic causes of terror and analyze the effect of charity donations on violence in Pakistan. Regarding terrorism and Ramadan, [Reese, Ruby, and Pape \(2017\)](#) do not find evidence of an increase in violent attacks during Ramadan in Iraq, Afghanistan, and Pakistan.

offers an alternative tool to study these issues with conceptually aligned results. The findings of this paper are also in line with the literature showing the relation between conflict and development projects (Croft, Felter, and Johnston (2014)), local trade shocks (Martin, Mayer, and Thoenig (2008), Amodio, Baccini, and Di Maio (forthcoming)), the transmission of international prices (Dube, García-Ponce, and Thom (2016), Berman, Couttenier, Rohner, and Thoenig (2017), Carreri and Dube (2017)), and its long-term implications (Sviatschi (2019)).⁶

The rest of the paper is as follows. Section 2 presents a conceptual framework and offers some institutional aspects of the Zakat levy and the role of silver prices. Section 3 presents the data and the identification strategy on the relation between silver prices and Zakat donations. Section 4 investigates the evidence on silver prices and terrorism, the capital intensity of attacks, and the measure of recruitment. It also describes a method to dissect the demand and supply of terrorism and reports the Eid Adha placebo and some additional robustness checks. Section 5 concludes.

2. CONCEPTUAL AND INSTITUTIONAL FRAMEWORK

This section presents a conceptual framework relating terrorism financing, recruitment, and attacks and introduces the natural experiment in terrorism financing. Through the conceptual framework, I spell out the hypotheses tested in the paper and reconnect these with the literature on the organizational economics of terrorist and violent groups. In the remaining part of this section, I provide evidence on the natural experiment that induces a source of unintended and quasi-experimental variation in terrorism financing.

2.1. *Conceptual Framework*

The relation between terrorism financing, recruitment, and attacks has been investigated by foundational papers in the theoretical literature on the organizational economics of terrorist groups, which are key to this empirical analysis. My conceptual framework follows the work of Bueno de Mesquita (2005b) and Shapiro and Siegel (2007). This class of models presents a relation between a central terrorist organization and a local level operative. Two forces guide the essence of these frameworks. First, both parties derive utility from a terrorist attack, which is a means to achieve a certain objective, and the attack's location producing the highest utility may be either where the local operative is or where the central organization lies. Second, the players must make a financial decision for the attack to take place, and financial frictions play a prominent role in these settings. For example, Bueno de Mesquita (2005b) includes a function that captures the cost of devoting resources to an attack, while Shapiro and Siegel (2007) model a parameter that identifies a reduced-form agency cost that emerges from the possible appropriation of funds by a local operative.

Appendix A in the Online Supplementary Material (Limodio (2022)) sketches an essential framework, which summarizes the results of this theoretical literature. This shows that in the presence of financial frictions to a terrorist group's internal capital market, a positive shock to the availability of capital in the local operative's location leads to an increase in local terrorist attacks. This effect is increasing in the availability of recruited individuals.

⁶Some of these insights relate to the literature on the determinants of terrorism: Krueger and Malečková (2002), Abadie (2006), Jaeger and Paserman (2006), Benmelech and Berrebi (2007), Krueger (2008), Jaeger and Paserman (2008), Krueger and Malečková (2009), and Blair, Fair, Malhotra, and Shapiro (2013).

2.2. Institutional Setting

This section presents the institutional features of Zakat and its relation to Islam and the price of silver. It also presents newspaper articles and reports on the relation between charitable donations, terrorism financing, and terrorist groups.

2.2.1. Government Revenue, Zakat, and Silver Prices

Zakat is one of the five pillars of Islam and part of Sharia law. As Ramadan begins, Muslims must donate to charity in exchange for a religious regeneration of their wealth. While this donation is left as an individual contribution in most countries, Pakistan adopts a government-run scheme to collect and allocate these resources. In fact, the Pakistani system to manage revenue from Zakat relies on a Sharia-compliant obligation, creating a useful natural experiment. On the first day of Ramadan, individuals are subject to a 2.5% levy on deposit accounts above an eligibility threshold (*Nisab-i-Zakat*). The definition of the threshold is grounded in the local interpretations of Sharia law by Pakistani scholars and is defined by the international price of silver. As a result, the value of this threshold changes every year and is calculated as the price of 52 tolas of silver (corresponding to approximately 612.32 grams) on the day of the threshold announcement. This levy affects individuals across a large part of the income distribution: the average value of the threshold is 250 USD, with 65% of Pakistan's deposit accounts being above this, as the average account contains 868 USD (Choudhary and Limodio (2022))

Three key characteristics of this levy's implementation play an important role. First, Pakistan is an Islamic Republic professing the Sunni school of Islam, closer in its interpretation to Saudi Arabia. Sunni Pakistanis are the only religious group subject to this levy and account for 76% of the population. The other religious groups are exempt, in particular, the Shia school of Islam (with this religious branch being professed by the majority in Iran), which is the second largest group and accounts for 19% of the country. The remaining 5% is composed of Hindus, Christians, Animists, and other smaller groups. Given that only one particular religious group is subject to the levy, I exploit a religious map of the country to compare Sunni majority versus non-Sunni-majority cities.⁷ Figure 1 reports the map and its geographic specification across religious groups, with Sunni-majority areas specified in bright grey and white, Shia-majority areas in dark grey, Sunni-Shia mixed areas with horizontal stripes of bright and dark grey, and vertical lines refer to areas with a Hindu or Christian majority.

Second, the local authorities (State Bank of Pakistan and Ministry of Religious Affairs) announce the threshold only 2 days before the collection. This implies that the international price of silver on the announcement day determines the threshold, and consequently, the tax base and revenue collection. Figure 2 shows the high correlation between the Zakat threshold and the international price of silver on the announcement day. Appendix B in the Online Supplementary Material offers additional institutional features on the functioning of the Zakat levy, including descriptives on government revenue from the levy and its negative correlation with silver prices (Figure B.1). It also plots on the evolution of silver and gold prices over time (Figure B.2), showing that silver prices are more unpredictable than gold prices given their higher volatility. It is also important to clarify that these funds are collected and managed by the central government through the Central Zakat Council, State Bank of Pakistan, and the Ministry of Religious Affairs. These

⁷The original map is entitled "Pakistan Religions" and is available at this page <https://gulf2000.columbia.edu/maps.shtml>

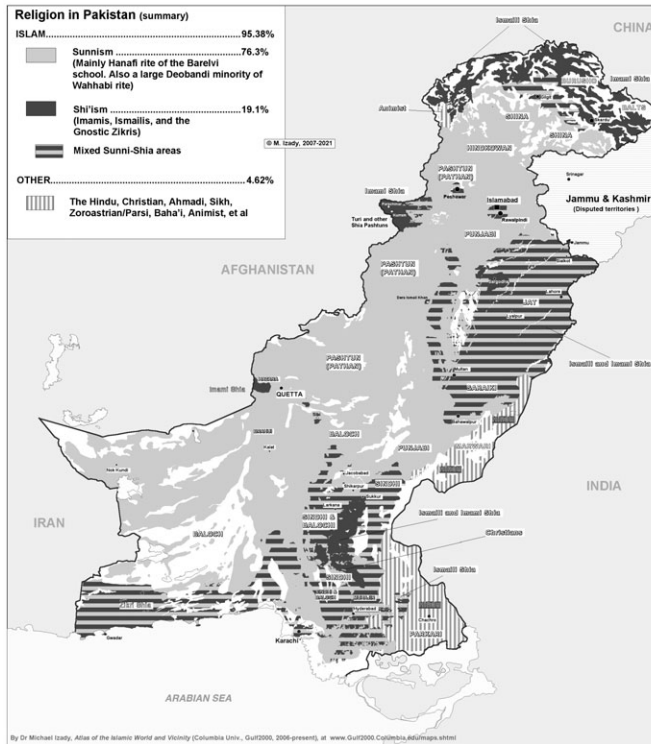


FIGURE 1.—Religious Map of Pakistan. *Notes:* This map reports the geocoding of the main religions and their composition in Pakistan. Sunni-majority cities are indicated in light grey and white, and they account for 76% of the Pakistani population. Non-Sunni cities are marked in dark grey. Cities with other religions (Hindus, Christians, Animists, and others) are indicated with vertical lines. Areas colored with horizontal lines in light and dark grey are cities mixed with Sunni and Shias. The area included with dashed lines corresponds to disputed territories in Jammu and Kashmir, which are not considered in the analysis. This map is created by Dr. Izady and the Columbia University Gulf/2000 project.

authorities transfer the funds to councils managed by local governments, who administer them through their officials.⁸

Third, most Pakistanis give their Zakat offers to both vulnerable individuals and charities in the location where they live. A study conducted by Pakistan Center for Philanthropy explores a representative sample of donors and finds that households prefer to donate to mosques and madrassahs that are nearby and address local needs. The share going to local charitable organizations appears to lie at 50% in most provinces of Pakistan.⁹

2.2.2. Charitable Donations, Financing, and Terrorist Attacks

Several local NGOs operating in Pakistan conduct admirable work and provide critical public goods: schooling, health services, shelter, assistance to elderly and vulnerable,

⁸Refer to Chapter V, points 12, 13, and 14 of the original “Zakat & Ushr Ordinance, 1980.”

⁹Refer to pages 22 and 24 of the report “The State of Individual Philanthropy in Pakistan 2016” published by the Pakistan Center for Philanthropy and available at <https://www.pcp.org.pk/uploads/nationalstudy.pdf>. This report clarifies that on average 33% of all donations go to charities, while 67% go to individuals. However, once Balochistan is considered separately, the share of donations going to charities is close to 50%.

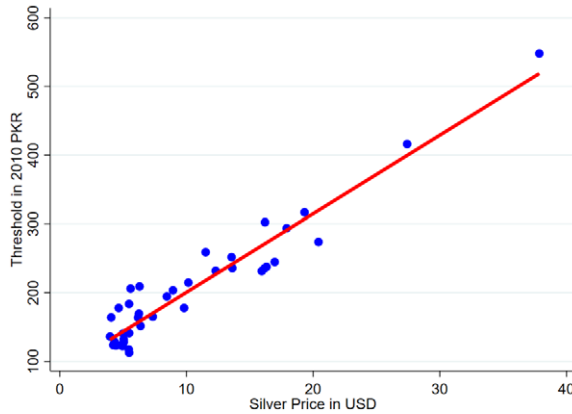


FIGURE 2.—Zakat Threshold and Silver Prices. *Notes:* This figure reports a scatterplot showing the relation between the Zakat threshold in 2010 PKR, on the *y*-axis, and the international price of silver per ounce in USD at the announcement day, on the *x*-axis. The correlation between the two is 0.95.

and many more. In this respect, the Zakat-led increase in their funding promotes a more inclusive, extensive, and comprehensive access to these goods and services.

At the same time, it is important to note that the distance between charities and terrorism financing in Pakistan is particularly blurry. The country is on the “grey list” of the Financial Action Task Force, and the ambiguity of charity oversight is a key problem behind this.¹⁰ While several local NGOs conduct admirable work, others are different. In fact, multiple charities have been directly associated with terrorist groups over the past decade. For example, Hafiz Saeed, one of the founders of a prominent terrorist group (Lashkar-e-Taiba), was wanted by the US State Department for 10 million USD while being head of a charitable foundation in Pakistan until February 2018.¹¹ Similarly, the terrorist group Jihad bi al-Saif has been linked to the charity Tablighis Jamaat.¹² Other groups have actively used charities to promote their fundraising, such as Harkat-ul-Mujahedeen, led by Maulana Fazlur Rehman Khalil and Jammāt-ul-Furqan, led by Maulana Abdullah Shah Mazhar, two banned militant outfits linked to the Tehrik-i-Taliban terrorist group (TTP) and Al-Qaeda. These terrorist groups created charitable foundations, under the new names Ansar-ul-Umma and Tehreek-e-Ghalba Islam, to boost their funding.¹³ Given the difficulty in measuring the financing of terrorist groups, Pakistan is an ideal setting to investigate the relation between terrorist financing and attacks because some of the local charities are particularly opaque.

It is also important to discuss another critical aspect of this setting: the cost of a terrorist attack. Estimating a specific amount per attack is particularly challenging at least for two reasons. First, the costs of committing a single attack are low compared to the total administrative funds needed to support the organization, the possible political and security coverage, and the infrastructure. Hence, the operational costs probably underestimate the real amount needed to commit a terrorist attack (Biersteker, Eckert, and Romaniuk (2007)). Second, the funding required depends on the nature of the attack and

¹⁰See <https://www.dawn.com/news/1428015>

¹¹See <https://www.reuters.com/article/us-pakistan-militants-financing-idUSKCN1FY1SN>

¹²See <https://worldview.stratfor.com/article/tablighi-jamaat-indirect-line-terrorism>

¹³See <https://web.archive.org/web/20170429090718/https://globalecco.org/pakistan-money-for-terror>

the material-specific costs (e.g., transport, weapons, etc.). The UN Security Council Committee (2004) published an analysis of attacks conducted by Al-Qaeda against the United States in the past 20 years. These are typically capital intensive attacks, which employ a combination of vehicles, heavy arms, and explosives and, therefore, offer a relevant perspective given the object of this study. The cost of the truck bombings against the United States embassies in East Africa (August 1998) is estimated to be \$50,000 or less; the attack on the USS Cole in Aden (October 2000) \$10,000 or less; the Bali bombings (October 2002) \$50,000 or less; the bombing of the Marriott Hotel in Jakarta (2003) about \$30,000; the attacks in Istanbul (November 2003) less than \$40,000; and Madrid bombing (March 2004) about \$10,000.¹⁴

3. DATA AND IDENTIFICATION

This section describes the data sets employed in this analysis and offers insights on the identification strategy by analyzing the data on charity donations at the individual level. In particular, the identification strategy verifies that donations increase with silver prices in Sunni-majority areas and, in particular, by individuals who are marginally tax-free because of silver fluctuations.

3.1. Data

Pakistan presents excellent statistical documentation essential to this study. The main databases employed in this research are listed as follows:

1. Terrorist attacks. The Global Terrorism Database (GTD) is published by the National Consortium for the Study of Terrorism and Responses to Terrorism, *START* (2020). It contains the universe of terrorist attacks in Pakistan and includes more than 14,000 events. To make the panel reliable and usable, I harmonize the names of the cities that could have multiple spellings (given the transliteration from Urdu to English or incorrect entries) and group terrorist organizations based on their proclaimed connections (e.g., multiple small cells declare their allegiance to the Taliban and are grouped as belonging to such group). Appendix C in the Online Appendix provides more information on this. From this data set of terrorist events, I build two balanced panels: a city-level panel which covers 1750 cities over 588 month-year periods from 1970 to 2018; a city-organization-level panel, which follows 29 terrorist groups operating in 1750 cities over 588 month-year periods from 1970 to 2018.

2. Silver prices. The London Bullion Market Association silver price database contains daily silver prices for the variable Silver Price per Ounce in USD from 1968 and 2019 (1 ounce equals approximately 28 grams). This is the resulting price of the auction that takes place every day at noon UK time, and it is used to measure the international price during the threshold announcement, typically 2 days before the execution of the Zakat levy. In the analysis, this variable is standardized to simplify its interpretation.

3. Individual Zakat donations. The Pakistan Social and Living Standards Measurement Survey (PSLM) is conducted by the Pakistan Bureau of Statistics and provides information on individual Zakat donations. Each survey contains a repeated cross-section and reports several economic indicators across the divisions of Pakistan for 7 years (2005, 2007,

¹⁴Refer to the “First report of the Analytical Support and Sanctions Monitoring Team appointed pursuant to resolution 1526 (2004) concerning Al-Qaeda and the Taliban and associated individuals and entities” issued by the Security Council of the United Nations, Financial Issue C, page 12, available at the following link <https://www.undocs.org/S/2004/679>

2010, 2011, 2013, 2015, and 2018). The survey is stratified at the division level rather than the city level and asks the amount that an individual donates for Zakat through relatives, friends, and NGOs (excluding transfers to the public sector, and hence the deposit levy). This makes it an ideal source of data for this research.

4. Charities. The Nonprofitable Organizations Central Registry is collected by the Federal Board of Revenue and offers information on the universe of charities operating in Pakistan. This data set contains several indicators for each charity (e.g., name, address, etc.). The address allows me to match the charity to its division, which describes the “labor market” in which this entity may be active. It also contains another central piece of information for each charity: its primary means of payment, which can be cash, bank, check, or others. I use this information to define a division-year panel containing the total number of charities and the number of each charity by means of payment.

5. Recruitment. The Geopolitical Web Research project (GeoWeb) is developed by the Artificial Intelligence Lab at the University of Arizona and provides data sets from several online fora in multiple countries from 2003 until 2012. Pakistan is among the countries covered by this project and data sets for six fora are available in their original language, typically Urdu and Roman Urdu with minor references in English and Arabic. Each data set contains all messages exchanged in the platform (more than four million in total), the sender’s username, the corresponding thread and information on the message’s date and time. Given that these platforms have been routinely used by terrorist groups to disseminate Jihadist-friendly material and other propaganda (Fernandez (2015), D’Souza (2017)), I combine these in a single source and use textual information to geolocalize its users. Finally, I apply the technologies introduced by Scanlon and Gerber (2014) to detect messages intended to recruit individuals in violent and extremist groups (as discussed in detail in Section 4.2 and Appendix D in the Online Appendix). This information leads to the creation of a city-level panel of messages and recruitment messages exchanged on these platforms for 111 cities, which can be identified in this data set, and 120 month-year periods between 2003 and 2012.

6. Islamic calendar. I digitize data on the first day of every Ramadan and Eid Adha from 1970 until 2018 using the standard Islamic calendar available from multiple sources. In addition, I match each year of the Gregorian calendar with the corresponding Islamic year (Hijri), which is based on the lunar calendar. For tractability, I define each Islamic year as the 12 months centered around the beginning of every Ramadan.

Table I reports summary statistics for the main variables in each data set. Panel A presents three variables with a subscript cm_y , which labels a variable that varies by city c during month m of year y : Probability of Attack is a dummy that takes unit value whenever a city is hit by at least one terrorist attack in a month-year; Number of Attacks describes the number of attacks a city experienced in a given month-year; and Number of Casualties indicates the number of dead and wounded individuals for each city and month-year. The subpanels A.1 and A.2 further report descriptives on attacks that are classified as capital intensive, A.1, and noncapital intensive, A.2.¹⁵ Panel B presents summary statistics from the religious indicator coded from Figure 1. The variable Sunni presents a subscript c , because only varies between cities and takes a value of 1 in Sunni-majority cities, 0.5 in cities that have a mix of Sunni and other religious groups, and 0 in cities that are mostly composed of other religious groups.

¹⁵The Global Terrorism Data Set describes the types of terrorist events, and following this classification, capital intensive attacks are those described as Bombing/Explosion and Armed Assault. The remaining types of attacks are defined as noncapital intensive: Hijacking, Kidnapping, Barricade, Unarmed Assault, Facility/Infrastructure Attack, and Assassination. For a more extensive discussion on this, refer to Section 4.1.1.

TABLE I
SUMMARY STATISTICS.

Variable	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Max
Panel A—Terrorist Attacks in Cities					
<i>Probability of Attack</i> _{cm_y}	1,029,000	0.00754	0.0865	0	1
<i>Number of Attacks</i> _{cm_y}	1,029,000	0.0140	0.357	0	122
<i>Number of Casualties</i> _{cm_y}	1,029,000	0.0617	2.385	0	613
A.1 Capital Intensive Attacks in Cities					
<i>Probability of Attack</i> _{cm_y}	1,029,000	0.00635	0.0794	0	1
<i>Number of Attacks</i> _{cm_y}	1,029,000	0.0111	0.263	0	88
<i>Number of Casualties</i> _{cm_y}	1,029,000	0.0553	2.222	0	476
A.2 Noncapital Intensive Attacks in Cities					
<i>Probability of Attack</i> _{cm_y}	1,029,000	0.00174	0.0417	0	1
<i>Number of Attacks</i> _{cm_y}	1,029,000	0.00261	0.141	0	63
<i>Number of Casualties</i> _{cm_y}	1,029,000	0.00391	0.377	0	170
Panel B—Sunni-Majority Cities					
<i>Sunni</i> _c	1750	0.856	0.276	0	1
Panel C—International Price of Silver					
<i>Silver</i> _{my}	588	9.016	7.149	1.340	39.63
Panel D—Charitable Organizations					
<i>Number</i> _{dmy}	1450	73.72	125.7	0	728
<i>Cash Share</i> _{dmy}	1314	0.369	0.724	0	5
Panel E—Recruitment and Messages					
<i>Recruitment</i> _{cm_y}	13,320	144.8	941.6	0	17,796
<i>Messages</i> _{cm_y}	13,320	829.9	6187	0	130,209

Note: This table presents summary statistics for the databases presented in Section 3.1. Panel A reports descriptives for all variables related to terrorist attacks in city c and month-year period my : (1) the probability of an attack in a city, (2) the number of terrorist attacks, and (3) the number of attack-related casualties. Panels A.1 and A.2 report the statistics for attacks that are classified as capital intensive, A.1, and noncapital intensive A.2. The Global Terrorism Data set describes the types of terrorist events, and following this classification, capital intensive attacks are those described as “Bombing/Explosion” and “Armed Assault.” The remaining types of attacks are defined as noncapital intensive: Hijacking, Kidnapping, Barricade, Unarmed Assault, Facility/Infrastructure Attack, and Assassination. For a more extensive discussion on this, refer to Section 4.1.1. Panel B presents summary statistics for the variable coding whether cities c are Sunni majority, which are assigned a 1; Sunni mixed, which are assigned a 0.5; or non-Sunni, which are assigned a zero. Refer to Figure 1 for the underlying map produced by Dr. Izady and the Columbia University Gulf/2000 project. Panel C summarizes data on the international price of silver at the announcement of the Zakat threshold in month m of year y . Panel D reports statistics on the total number of charities active in a division d and month-year period my and the share of charities using cash over the number of charities using other means of payment. Panel E displays descriptives on the number of recruitment and total messages in a city c and month-year period my . Column (1) reports the number of observations, (2) and (3) report each variable’s the mean and standard deviation, while (4) and (5) indicate their corresponding minimum and maximum values.

Panel C reports statistics on the international price of silver per ounce in USD, which presents a subscript my , as this variable varies for every month m of every year y . Panel D presents descriptive statistics on two variables extracted from the charity data set labeled with the subscript dmy : the number of charities operating in each division d over a given month m of year y and the ratio between the number of charities employing cash as the mode of payment over charities using other modes of payment. Finally, Panel E reports statistics on a city-level panel of messages exchanged in the platform and recruitment messages identified by the algorithm, which vary by cm_y as described above.

3.2. Identification

In this section, I use individual data on charitable donations and verify that silver prices affect donors in Sunni-majority areas during the Ramadan period. For each individual in the data set, I can observe the survey year, the division in which the individual is located and the yearly income. Using these three variables, I divide survey respondents in terciles according to the income distribution in a particular division and year. This information is valuable for studying the following empirical model:

$$\text{Zakat Donation}_{idyt} = a_1 \text{Sunni}_d \times \text{Silver}_t + \nu_{dy} + \nu_t + u_{idyt}, \quad (1)$$

where the Zakat donated by individual i in division d belonging to income tercile y in year t , $\text{Zakat Donation}_{idyt}$, is regressed over an interaction between the standardized international price of silver and a variable describing the average share of Sunni cities in a division, $\text{Sunni}_d \times \text{Silver}_t$; with the presence of division-tercile and time fixed effects, ν_{dy} and ν_t .

In addition to the previous test, I offer further evidence linking a higher silver-induced tax to donations. The price of silver only affects the charitable donations of individuals around the threshold, hence in the middle of the deposit distribution. Wealthy people are always taxed regardless of the price of silver, as they stand well above the threshold. On the contrary, poor individuals are never taxed, as they may lack a bank account or do not hold sufficient deposits. As a result, in the absence of data on bank deposits from the PSLM, I exploit information on the income distribution, which is available, and verify whether the elasticity of donations to silver prices differs across terciles. I explore the following empirical model:

$$\begin{aligned} \text{Zakat Donation}_{idyt} = & \sum_{j=1}^2 b_{1j} \text{Tercile}_j \times \text{Silver}_t \\ & + \sum_{j=1}^3 b_{2j} \text{Tercile}_j \times \text{Silver}_t \times \text{Sunni}_d + \nu_{dy} + \nu_t + u_{idyt}, \end{aligned} \quad (2)$$

where the Zakat donated by individual i in division d belonging to income tercile y in year t , $\text{Zakat Donation}_{idyt}$, is regressed over two sets of interactions. The first interaction is between a fixed effect describing the tercile to which an individual belongs to and the standardized price of silver, $\text{Tercile}_j \times \text{Silver}_t$. The second interaction is between the two previous variables and the average share of Sunni cities in a division, $\text{Tercile}_j \times \text{Silver}_t \times \text{Sunni}_d$. The former interaction describes the elasticity of Zakat donations to silver prices by individuals living in non-Sunni-majority divisions and belonging to different terciles of the income distribution. The latter interaction describes the differential elasticity of Zakat donations to silver prices by individuals living in Sunni-majority cities, according to the tercile of their income distribution. In this specification, the omitted category are individuals in non-Sunni-majority cities, who belong to the third tercile of the income distribution. In both equations (1) and (2), I cluster the standard errors at the division-tercile level.

Columns (1) and (2) of Table II show the results of equation (1) and present one important result. When silver prices are one-standard deviation higher, Zakat donations increase by 6%–8% in divisions that present a one-standard deviation higher share of Sunni-majority cities. The difference between the two coefficients is given by the presence

TABLE II
ZAKAT DONATIONS, SUNNI DIVISIONS, AND SILVER PRICES.

Variable	(1)	(2)	(3)	(4)
		Zakat Donation		
$Sunni_d \times Silver_y$	0.0781 (0.0228)	0.0650 (0.0224)		
$1stTercile_i \times Silver_y$			0.00721 (0.0567)	0.0173 (0.0548)
$2ndTercile_i \times Silver_y$			0.00608 (0.0549)	0.00655 (0.0527)
$1stTercile_i \times Silver_y \times Sunni_d$			0.0752 (0.0373)	0.0662 (0.0347)
$2ndTercile_i \times Silver_y \times Sunni_d$			0.111 (0.0401)	0.0964 (0.0396)
$3rdTercile_i \times Silver_y \times Sunni_d$			0.0463 (0.0451)	0.0301 (0.0457)
Controls		Yes		Yes
Division-Income Tercile FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	8641	8641	8641	8641
Adj. R sq.	0.296	0.352	0.296	0.352
Mean Dep. Var.	9499	9499	9499	9499
S.D. Dep. Var.	21,258	21,258	21,258	21,258

Note: This table presents ordinary least squares (OLS) estimates, where the unit of observation is an individual belonging to tercile i in division d in year y . Division tercile and year fixed effects are present in all columns and standard errors are clustered at the division-tercile level. The dependent variable is the natural logarithm of 0.01 plus the Zakat charitable donation. This is regressed over the interactions of the following variables: the average Sunni composition of cities in a division, $Sunni_d$; the standardized price of silver at the announcement of the Zakat threshold, $Silver_y$; and a dummy describing the income quartile to which an individual belongs to in a given division and year, $Tercile_i$. The controls included in columns (2) and (4) are the natural logarithm of annual income, number of family members and children, and a fixed effect for the level of education. The mean and standard deviation of the dependent variable without log transformation are reported as the last two rows of the table.

of controls. I do not introduce any control in column (1), while in column (2), I control for the natural logarithm of annual income, number of family members and children, and a fixed effect for the level of education.¹⁶ To quantify these numbers beyond standard deviations, these estimates imply that when silver prices increase from their mean of 9 USD to 16.1 USD (1 standard deviation, corresponding to 7.1 USD), then the average donation in a Sunni division increases from 9500 Pakistani Rupees (PKRs, corresponding to 55 USD) to 10,240 PKRs (60 USD).

Columns (3) and (4) of Table II expand the findings of the previous two columns and report the results of equation (2). Two central elements emerge from these columns. First, in all terciles the Zakat donations of individuals living in non-Sunni-majority divisions are unresponsive to changes in silver prices. In both columns, the point estimates of the interactions between the first and second tercile of the income distribution, and silver prices cannot be rejected to be different from zero and are minuscule in magnitude. Second, the most reactive Zakat donations to silver prices are those of individuals living in Sunni-majority divisions and belonging to the second tercile of the income distribution. The coefficient of the triple interaction between $2ndTercile_i$, $Silver_i$ and $Sunni_d$ is 11% in column

¹⁶The variable Education in the PSLM survey takes the following values: 0 unknown education level, 1 other, 2 less than 6 years, 3 between 6 and 10 years, 4 between 10 and 15 years, 5 more than 15 years.

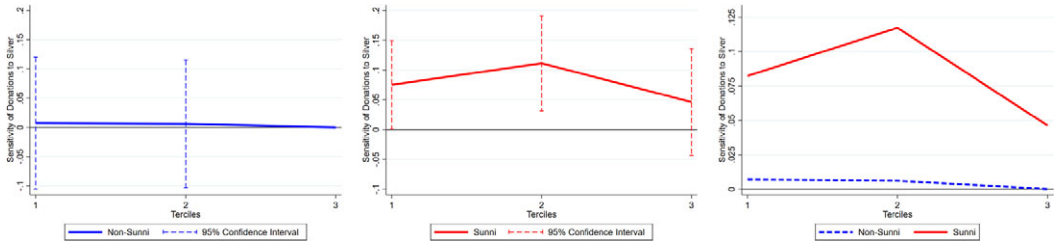


FIGURE 3.—Zakat Donations, Sunni Divisions, and Silver Prices. *Notes:* This figure reports the elasticity of Zakat donations to silver prices across the three tertiles of the income distribution in non-Sunni-majority divisions, left panel, and in Sunni-majority divisions, center panel. The right panel combines the point estimates from the left and center panel. Equation (2) presents the empirical model behind this result and column (3) of Table II displays the coefficients reported in this figure. The bars around each observation represent the 95% confidence interval, and standard errors are clustered at the division-tertile level.

(3) and 9.6% in column (4). These coefficients are three times as large as those for individuals belonging to the *3rdTertile* and 50% larger than those belonging to the *1stTertile*. Once again, to quantify these numbers beyond standard deviations, my estimates on individuals in the second tertile imply that when silver prices increase from their mean of 9 USD to 16.1 USD (1 standard deviation, corresponding to 7.1 USD), then the average donation from an individual belonging to the second tertile of the income distribution in a Sunni division increases from 8160 Pakistani Rupees (PKRs, corresponding to 46 USD) to 9058 PKRs (52 USD).

Figure 3 summarizes the findings of column (3) in Table II. The left panel shows the elasticity of Zakat donations to silver prices in non-Sunni-majority divisions and for the three tertiles. None of these coefficients are different from zero and all are small in magnitude. The center panel shows that the elasticity of donations to silver prices is positive in Sunni-majority divisions and is highest and statistically different from zero below the 1% threshold for individuals belonging to the second tertile, with the point estimate of the elasticity being 11%. The coefficients for individuals living in Sunni-majority areas and in the first and third tertile are positive but not precise. Finally, the right panel combines the point estimates of the previous two figures, indicating that the elasticity of Zakat donations to silver prices for individuals living in Sunni-majority areas and in the second tertile of the income distribution is overall close to 12%.

4. EMPIRICAL MODEL AND RESULTS

This section presents the empirical analysis on the relation between terrorism financing, recruitment, and attacks through an analysis of city level, city-organization level and recruitment data.

4.1. *Terrorism Financing and Attacks: City-Level Analysis*

The empirical analysis proceeds in two steps. First, I use an event study specification to study the differential evolution of terrorist attacks in Sunni-majority cities around Ramadan and depending on silver prices. The identification of these effects is possible because of the lunar calendar and because Ramadan begins in different months over time. This additional variation also nets out the effect of seasonality and agricultural cycles on terrorism. Second, since I observe parallel trends between Sunni-majority and non-Sunni-majority cities before Ramadan and record an increase in terrorist attacks only in

the month in which the financing occurs (Ramadan) and the following month exclusively in Sunni-majority cities, I bundle these 2 months into a single dummy and proceed with a difference-in-difference estimation. The following empirical model presents the event study specification:

$$\begin{aligned} \text{Error}_{cmy} = & \sum_{j \neq -1, j = -5}^6 c_{1j} \text{Sunni}_c \times D_j + \sum_{j \neq -1, j = -5}^6 c_{2j} \text{Sunni}_c \times D_j \times \text{Silver}_y \\ & + \iota_{cy} + \iota_{my} + \varepsilon_{cmy}, \end{aligned} \quad (3)$$

where the probability that a terrorist attack takes place in city c during month m of year y , Error_{cmy} , is regressed on two interactions and various fixed effects. The first set of regressors is composed of an interaction between a variable measuring the Sunni composition of a city, Sunni_c , and a set of 12 Ramadan counter-month fixed effects, D_j , which span from 5 months before the month marking the beginning of Ramadan, when Zakat donations are paid, (-5), to 6 months after the month of Ramadan. The second set of regressors are composed of the previous variables, $\text{Sunni}_c \times D_j$, which are further interacted with the standardized international price of silver used to calculate the Zakat threshold and recorded 2 days before the beginning of Ramadan, Silver_y . In equation (3), all coefficients are relative to the month before the beginning of Ramadan (D_{-1}), which is the omitted category. Standard errors are clustered at the city level.

Two layers of fixed effects are included in equation (3): city-year fixed effects, which remove the heterogeneous nonlinear trends in terrorism that different cities across Pakistan may exhibit, and month-year fixed effects, which absorb all common shocks across all months of all years in the sample.¹⁷ The combination of city-year fixed effects and the changes in the beginning of Ramadan due to the lunar calendar are central for identifying the causal impact of Zakat donations on terrorism. In fact, these two elements lead me to focus exclusively on the variation occurring across months and within a city-year cell.

Figure 4 presents the results from estimating equation (3). The left panel reports the coefficients c_{1j} , which describe the probability of an attack in Sunni-majority cities when silver prices are at their average value during the 12 months around the first month of Ramadan. These coefficients are not statistically different from zero for the 6 months preceding the beginning of Ramadan. They exhibit a small and significant increase during the month that Ramadan begins and the following month; they then go back close to zero and are not statistically different from zero. For this reason, even at the average level of silver (which implies the average level of donations), Sunni-majority cities exhibit a higher probability of terrorist attacks during the month of Ramadan and the following one compared to non-Sunni-majority cities.

The middle panel of Figure 4 reports the coefficients c_{2j} that describe the additional probability that Sunni-majority cities experience a terrorist attack when the silver prices used to compute the Zakat threshold are one-standard deviation higher than the mean. These coefficients state how much more likely it is that a Sunni-majority city is attacked relative to the baseline probability expressed by the coefficient c_{1j} . This is the key source of variation in the estimation: high silver prices imply low government Zakat revenue and

¹⁷As described in Section 2, it is important to remember that the year subscript in this specification, y , refers to the Islamic year defined as the 12-month period going from 5 months before to 6 months after the beginning of Ramadan. This does not correspond one-to-one with the Gregorian year, as the Islamic year changes with the lunar calendar.

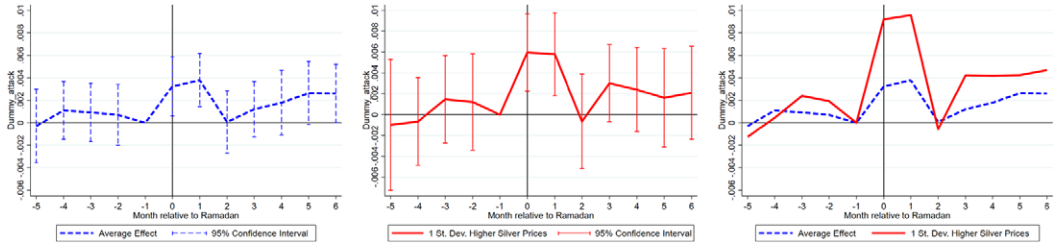


FIGURE 4.—Terrorism, Zakat, and Silver Prices—Event Study. *Notes:* This figure reports the coefficients of the event study specification described in equation (3). The left panel displays the value of the coefficients, c_{1j} , which describe differential evolution in the probability of a terrorist attack in a Sunni-majority city relative to a non-Sunni-majority city around the 12 months around the month when Ramadan starts and when silver prices present their average level. The center panel displays the value of the coefficients, c_{2j} , which describe the additional probability of a terrorist attack in a Sunni-majority city relative to a non-Sunni-majority city around the 12 months around the month when Ramadan starts and when silver prices are one-standard deviation higher than their average level. The right panel reports the point estimates of both panels. The month marking the beginning of the Ramadan festivity is month zero on the x -axis and exhibits a vertical black line. Bars around each observation represent the 95% confidence interval. Standard errors are clustered at the city level, and the empirical specification includes city-year and month-year fixed effects. Column (1) in Table E.1 in Appendix E reports the coefficients of this estimation for this variable, as well as for the number of attacks and casualties.

high charity donations, with some of these funds financing terrorist organizations. Similar to the right panel, the months from -5 to -1 report small magnitudes and coefficients not statistically different from zero. However, there is a spike in the likelihood of attacks during the month of Ramadan and the following month, with an effect that is twice as large as the average effect reported in the right panel and statistically different from zero below the 1% level. As in the previous case, the months from $+2$ onward report c_{2j} coefficients that are small and not statistically different from zero.

The right panel of Figure 4 presents the point estimates of c_{1j} and c_{2j} that clearly show the spike in terrorist attacks that exclusively occur during the month of Ramadan and the following one. There is also a small increase in the likelihood of attacks from the month $+3$ onward; however, this is not statistically different from zero neither in the left nor in the middle panel. Table E.1 in Online Appendix E reports the table estimating the coefficients of Figure 4 for the probability of a terrorist attack as well as coefficients for the number of attacks and casualties. All of these present a similar pattern.

Verifying the parallel trends between Sunni-majority cities (treated) and non-Sunni-majority cities (control) before the month of Ramadan is useful to proceed with a difference-in-difference estimation. Given that the effect of the Zakat levy on terrorist attacks takes place exclusively in the month of the Ramadan and the following one, I define a dummy variable that takes unit value exclusively for these 2 months, $Ramadan_{my}$.

In the presence of extremely detailed and granular data on the Zakat donations, I would regress the variables measuring terrorist attacks at the city-level on measures of Zakat at the corresponding geographic variation and instrument these donations using the religious-majority of the city with silver prices. However, because the Zakat data is only observed at an aggregate level, I study a reduced-form specification in which the instrument is directly used to induce variation in terror and the dummy $Ramadan_{my}$ serves the purpose of isolating the months during which the effect of the Zakat-levy takes place.

For this reason, I estimate the following empirical model:

$$\begin{aligned} \text{Error}_{cmy} = & d_1 \text{Sunni}_c \times \text{Ramadan}_{my} + d_2 \text{Sunni}_c \times \text{Ramadan}_{my} \times \text{Silver}_y \\ & + \iota_{cy} + \iota_{my} + \varepsilon_{cmy}, \end{aligned} \quad (4)$$

where the terror variable observed in city c in month m of year y , Error_{cmy} , is regressed on (1) an interaction between the Sunni-majority dummy, Sunni_c , and the Ramadan dummy, Ramadan_{my} ; and (2) an interaction between the previous two variables, $\text{Sunni}_c \times \text{Ramadan}_{my}$, and the price of silver at the threshold announcement, Silver_y . In line with equation (3), I include fixed effects at the city-year and month-year level and cluster the standard errors at the city level.

The coefficient d_1 shows the differential probability of a terrorist attack in Sunni-majority cities during Ramadan, while d_2 identifies the key coefficient of equation (4), which is the differential effect in attacks in Sunni-majority cities, when silver prices are one-standard deviation higher during the month of Ramadan and the following month. Table III reports the results of (4) for the probability of a terror attack in column (1), the natural logarithm of the number of terror attacks in column (2), and the number of terror-related casualties in column (3).

For all three measures of terror, the first coefficient highlights the increase in terrorist attacks when the Zakat levy is paid in Sunni-majority cities during the Ramadan month and the following one, and when the price of silver is at its mean. This effect is statistically different from zero below the 1% conventional threshold, and the magnitudes are sizeable: a 0.2% higher probability of an attack, a 1% increase in the number of attacks, and a 0.8% increase in the number of casualties. The second regressor shows there is a large increase in terrorist activities when the price of silver is one-standard deviation above its mean during Ramadan and in Sunni-majority cities. In fact, all three measures of terrorism record positive, highly significant coefficients and sizeable estimates. In the presence of a one-standard deviation higher silver price, Sunni-majority cities during the

TABLE III
TERRORIST ATTACKS, SUNNI CITIES, AND SILVER.

Variables	(1) Probability of Attack	(2) Number of Attacks	(3) Number of Casualties
$\text{Sunni}_c \times \text{Ramadan}_{my}$	0.00239 (0.000553)	0.0112 (0.00261)	0.00872 (0.00293)
$\text{Sunni}_c \times \text{Ramadan}_{my} \times \text{Silver}_y$	0.00481 (0.000920)	0.0223 (0.00440)	0.0193 (0.00425)
City-Year FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Obs.	1,029,000	1,029,000	1,029,000
Adj. R sq.	0.281	0.325	0.271
Mean Dep. Var.	0.00754	0.0140	0.0617
S.D. Dep. Var.	0.0865	0.357	2.385

Note: This table presents ordinary least squares (OLS) estimates, where the unit of observation is city c in month-year my . City-year and month-year fixed effects are present in all columns, and standard errors are clustered at the city level. The dependent variables are the probability of a terror attack in column (1); the natural logarithm of 0.01 plus the number of terrorist attacks in column (2); and the natural logarithm 0.01 plus the number of terrorist-related casualties in column (3). These are regressed over the Sunni composition of a city, Sunni_c ; the standardized price of silver at the announcement of the Zakat threshold, Silver_y ; and a dummy taking unit value for the month in which Ramadan begins and the following month, Ramadan_{my} . The dependent variable's mean and standard deviation without log transformation are reported as the last two rows of the table.

2 Ramadan months present an additional 0.4% higher probability of an attack, 2% higher attacks, and 1.9% higher casualties. These effects are typically twice as large as the baseline effects for the average price of silver and represent the key finding of this paper.

4.1.1. *Capital Intensive Attacks*

To verify whether the results of Table III are compatible with an organization-financing channel, I study which types of attacks change at Ramadan and analyze whether capital intensive ones increase as funding flows toward terrorist groups. To do this, I combine two sources. First, I follow the definitions of capital intensive attacks of the United Nations Office on Drugs and Crime (UNODC) and the European Union Agency for Law Enforcement Cooperation (EUROPOL). Both agencies categorize bombs and heavy arms as requiring a high capital, while they classify the remaining types of attacks and weapons as noncapital intensive.¹⁸ Second, I take advantage of the fact that the GTD reports the specific type of attack for each event, which can be one of the following eight: bombing/explosion, armed assault, hijacking, kidnapping, barricade, unarmed assault, facility/infrastructure attack, and assassination.¹⁹ With these two sources, I can aggregate attacks as being capital intensive if they are bombing/explosion and armed assault. The remaining types of attacks are defined as noncapital intensive: hijacking, kidnapping, barricade, unarmed assault, facility/infrastructure attack, and assassination.

As a result, I define six new left-hand side variables: the probability to experience a capital intensive and noncapital intensive attack, the corresponding number of attacks and related casualties by each type. In this section, I study whether the attacks I group as “capital intensive” and “noncapital intensive” respond to the funding shock according to equation (4). In addition to this, Section 4.4 explores the more disaggregated data and each type of attack and weapon separately, with similar findings.

Table IV presents the results from this test, with column (1) measuring the probability of a capital intensive attack, column (2) the number of capital intensive attacks, and (3) the corresponding number of casualties from capital intensive attacks. Columns (4), (5), and (6) describe the same measures of terrorism but associated to noncapital intensive attacks. In line with Table III, the variable $Sunni_c \times Ramadan_{my}$ in columns (1), (2), and (3) of Table IV shows that Sunni-majority cities during the 2 Ramadan months experience an increase in the probability, number, and casualties of capital intensive terrorist attacks (0.1%, 0.8%, and 0.6%, respectively). There appears to also be changes in the measures of noncapital intensive attacks for the same variable. However, these effects are much smaller (0.06%, 0.3%, and 0.1%) and are statistically different from zero below the 5% threshold only in one case out of three (the number of attacks, in column (5)).

¹⁸My definition of capital intensive attack includes bombs and heavy armed assaults, which are defined as “manufactured firearm” by the UNODC. Refer to UNODC, “Conventional Terrorist Weapons,” 2020, available at https://www.unodc.org/images/odccp/terrorism_weapons_conventional.html. EUROPOL is more explicit in classifying attacks as capital intensive or noncapital intensive: “Attacks by lone actors or small groups often use unsophisticated modi operandi such as stabbing. Such attacks do not require extensive expenditure, and thus, might be self-funded by the perpetrators. Financing needs are greater in cases in which the perpetrators intend to use firearms, explosives, or other more sophisticated attack methodologies.” Refer to the European Union Agency for Law Enforcement Cooperation, “European Union Terrorism Situation and Trend report 2021 (TESAT),” 2021, available at <https://www.europol.europa.eu/activities-services/main-reports/european-union-terrorism-situation-and-trend-report-2021-tesat>.

¹⁹Refer to the codebook of the GTD for each type of attack’s definition. This can be found at <https://www.start.umd.edu/gtd/downloads/Codebook.pdf>. Alternatively, the data folder contains the original GTD data sets and the corresponding codebook.

TABLE IV
TERRORIST FINANCING, ATTACKS, AND CAPITAL INTENSITY.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Probability of Attack	Number of Attacks	Number of Casualties	Probability of Attack	Number of Attacks	Number of Casualties
	Capital Intensive			Noncapital Intensive		
$Sunni_c \times Ramadan_{my}$	0.0017 (0.0005)	0.0081 (0.0022)	0.0063 (0.0027)	0.0006 (0.0003)	0.0031 (0.0016)	0.0019 (0.0012)
$Sunni_c \times Ramadan_{my} \times Silver_y$	0.0038 (0.0008)	0.0181 (0.0037)	0.0160 (0.0042)	0.0007 (0.0004)	0.0031 (0.0021)	0.0008 (0.0017)
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,029,000	1,029,000	1,029,000	1,029,000	1,029,000	1,029,000
Adj. R sq.	0.269	0.310	0.256	0.167	0.194	0.171
Mean Dep. Var.	0.0063	0.0111	0.0553	0.0017	0.0026	0.0039
S.D. Dep. Var.	0.0794	0.263	2.222	0.0417	0.141	0.377

Note: This table presents ordinary least squares (OLS) estimates, where the unit of observation is city c in month-year my . City-year and month-year fixed effects are present in all columns and standard errors are clustered at the city level. The dependent variables are the probability of a terror attack in columns (1) and (4); the natural logarithm of 0.01 plus the number of terrorist attacks in columns (2) and (5); and the natural logarithm 0.01 plus the number of terrorist-related casualties in columns (3) and (6). The dependent variables in columns (1), (2), and (3) describe exclusively terrorist events from capital intensive attacks, defined as those involving bombings/explosions and armed assaults. The dependent variables in columns (4), (5), and (6) group exclusively terrorist events from noncapital intensive attacks, which are all other types of attacks. These are regressed over the Sunni composition of a city, $Sunni_c$; the standardized price of silver at the announcement of the Zakat threshold, $Silver_y$; and a dummy taking unit value for the month in which Ramadan begins and the following month, $Ramadan_{my}$. The mean and standard deviation of the dependent variable without log transformation are reported as the last two rows of the table.

Analyzing the second regressor of Table IV is particularly important since it explores the mechanism of this paper: the reaction of terrorist attacks to changes in terrorism financing. The triple interaction, $Sunni_c \times Ramadan_{my} \times Silver_y$, for the first three columns of Table IV shows that in the presence of a one-standard deviation higher silver price during the 2 Ramadan months, Sunni-majority cities present a higher probability of capital intensive terrorist attacks (0.3%), and a larger number of capital intensive attacks and associated casualties (1.8% and 1.6%, respectively). In contrast, the triple interaction for the last three columns of Table IV reveals a lack of response in terms of noncapital intensive attacks to higher terrorism financing. The coefficients on $Sunni_c \times Ramadan_{my} \times Silver_y$ in columns (4), (5), and (6) are nearly one order of magnitude smaller than in (1), (2), and (3), and they are not statistically different from zero in two cases out of three.

4.1.2. Charities and Cash

The Zakat variation affects terrorism financing through a unique channel: an increase in charitable donations. To validate the role of charities, I use data from a novel data set and explore an additional heterogeneity of Table III. In particular, I focus on the means of payment used by charities. As acknowledged by the National Counter Terrorism Authority in Pakistan²⁰ and the evidence presented in Section 2.2.2, a significant number of charities in Pakistan operate with terrorist groups and use cash as means of payment because checks or bank transfers have a higher probability of detection. For this reason, terrorist groups operating in cities with a high share of charities using cash may be more

²⁰See <https://nacta.gov.pk/counter-financing-of-terrorism/>.

prone to receiving additional funding and using this for terrorist attacks. For this reason, I explore the following empirical specification:

$$\begin{aligned}
 \text{ Terror}_{cmy} = & f_1 \text{Sunni}_c \times \text{Ramadan}_{my} + f_2 \text{Sunni}_c \times \text{Ramadan}_{my} \times \text{Silver}_y \\
 & + f_3 \text{Sunni}_c \times \text{Ramadan}_{my} \times \text{Charity}_d + f_4 \text{Sunni}_c \times \text{Ramadan}_{my} \\
 & \times \text{Silver}_y \times \text{Charity}_d + \iota_{cy} + \iota_{dmy} + \varepsilon_{cmy}
 \end{aligned} \tag{5}$$

which presents the same empirical design expressed in equation (4) and adds two sets of additional interactions. First, the two main interactions of this strategy ($\text{Sunni}_c \times \text{Ramadan}_{my}$ and $\text{Sunni}_c \times \text{Ramadan}_{my} \times \text{Silver}_y$) are further interacted with a vector containing two charity variables, Charity_d , which express the average value the division level across years of: (1) the share of charities using cash as a means of payment, over the total of other means of payment, Cash Share_d ; and (2) the total number of charities operating in the division, Number_d . This specification leads to study what happens when the Zakat donation takes place in cities with the same number of charities operating on the ground but with a different share of charities using cash as a means of payment. Second, I employ division-month-year fixed effects in equation (5) instead of only month-year fixed effects. I do this to remove any effect of charitable organizations on terrorism in a division except during the Zakat donation period, which is the object of my analysis.

Table V presents the estimates of equation (5). The first three columns replicate exactly the specification of Table III and show that these results are robust to replacing month-year fixed effects with division-month-year fixed effects. The point estimates of the double and triple interactions are close and statistically indistinguishable from those in Table III. Columns (4), (5), and (6) introduce the interactions with the share of cash and the number of charities. These variables have profound effects on the main results. In fact, the first two coefficients decline markedly in point estimate and are no longer statistically different from zero.

This specification shows three important results for this paper. First, the average effect of charities operating during the 2 Ramadan months, in Sunni-majority cities with average silver prices is positive, but small in magnitude and not statistically different from zero. This result suggests that local charities linked to local terrorist groups are not relevant in promoting terrorist attacks in the absence of a significant increase in donations. Second, cities in divisions that present a one-standard deviation higher share of charities using cash show a 1.4% higher probability of attacks and a 6% higher number of attacks and casualties in the presence of a one-standard deviation higher silver price during the Ramadan months. These point estimates are three to six times larger than those in the triple interaction, presented in columns (1), (2), and (3), and indicate that the use of cash by charities during the Zakat levy severely amplifies terrorism financing and attacks. Second, the last two interactions offer a sobering assessment about the role of charities in general and indicate that during the Zakat levy, areas presenting a higher number of charities exhibit a decline in the probability and number of terrorist attacks. Therefore, the combination of these two results offers a critical message on the role of charities: their presence and increased funding during the Zakat period reduces terrorism (e.g., due to a higher provision of public goods); at the same time, the existence of charities operating through cash and linked to terrorist groups promotes terrorist attacks, by channeling funding to extremist organizations.

The next three columns, (7), (8), and (9), offer the same specification as in the previous three columns but focus exclusively on capital intensive attacks. In line with Section 4.1.1,

TABLE V
TERRORISM FINANCING, CHARITIES, AND CASH.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability of Attack	Number of Attacks	Number of Casualties	Probability of Attack	Number of Attacks	Number of Casualties	Probability of Attack	Number of Attacks	Number of Casualties
$Sunni_c \times Ramadan_{my}$	0.0020 (0.0006)	0.0094 (0.0030)	0.0075 (0.0035)	0.000811 (0.000850)	0.00432 (0.00395)	0.00208 (0.00468)	0.000507 (0.000724)	0.00272 (0.00340)	0.00232 (0.00444)
$Sunni_c \times Ramadan_{my} \times Silver_y$	0.0041 (0.0010)	0.0192 (0.0050)	0.0199 (0.0051)	0.00190 (0.00128)	0.00904 (0.00611)	0.0105 (0.00667)	0.000783 (0.00112)	0.00417 (0.00532)	0.00910 (0.00661)
$Sunni_c \times Ramadan_{my} \times Cash Share_d$				0.00475 (0.00533)	0.0192 (0.0243)	0.0209 (0.0376)	0.00509 (0.00408)	0.0220 (0.0192)	0.0160 (0.0219)
$Sunni_c \times Ramadan_{my} \times Silver_y \times Cash Share_d$				0.0147 (0.00720)	0.0661 (0.0344)	0.0662 (0.0431)	0.0211 (0.00775)	0.0965 (0.0367)	0.0850 (0.0514)
$Sunni_c \times Ramadan_{my} \times Number_d$				-0.00302 (0.00115)	-0.0135 (0.00521)	-0.0144 (0.00525)	-0.00271 (0.000935)	-0.0125 (0.00436)	-0.0155 (0.00536)
$Sunni_c \times Ramadan_{my} \times Silver_y \times Number_d$				-0.00437 (0.00156)	-0.0203 (0.00746)	-0.0173 (0.00680)	-0.00491 (0.00141)	-0.0231 (0.00679)	-0.0213 (0.00705)
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division-Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,029,000	1,029,000	1,029,000	1,029,000	1,029,000	1,029,000	1,029,000	1,029,000	1,029,000
Adj. R sq.	0.293	0.338	0.286	0.293	0.338	0.286	0.280	0.323	0.273
Mean Dep. Var.	0.0075	0.0140	0.0617	0.0075	0.0140	0.0617	0.0063	0.0111	0.0553
S.D. Dep. Var.	0.0865	0.357	2.385	0.0865	0.357	2.385	0.0794	0.263	2.222

Note: This table presents ordinary least squares (OLS) estimates, where the unit of observation is city c in month-year my . City-year and division-month-year fixed effects are present in all columns and standard errors are clustered at the city level. The dependent variables are the probability of a terror attack in column (1); the natural logarithm of 0.01 plus the number of terrorist attacks in column (2); and the natural logarithm 0.01 plus the number of terrorist-related casualties in column (3). The dependent variables in columns (7), (8), and (9) describe exclusively terrorist events from capital intensive attacks, defined as those involving bombings/explosions and armed assaults. These are regressed over the Sunni composition of a city, $Sunni_c$; the standardized price of silver at the announcement of the Zakat threshold, $Silver_y$; a dummy taking unit value for the month in which Ramadan begins and the following month, $Ramadan_{my}$; the average share between the number of charities using cash as means of payment over the number of charities using all other means of payment in a division, $Cash Share_d$; the standardized average number of charities operating in a division, $Number_d$. The dependent variable's mean and standard deviation without log transformation are reported as the last two rows of the table.

the results are higher in point estimate by almost 50% and are much more precise statistically, indicating the results in the previous three columns are due to changes in capital intensive attacks.

4.2. *Terrorist Recruitment*

In this section, I verify whether the positive funding shocks affect the recruitment activities of terrorist organizations, and relatedly, whether more attacks occur when the availability of both funds and recruits is more prominent.

Measuring the “recruitment” of terrorist or criminal organizations is an inherently difficult task because it is distinctively unobservable. For this reason, I adopt an innovative method relying on novel data and methods from computer science. To analyze a consistent and impartial source of data, I access data from GeoWeb. This database contains more than four million messages from six message boards operating in Pakistan and containing messages in English, Urdu, and Roman Urdu between 2003 and 2012.²¹ Each data set contains the universe of messages exchanged on platforms and fora, in which a significant share of members sympathizes with extremist and terrorist groups and the concept of war against the unfaithful (Jihad). This is a rich database that includes a set of specific characteristics per forum: the thread which the topic is discussed under, each message’s date/time, each member’s name as registered on the platform and the content of each specific message.

After cleaning the data set from duplicates, nonalphabetic symbols, non-Urdu language threads, users with nonidentifiable or non-Pakistani locations, I analyze a compact data set with 2300 users from 111 Pakistani cities. This source is key to measuring terrorist recruitment by following a method in the computer science literature by Scanlon and Gerber (2014) on the automatic detection of cyber recruitment by violent extremists. The authors apply this exclusively to one platform, while I expand their method to additional online fora by using the original evaluations. Scanlon and Gerber (2014) submitted a random set of messages to two judges operating in the US, who evaluated these messages and marked with a dummy variable each message that “contains violent extremist recruitment.” Subsequently, I train an algorithm on the original set of messages and extend their prediction to the messages from the Pakistani online fora and geolocalize their users. In so doing, my variable of terrorist recruitment measures the number of messages sent on these online fora with the intent to recruit individuals. Online Appendix D describes the algorithm’s detailed steps, reports the geolocalization procedure and presents two recruitment messages identified by this algorithm.²²

Furthermore, Figure D.2 and Table D.1 in Online Appendix D apply respectively the event study specification of Figure 4 and the difference-in-difference design of Table III to study whether and how the number of recruitment messages responds to terrorism financing. Both of these tests indicate that recruitment messages on these online fora do not appear to increase in Sunni-majority cities during the Ramadan months and in the presence of high silver prices. This may be due to the fact that while the availability of financing is a binding constraint to the operations of a terrorist organization, the access to a pool of recruits does not appear to constrain extremist groups.

²¹A detailed description of the platforms operating in Pakistan and used in the analysis, with their corresponding characteristics, can be found at <https://www.azsecure-data.org/geoweb-forums.html>.

²²Figure D.1 complements this information with two figures: one describing the evolution of the recruitment and total messages over time and another showing the geography of recruitment messages.

Given that recruitment does not change during the Zakat period, I study whether the Zakat funding shock produces a stronger effect on terrorist attacks in periods during which recruitment is particularly intense. I explore the following empirical model:

$$\begin{aligned} Terror_{cmy} = & h_1 Sunni_c \times Ramadan_{my} + h_2 Sunni_c \times Ramadan_{my} \times Silver_y \\ & + h_3 Sunni_c \times Ramadan_{my} \times Recruit_{dmy} + h_4 Sunni_c \times Ramadan_{my} \\ & \times Silver_y \times Recruit_{dmy} + \nu_{cy} + \iota_{my} + \varepsilon_{cmy}, \end{aligned} \quad (6)$$

which presents the same empirical design expressed in equation (4) while adding two interactions between the first and second terms with the recruitment variable, $Recruit_{dmy}$. This variable is defined as the natural logarithm of 0.01 plus the average number of recruitment messages classified by the algorithm in a division and year. Fixed effects are introduced for city-year and month-year, while standard errors are clustered at the city level. It is important to remember that the sample during which this exercise occurs is smaller than the other empirical exercises because the *Recruitment* variable is only available between 2003 and 2012.

Table VI reports the empirical estimates of equation (7). Columns (1), (2), and (3) replicate the results of Table III for this smaller sample. These columns show that the point estimates on the first term, $Sunni_c \times Ramadan_{my}$, are much smaller than in Table III and are no longer statistically different from zero, implying the lack of a differential increase in terrorist attacks in Sunni-majority cities during Ramadan between 2003 and 2012. However, the key finding of this paper is given by the triple interactions of Table VI and Table III, $Sunni_c \times Ramadan_{my} \times Silver_y$, which are nearly identical in sign, point estimate, and statistical precision.

In columns (4), (5), and (6), I introduce an interaction between the previous two terms and a measure of recruitment messages for division d in year y . Instead of exploring recruitment at the city level, I abstract at a higher level of geographic aggregation, the division, as the appropriate “labor market” in which a terrorist recruit may operate. These three columns show how the results of the first two terms of equation (7) change as these additional interactions are introduced: the first term is still not statistically different from zero, while the magnitudes of the second term decline around 30% but remain positive and statistically different below the usual 5% threshold.

The second set of interactions shows two interesting additions to the previous findings. On the one hand, the triple interaction between the Sunni-majority city, Ramadan months, and recruitment variables is not statistically different from zero and is small in magnitude. On the other hand, the quadruple interactions in which the Sunni-majority and Ramadan variables are interacted with silver prices and recruitment exhibit a positive sign and a sizeable magnitude and are statistically different from zero below the 1% threshold. This coefficient reveals that in the presence of one-standard deviation higher silver prices and terrorist recruitment, Sunni-majority cities experience a 0.07% higher probability of terrorist attacks and a 0.3% larger number of terrorist attacks and casualties during Ramadan. These magnitudes are sizeable: during a Ramadan period with one-standard deviation high silver prices and terrorist recruitment, Sunni-majority cities experience a 20% higher probability of attacks relative to a period in which terrorist recruitment is at its average value. These magnitudes are similar for the number of terrorist attacks, 21%, and the number of casualties, 15%.

Finally, columns (7), (8), and (9) of Table VI replicate the results of columns (4), (5), and (6) and add an interaction with the overall number of messages net of the recruitment messages. I perform this exercise to verify the robustness of the findings in columns (4),

TABLE VI
TERRORISM FINANCING, RECRUITMENT, AND ATTACKS.

Variables	(1) Probability of Attack	(2) Number of Attacks	(3) Number of Casualties	(4) Probability of Attack	(5) Number of Attacks	(6) Number of Casualties	(7) Probability of Attack	(8) Number of Attacks	(9) Number of Casualties
$Sunni_c \times Ramadan_{my}$	0.000263 (0.00134)	0.00173 (0.00642)	0.00304 (0.00807)	-0.00104 (0.00153)	-0.00471 (0.00736)	-0.00227 (0.00888)	-0.00102 (0.00173)	-0.00515 (0.00826)	-0.00812 (0.00970)
$Sunni_c \times Ramadan_{my} \times Silver_y$	0.00560 (0.00147)	0.0259 (0.00711)	0.0273 (0.00539)	0.00347 (0.00161)	0.0156 (0.00778)	0.0183 (0.00599)	0.00124 (0.00215)	0.00447 (0.0104)	0.00726 (0.00881)
$Sunni_c \times Ramadan_{my} \times Recruitment_{dy}$				-0.000269 (0.000213)	-0.00138 (0.00101)	-0.00103 (0.00111)	-0.000176 (0.000225)	-0.000986 (0.00106)	-0.00135 (0.00124)
$Sunni_c \times Ramadan_{my} \times Silver_y \times Recruitment_{dy}$				0.000747 (0.000260)	0.00366 (0.00124)	0.00310 (0.00113)	0.000779 (0.000282)	0.00385 (0.00134)	0.00366 (0.00124)
$Sunni_c \times Ramadan_{my} \times Messages_{dy}$							-0.000493 (0.000655)	-0.00193 (0.00304)	0.00340 (0.00391)
$Sunni_c \times Ramadan_{my} \times Silver_y \times Messages_{dy}$							0.00125 (0.000520)	0.00615 (0.00249)	0.00488 (0.00249)
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	212,352	212,352	212,352	212,352	212,352	212,352	212,352	212,352	212,352
Adj. R sq.	0.326	0.368	0.308	0.326	0.368	0.308	0.326	0.368	0.308
Mean Dep. Var.	0.0127	0.0231	0.125	0.0127	0.0231	0.125	0.0127	0.0231	0.125
S.D. Dep. Var.	0.112	0.317	3.387	0.112	0.317	3.387	0.112	0.317	3.387

Note: This table presents ordinary least squares (OLS) estimates, where the unit of observation is city c in month-year my . City-year and month-year fixed effects are present in all columns and standard errors are clustered at the city level. The dependent variables are the probability of a terror attack in columns (1), (4), and (7); the natural logarithm of 0.01 plus the number of terrorist attacks in columns (2), (5), and (8); and the natural logarithm 0.01 plus the number of terrorist-related casualties, in columns (3), (6), and (9). These are regressed over the Sunni composition of a city, $Sunni_c$; the standardized price of silver at the announcement of the Zakat threshold, $Silver_y$; a dummy taking unit value for the month in which Ramadan begins and the following month, $Ramadan_{my}$; the natural logarithm of 0.01 plus the average number of recruitment messages classified by the algorithm in a division and year, $Recruitment_{dy}$; the natural logarithm of 0.01 plus the average number of nonrecruitment messages exchanged in the online fora in a division and year, $Messages_{dy}$. The dependent variable's mean and standard deviation without log transformation are reported as the last two rows of the table.

(5), and (6) and to investigate whether a more active use of these Jihadist-friendly online fora may be, per se, a measure of recruitment. The results from the final three columns of Table VI show that including these additional two interactions do not lower neither the point estimates nor the precision of the quadruple interactions with the *Recruitment_{dy}* variable. The quadruple interactions with the *Messages_{dy}* variable exhibit a positive, large and significant effect in addition to the recruitment counterpart. This may occur because periods of higher activities on these chats may indicate a higher pool of potential candidates or informers, which may facilitate the organization and the deployment of terrorist attacks.

4.3. *Terrorism Financing and Attacks: City-Organization-Level Analysis*

The results on the relation between financing and terrorist attacks may be rationalized through two complementing stories: (1) an increase in the supply of terrorist attacks by extremist organizations as a result of increased funding given by charitable donations, which is a testable implication of the of theoretical framework in Section 2 and Appendix A of the Online Appendix and (2) changes in city sentiments and characteristics due to a stronger activity of charities after a Zakat funding boost. It is typically hard to dissect these elements in the terrorism and conflict literature, and Dube and Vargas (2013) pioneered this field by focusing on different types of shocks to isolate the “rapacity” effect (supply) from the “opportunity cost” effect (demand).

I introduce an alternative method to investigate the effect of this natural experiment, which can be generalized in other studies on conflict and violence. I build an additional panel in which I follow 1750 cities and 29 terrorist organizations over 588 month-year periods from 1970 to 2018 containing more than 20 million observations. In addition, I enrich and cross-check information on terrorist organizations from the GTD database with local newspapers (in English and Urdu) and cross-validate the names/affiliations of the terrorist organizations claiming the attack, as described in Online Appendix C.²³

In so doing, I can isolate the role of terrorist groups by analyzing the within-city variation and exploiting the cross-sectional variation in attacks between Sunni and non-Sunni organizations, which measures changes in the supply of terrorist attacks by an organization. Analogously, I can focus on the within-organization and exploit the cross-sectional variation between Sunni-majority and non-Sunni-majority cities, which can be interpreted as the demand of terrorist attacks due to city shocks to policing or labour markets. Given this novel method, I expand equation (4) through this richer empirical model:

$$\begin{aligned} \text{ Terror}_{comy} = & g_1 \text{Sunni}_c \times \text{Ramadan}_{my} + g_2 \text{Sunni}_c \times \text{Ramadan}_{my} \times \text{Silver}_y \\ & + g_3 \text{Sunni}_o \times \text{Ramadan}_{my} + g_4 \text{Sunni}_o \times \text{Ramadan}_{my} \times \text{Silver}_y \\ & + \nu_o + \nu_{cy} + \nu_{my} + \varepsilon_{comy}. \end{aligned} \quad (7)$$

²³Online Appendix C reports the list of terrorist organizations and their corresponding religious affiliations. As Pakistan is a Sunni-majority country, most religious groups are associated with the Sunni school of Islam (24 out of 29), while only a minority can be identified as non-Sunni. Most of these groups typically fight against the Pakistani government, with varying degrees of political ambition. For example, the Taliban (Tehrik-i-Taliban Pakistan or TTP) fight for a more extensive application of the Sharia law, and others favor an Islamic state across South Asia (Lashkar-e-Taiba) or have more restricted territorial ambitions (Baloch groups in the Balochistan state, Jaish-e-Mohammad in Kashmir, the Sindhu army in the Sindh state), while others engage in sectarian violence (most Sunni groups, Sipah-I-Mohammed among the non-Sunni, etc.). Online Appendix C reports a detailed description of each group, including materials that support the religious classification.

Equation (7) regresses the measures of terrorism in city c from organization o in month-year my on the fixed effects for organization, city-year, and month-year ($\iota_o, \iota_{cy}, \iota_{my}$). It includes the same regressors from equation (4), hence the interactions between the standardized price of silver, $Silver_t$; the Ramadan dummy, $Ramadan_t$; and the Sunni-majority dummy, $Sunni_c$. Finally, to account for the supply of terrorist attacks, it presents the same first two variables ($Silver_t$ and $Ramadan_{my}$) interacted with a dummy coding each terrorist organization as being Sunni, $Sunni_o$. Standard errors are clustered at the cross-sectional unit in which the shock takes place, hence at the city level. To focus on the organization channel, I also replace city-year and month-year fixed effects with city-month-year fixed effects and remove any city time-varying unobservables to focus exclusively on the within-city time and cross-group variation (which absorbs the interactions with $Sunni_c$ as well). To simplify the interpretation of the coefficients in Table VII, I standardize the left-hand side variables.

Table VII reports the results of equation (7). In columns (1), (2), and (3), I introduce only organization, city-year, and month-year fixed effects. The results of these columns replicate those of Table III and show that, during the 2 Ramadan months, Sunni-majority cities experience an increase in the probability of an attack by 0.3% of a standard deviation, in the number of attacks by 0.3 and number of casualties by 0.2% of a standard deviation. This effect is also larger when silver prices are one-standard deviation higher than the mean, with an additional increase in the probability of an attack by 0.4% of a standard deviation, in the number of attacks by 0.4 and number of casualties by 0.3% of a standard deviation.

Columns (4), (5), and (6) further investigate the escalation in attacks by separating the effect due to Sunni-majority cities—through the first two interactions employing the $Sunni_c$ variable—and Sunni terrorist organizations—through the $Sunni_o$ dummy. Adding these interactions introduces an important element compared to the previous three columns. While the estimates of the first two regressors, based on the $Sunni_c$ variable, stay unchanged, the last two regressors, based on the $Sunni_o$ variable, bring two valuable results.

First, the interaction $Sunni_o \times Ramadan_{my}$ is close to zero in point estimate and not statistically different from zero. It indicates that Sunni terrorist groups are not more active during the 2 Ramadan months, when silver prices are at their average level. This may imply that in the absence of a funding shock, a Sunni terrorist group does not attack more frequently during this festivity than a non-Sunni one. Second, the triple interaction $Sunni_o \times Ramadan_{my} \times Silver_y$ is positive and statistically different from zero and its magnitude is three times larger than the corresponding $Sunni_c \times Ramadan_{my} \times Silver_y$ coefficient. This variable states that in the presence of a one-standard deviation higher silver price during the Ramadan months, a Sunni terrorist group presents a higher probability of attack, a larger number of attacks, and produces more casualties by 1.2% of a standard deviation. This finding suggests that two-thirds of the increase in attacks related to the Zakat levy are attributable to more active Sunni terrorist groups.

Finally, columns (7), (8), and (9) replicate the results in columns (4), (5), and (6) but replace city- and month-year fixed effects with city-month-year fixed effects. This tighter specification with fixed effects should remove any variation coming from city time-varying unobservables that could proxy for changes in demand conditions. These last three columns of Table VII show that there are no changes in point estimates or precision, but only a large decline in the Adjusted R^2 , which may imply that the demand effects on terror induced by the Zakat levy are negligible and, therefore, these city-month-year fixed effects do not explain significant variation in terror.

TABLE VII
TERRORIST GROUPS AND TERRORIST ATTACKS.

Variables	(1) Probability of Attack	(2) Number of Attacks	(3) Number of Casualties	(4) Probability of Attack	(5) Number of Attacks	(6) Number of Casualties	(7) Probability of Attack	(8) Number of Attacks	(9) Number of Casualties
$Sunni_c \times Ramadan_{my}$	0.00309 (0.00120)	0.00308 (0.00118)	0.00233 (0.00130)	0.00309 (0.00120)	0.00308 (0.00118)	0.00233 (0.00130)			
$Sunni_c \times Ramadan_{my} \times Silver_y$	0.00418 (0.00189)	0.00410 (0.00186)	0.00351 (0.00207)	0.00418 (0.00189)	0.00410 (0.00186)	0.00351 (0.00207)			
$Sunni_o \times Ramadan_{my}$				0.000708 (0.000755)	0.000739 (0.000773)	0.000726 (0.000816)	0.000708 (0.000755)	0.000739 (0.000773)	0.000726 (0.000816)
$Sunni_o \times Ramadan_{my} \times Silver_y$				0.0124 (0.00164)	0.0123 (0.00169)	0.0121 (0.00188)	0.0124 (0.00164)	0.0123 (0.00169)	0.0121 (0.00188)
Organization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes			
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes			
City-Month-Year FE							Yes	Yes	Yes
Obs.	29,841,000	29,841,000	29,841,000	29,841,000	29,841,000	29,841,000	29,841,000	29,841,000	29,841,000
Adj. R sq.	0.00947	0.0104	0.00958	0.00948	0.0104	0.00958	0.00460	0.00492	0.00458
Mean Dep. Var.	0.00007	0.000111	0.000975	0.00007	0.000111	0.000975	0.00007	0.000111	0.000975
S.D. Dep. Var.	0.00892	0.0189	0.318	0.00892	0.0189	0.318	0.00892	0.0189	0.318

Note: This table presents ordinary least squares (OLS) estimates, where the unit of observation is an attack in city c by terrorist organization o in month-year my . Organization, city-year, and month-year fixed effects are present in columns (1) to (6), while columns (7) to (9) include only organization and city-month-year fixed effects. Standard errors are clustered at the city level. The dependent variables are the standardized probability of a terror attack in columns (1), (4), and (7); the standardized natural logarithm of 0.01 plus the number of terrorist attacks in columns (2), (5), and (8); and the standardized natural logarithm 0.01 plus the number of terrorist-related casualties in columns (3), (6), and (9). These are regressed over a variable describing the Sunni composition of a city, $Sunni_c$; the standardized price of silver at the announcement of the Zakat threshold, $Silver_y$; a dummy taking unit value for the month in which Ramadan begins and the following month, $Ramadan_{my}$; and a variable describing the Sunni affiliation of a terrorist group, $Sunni_o$. The dependent variable's mean and standard deviation without log transformation are reported as the last two rows of the table.

4.4. *Placebo, Additional Test, and Robustness Checks*

In this section, I explore the Eid Adha placebo, one additional test of my main hypothesis and a number of alternative specifications.

4.4.1. *Eid Adha Placebo*

It could be argued that the estimates for the Zakat festivity may be present in any other Islamic celebration. For example, suppose the wealth of terrorist organizations is placed in an asset that correlates with commodities during religious holidays. It could also be possible that any other period might lead to the replication of Section 3's results. To verify that this is not the case, I replicate the previous empirical setting for another Islamic holiday (Eid Adha) and verify that I cannot reject a zero effect.

Figure E.1 replicates the event study specification around the Eid Adha holiday, as Figure 4 does for the beginning of Ramadan. The three panels show there is no differential increase in terrorist attacks in Sunni-majority cities neither when Eid Adha occurs nor when the silver prices in the 2 days before this celebration are one-standard deviation higher than the mean. The only recorded spikes in attacks take place between 2 and 3 months before Eid Adha celebration, which corresponds to the Zakat effect. Table E.2 replicates the empirical specification reported in Table III but replaces the $Ramadan_{my}$ dummy with a dummy taking unit value for the month marking the beginning of Eid Adha and the following one, $Adha_{my}$. It also employs the standardized international price of silver calculated 2 days before the Adha festivity. None of the coefficients can be rejected to equal zero.

4.4.2. *Terrorism, Financing, and Sanctions*

To verify whether the months of Zakat donations are a period of increased alerts on terrorism financing, I build a data set on sanctions related to terrorism and terrorism financing administered by the Office of Foreign Assets Control of the US Department of the Treasury, the European Union, and the United Nations. This sanction data set is available for 1750 cities over 192 month-year periods between 2002 and 2017 and allows me to measure the probability that a sanction is assigned and the number of assigned sanctions.²⁴

Table E.3 replicates the empirical specification presented in Table III but reports as left-hand side variables the probability that city c during month-year my receives a sanction and the number of sanctions received. Both columns (1) and (2) show that the first interaction between the Sunni-majority variable and the Ramadan dummy cannot be rejected to be different from zero. However, the triple interaction which includes silver prices can be rejected to be statistically different from zero below the 10% threshold and is close to the 5% threshold (the exact t lies between 6% and 7% for both coefficients). While these results are only suggestive, they offer evidence that organizations operating in Sunni-majority cities are more likely to be targeted by terrorism and terrorism financing sanctions during periods of high Zakat donations and high terrorism financing.

²⁴This data set is built using the data from Sanctions Explorer, available at the following website: <https://sanctionsexplorer.org/>. As indicated on their website: "This project initiated by a collaboration between Archer, a former Berkeley-based nonprofit using tech to improve human rights and human security, and C4ADS, a nonprofit dedicated to providing data-driven, evidence-based research on global conflict and transnational security issues. The current iteration of Sanctions Explorer was developed fully by C4ADS Data and Technology team, and is meant to be a comprehensive source of all current and historical sanctions data across all major sanctioning authorities."

4.4.3. Robustness Checks

The remaining tables in Online Appendix E report some useful additional tests, which show the robustness of these findings to alternative hypotheses and specifications. Table E.4 explores in greater detail the religious map of Pakistan and presents the same empirical specification of Table III. Columns (1), (2), and (3) restrict the sample to comparing only Sunni-majority cities with non-Sunni-majority cities and exclude Sunni-mixed cities. The results of these columns are in line with those of Table III. Columns (4), (5), and (6) further restrict their attention to cities located within a 75 km radius from the border between Sunni-majority and non-Sunni-majority cities. Despite the sample being substantially smaller, almost one-fifth of the original, the findings of these columns are aligned with Table III. Finally, columns (7), (8), and (9) of Table E.4 extend the radius to 150 km from the border without substantial differences in the results.

Table E.5 replicates the results of Table III but replaces the silver variable with three dummies expressing the tercile of silver prices in the sample. This test is meant to verify whether the effect of silver prices is symmetric so that terrorism increases when silver prices are higher and declines when silver prices go down. All three columns of Table E.5 show that all of the results are concentrated in periods of exceptionally high silver prices, hence when silver is in the third tercile. Therefore, the interpretation of this paper's findings should focus on positive funding shocks generated by high silver prices given that periods of low and median silver prices corresponding to the first and second tercile do not produce changes in terror.

Table E.6 investigates the importance of mines. In fact, high silver prices may imply an increase in terror around mine sites rather than the rest of the country since these resources become more valuable. Figure E.2 in Appendix E reports the map of mines in Pakistan, elaborated using the Geological Survey of Pakistan produced by the Ministry of Energy of Pakistan. In this case, I augment the specification of Table III by interacting the two interactions with $Mine_c$, which takes unit value if a city is within 50 km of a mine (columns (1)–(3)), 75 km of a mine (columns (4)–(6)), and 100 km of a mine (columns (7)–(9)). These two last interactions are meant to capture the differential effect of silver price shocks on terror in cities close to the mines. All nine columns of Table E.6 cannot reject a zero effect of the two interactions with the dummy $Mine_c$.

Tables E.7 and E.8 use disaggregated data on the types of terrorist attacks and the weapons used in these events. These tables are meant to complement the results on capital intensity presented in Table IV without imposing an ad hoc grouping of attacks. Columns (1) and (2) in Table E.7 show that the effects of Table IV are completely driven by an increase in bombings/explosions and armed assaults, which were described as capital intensive in Section 4.1.1. All other types of attacks do not respond to the shock to terrorism financing. In line with these results, column (1) of Table E.8 shows that explosives are the only weapon being used more extensively during the natural experiment in analysis.

Table E.9 studies a data set of terrorist attacks that exclusively focuses on terrorist organizations. This table is a version of Table III, which replaces the variable $Sunni_c$ with the organization-level dummy describing groups as Sunni or non-Sunni, $Sunni_o$. In line with the findings of Table VII, columns (1), (2), and (3) of Table E.9 show that Sunni terrorist groups increase their attacks during the 2 Ramadan months and when silver prices are one-standard deviation higher than the mean. Columns (4) to (9) decompose this increase in attacks between capital intensive attacks and noncapital intensive attacks following the definition given in Section 4.1.1. These columns provide evidence that both types of attacks are positively and statistically increasing with the triple interaction at the

organization level. However, the increase in capital intensive attacks exhibits larger magnitudes (between 20% and 200%).

Figure E.3 and Table E.10 address the possibility that local confounders may affect the role of charities using cash as mechanism to amplify terrorism financing and attacks. I show in Figure E.3 that the share of charities using cash at the division level is highly correlated with two important determinants of cash adoption: income per capita and level of education. To verify whether the findings of Table V are due to cash or such confounders, I augment that specification by including additional interactions between the variables $Sunni_c$, $Ramadan_{my}$, and $Silver_y$ with $Income_d$, as the average income per capita, and $Education_d$, as the average level of education at the division level. Table E.10 shows that these additional interactions do not affect the sign, magnitude, and statistical precision of the quadruple interaction between $Sunni_c$, $Ramadan_{my}$, $Silver_y$, and $Cash Share_d$.

Finally, Tables E.11 and E.12 verify that the results of Tables III and IV are robust to (1) replacing the natural logarithm of attacks and casualties with the inverse sine transformation and (2) replacing the ordinary least square estimates with a conditional fixed-effect Poisson method. The sign, magnitudes, and statistical significance are aligned to those of Tables III and IV.

5. CONCLUDING REMARKS

This paper provides quantitative evidence on the link between terrorism financing, recruitment, and attacks. The findings are in line with the existence of financial frictions to the internal capital market of terrorist organizations. Pakistan offers the ideal setting to verify this relation because of a unique natural experiment that induces quasi-experimental variation in a specific source of terrorism financing over time and across cities due to a Sharia-compliant obligation, Zakat. I build a variety of novel databases, in particular, a panel that follows 1750 cities over 588 month-year periods between 1970 and 2018. Through this, I verify that cities with higher terrorism financing exogenously determined to local conditions experience more terrorist attacks. This increase in terror occurs through a higher deployment of capital intensive attacks (e.g., bombings, explosions, armed assaults).

I introduce two methods to investigate the underlying mechanism behind this natural experiment and advance the identification of an organization-financing channel. First, I set up a panel that follows 29 terrorist organizations in 1750 cities over 588 month-year periods from 1970 to 2018. This novel method allows me to dissect the demand and supply of terrorist attacks by (1) studying the within-city and within-organization variation, and (2) classifying each organization as being a potential recipient of this exogenous increase in terrorism financing. I find that the effect of terrorism financing on terrorist attacks is due to a temporary increase in the supply of terrorist attacks by extremist organizations. I also measure terrorist recruitment by analyzing data from Jihad-friendly online fora using a machine-learning algorithm. Through this procedure, I verify that in periods of higher terrorist recruitment, there is a significantly larger effect of terrorism financing on attacks. The result is compatible with a complementarity between labour and capital in the production function of terrorist attacks.

These results are in line with the theoretical and empirical literature on the organizational economics of terrorist and violent groups. In particular, this paper tests directly the hypothesis that financial frictions have a critical role in shaping the behavior of terrorist organizations. Conceptually these findings support the activities of financial counterterrorism agencies, provided that these can amplify the financial frictions experienced by terrorist groups, and consequently lower the incidence of violent attacks.

At the same time, it is important to note that these findings are specific to Pakistan and to this unique empirical design. Therefore, additional evidence on the transmission of terrorism financing in other countries and settings may enrich the body of knowledge on this topical issue, and induce more research on the role of financial counterterrorism and the oversight of charitable organizations.

REFERENCES

- ABADIE, ALBERTO (2006): "Poverty, Political Freedom, and the Roots of Terrorism," *American Economic Review*, 96 (2), 50–56. [1715]
- AMAN-RANA, SHAN (2014): "The Economic Causes of Terror: Evidence From Rainfall Variation and Terrorist Attacks in Pakistan," Working Paper. [1714]
- (2017): "Charitable Donations and Violence: Empirical Evidence From Pakistan," Working Paper. [1714]
- AMODIO, FRANCESCO, LEONARDO BACCINI, AND MICHELE DI MAIO (forthcoming) "Security, Trade, and Political Violence," *Journal of the European Economic Association*. [1715]
- BASILE, MARK (2004): "Going to the Source: Why al Qaeda's Financial Network Is Likely to Withstand the Current War on Terrorist Financing," *Studies in Conflict & Terrorism*, 27 (3), 169–185. [1714]
- BATTISTON, GIACOMO, GIANMARCO DANIELE, MARCO LE MOGLIE, AND PAOLO PINOTTI (2022): "Fueling Organized Crime: The Mexican War on Drugs and Oil Thefts," BAFFI CAREFIN Centre Research Paper (2022-171). [1714]
- BEATH, ANDREW, FOTINI CHRISTIA, AND RUBEN ENIKOLOPOV (2017): "Can Development Programs Counter Insurgencies? Evidence From a Field Experiment in Afghanistan." [1714]
- BENMELECH, EFRAIM, AND CLAUDE BERREBI (2007): "Human Capital and the Productivity of Suicide Bombers," *Journal of Economic Perspectives*, 21 (3), 223–238. [1715]
- BERMAN, ELI (2003): " Hamas, Taliban and the Jewish Underground: An Economist's View of Radical Religious Militias", Technical Report, National Bureau of Economic Research. [1714]
- (2011): *Radical, Religious, and Violent: The New Economics of Terrorism*. MIT press. [1714]
- BERMAN, ELI, JACOB N. SHAPIRO, AND JOSEPH H. FELTER (2011): "Can Hearts and Minds Be Bought? The Economics of Counterinsurgency in Iraq," *Journal of Political Economy*, 119 (4), 766–819. [1714]
- BERMAN, NICOLAS, MATHIEU COUTTENIER, DOMINIC ROHNER, AND MATHIAS THOENIG (2017): "This Mine Is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review*, 107 (6), 1564–1610. [1715]
- BIERSTEKER, THOMAS J., SUE E. ECKERT, AND PETER ROMANIUK (2007): *International Initiatives to Combat the Financing of Terrorism*. Routledge. [1718]
- BLAIR, GRAEME, C. CHRISTINE FAIR, NEIL MALHOTRA, AND JACOB N. SHAPIRO (2013): "Poverty and Support for Militant Politics: Evidence From Pakistan," *American Journal of Political Science*, 57 (1), 30–48. [1715]
- BUENO DE MESQUITA, ETHAN (2005a): "Conciliation, Counterterrorism, and Patterns of Terrorist Violence," *International Organization*, 59 (1), 145–176. [1714]
- (2005b): "The Quality of Terror," *American Journal of Political Science*, 49 (3), 515–530. [1713-1715]
- (2007): "Politics and the Suboptimal Provision of Counterterror," *International Organization*, 61 (1), 9–36. [1714]
- (2013): "Rebel Tactics," *Journal of Political Economy*, 121 (2), 323–357. [1714]
- CARRERI, MARIA, AND OEINDRILA DUBE (2017): "Do Natural Resources Influence Who Comes to Power, and How?" *The Journal of Politics*, 79 (2), 502–518. [1715]
- CHOUDHARY, ALI M., AND NICOLA LIMODIO (2022): "Liquidity Risk and Long-Term Finance: Evidence From a Natural Experiment," *The Review of Economic Studies*, 89 (3), 1278–1313. [1716]
- CROST, BENJAMIN, JOSEPH H. FELTER et al. (2016): "Export Crops and Civil Conflict," *Empirical Studies of Conflict Working Paper* (4). [1714]
- CROST, BENJAMIN, JOSEPH H. FELTER, AND PATRICK JOHNSTON (2014): "Aid Under Fire: Development Projects and Civil Conflict," *American Economic Review*, 104 (6), 1833–1856. [1715]
- D'SOUZA, SHANTHIE M. (2017): "Countering Insurgencies, Terrorism and Violent Extremism in South Asia," *Small Wars and Insurgencies*. [1720]
- DUBE, OEINDRILA, AND JUAN F. VARGAS (2013): "Commodity Price Shocks and Civil Conflict: Evidence From Colombia," *The Review of Economic Studies*, 80 (4), 1384–1421. [1712,1714,1735]
- DUBE, OEINDRILA, OMAR GARCÍA-PONCE, AND KEVIN THOM (2016): "From Maize to Haze: Agricultural Shocks and the Growth of the Mexican Drug Sector," *Journal of the European Economic Association*, 14 (5), 1181–1224. [1715]

- FERNANDEZ, ALBERTO (2015): “Contesting the Space: Adversarial Online Engagement as a Tool for Combating Violent Extremism,” *Soundings: An Interdisciplinary Journal*, 98 (4), 488–500. [1720]
- FETZER, THIEMO (2014): “Social Insurance and Conflict: Evidence From India,” Working Paper 14. [1714]
- FETZER, THIEMO, PEDRO C. SOUZA, OLIVER VANDEN EYNDE, AND AUSTIN L. WRIGHT (2021): “Security Transitions,” *American Economic Review*, 111 (7), 2275–2308. [1714]
- JAEGER, DAVID A., AND M. DANIELE PASERMAN (2006): “Israel, the Palestinian Factions, and the Cycle of Violence,” *American Economic Review*, 96 (2), 45–49. [1715]
- (2008): “The Cycle of Violence? An Empirical Analysis of Fatalities in the Palestinian-Israeli Conflict,” *American Economic Review*, 98 (4), 1591–1604. [1715]
- KRUEGER, ALAN B. (2008): “What Makes a Homegrown Terrorist? Human Capital and Participation in Domestic Islamic Terrorist Groups in the usa,” *Economics Letters*, 101 (3), 293–296. [1715]
- KRUEGER, ALAN B., AND JITKA MALEČKOVÁ (2002): “Education, Poverty, Political Violence and Terrorism: Is There a Causal Connection?” NBER Working Paper, 9074. [1715]
- (2009): “Attitudes and Action: Public Opinion and the Occurrence of International Terrorism,” *Science*, 325 (5947), 1534–1536. [1715]
- LEVI, MICHAEL (2010): “Combating the Financing of Terrorism: A History and Assessment of the Control of Threat Finance,” *The British Journal of Criminology*, 50 (4), 650–669. [1714]
- LIMODIO, NICOLA (2022): “Supplement to ‘Terrorism Financing, Recruitment, and Attacks’,” *Econometrica Supplemental Material*, 90, <https://doi.org/10.3982/ECTA18530>. [1715]
- MARTIN, PHILIPPE, THIERRY MAYER, AND MATHIAS THOENIG (2008): “Civil Wars and International Trade,” *Journal of the European Economic Association*, 6 (2–3), 541–550. [1715]
- MILTON-EDWARDS, BEVERLEY (2017): “Securitizing Charity: The Case of Palestinian Zakat Committees,” *Global Change, Peace & Security*, 29 (2), 161–177. [1714]
- MUELLER, HANNES F., AND CHRISTOPHER RAUH (2018): “Reading Between the Lines: Prediction of Political Violence Using Newspaper Text,” *American Political Science Review*, 112 (2), 358–375. [1713]
- REESE, MICHAEL J., KEVEN G. RUBY, AND ROBERT A. PAPE (2017): “Days of Action or Restraint? How the Islamic Calendar Impacts Violence,” *American Political Science Review*, 111 (3), 439–459. [1714]
- SCANLON, JACOB R., AND MATTHEW S. GERBER (2014): “Automatic Detection of Cyber-Recruitment by Violent Extremists,” *Security Informatics*, 3 (1), 5. [1713,1720,1732]
- SHAPIRO, JACOB N. (2007): “Terrorist Organizations Vulnerabilities and Inefficiencies,” in *Terrorism Financing and State Response*, 58. [1714]
- (2013): *The Terrorist’s Dilemma: Managing Violent Covert Organizations*. Princeton University Press. [1714]
- SHAPIRO, JACOB N., AND DAVUD A. SIEGEL (2007): “Underfunding in Terrorist Organizations,” *International Studies Quarterly*, 51 (2), 405–429. [1714,1715]
- START (2020): “Global Terrorism Database, National Consortium for the Study of Terrorism and Responses to Terrorism,” University of Maryland. [1719]
- SVIATSKI, MARIA M. (2019): “Making a Narco: Childhood Exposure to Illegal Labor Markets and Criminal Life Paths,” Working Paper, Princeton University. [1715]
- WRIGHT, AUSTIN L. (2016): “Economic Shocks and Rebel Tactics,” HiCN WP, 232. [1714]

Co-editor Alessandro Lizzeri handled this manuscript.

Manuscript received 29 May, 2020; final version accepted 15 March, 2022; available online 25 March, 2022.