Sanctions, Financial Frictions, and the Organization of Conflict*

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Abstract

This paper studies how financial sanctions reshape the organization of conflict by increasing financial frictions. We exploit staggered sanctions on Pakistani terrorist leaders, linked to unique administrative data matching leaders' identities to charities, fundraising, and attacks. After sanctions, unsanctioned associates of sanctioned terrorist leaders create more charities, exposed charities raise more funds, and terrorist groups fragment across organizations. This reallocates terror: attacks increase in Pakistan but decline in the US and Western Europe. A multi-agent LLM maps the evidence into our model, yielding financial friction intervals with a midpoint near 20 percent, comparable to a wealth tax on terrorist organizations.

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1 Introduction

Financial coercion has become a central instrument of statecraft, as sanctions on banks, firms, and individuals increasingly operate through the architecture of global finance, such as payment systems, reserve currencies, correspondent banking, and cross-border capital flows, rather than through traditional trade or military channels (Baldwin, 1985; Drezner, 2024; Clayton et al., 2025a,b,c). Yet, as recent surveys of geoeconomics emphasize, we still have limited micro-level evidence on how these sanctions affect the behavior and organization of their targets (Mohr and Trebesch, 2025), especially when enforcement is shaped by information frictions (Dutt et al., 2025). This gap is particularly important in conflict settings, where finance and violence are jointly determined: armed conflict reshapes financial networks, while the structure of intermediation conditions the resources available for violence (Limodio, 2022; de Haas et al., 2025). Recent evidence shows that financial shocks often generate reallocation, not only retrenchment (Efing et al., 2023; Fisman et al., 2025; Keerati, 2022). As a result, targeted financial sanctions may alter not only the amount of funding available to violent organizations, but also its composition and the organizational channels through which it flows.

This paper studies how individual financial sanctions on leaders of violent organizations affect fundraising, organizational structure, and conflict. Such sanctions operate through the global financial system, dollar clearing, correspondent banking, and compliance rules, and are enforced domestically through know-your-customer and anti-money laundering regulation. They are therefore designed to tighten leaders' financial constraints and reduce violence. Their net effect, however, is theoretically ambiguous: while restricted access to finance may weaken operations, sanctioned leaders may also adapt by decentralizing fundraising and reallocating resources through broader organizational networks. Which force dominates is an empirical question, as related evidence on leadership disruption shows in other violent settings (Vargas, 2014; Phillips, 2015; Dell, 2015). We study this question in Pakistan, where individual sanctions on terrorist leaders can be linked to administrative data on charities, fundraising, networks, and violence.

Pakistan provides an ideal setting for this analysis. We can observe the identity and timing of individual sanctions issued by major international authorities, match sanctioned leaders to registered non-profit organizations in which they appear as board members, and through this reconstruct the charity networks through which they operate. These organizations are both a central source of charitable giving and a documented channel of terrorist financing (Limodio, 2022). Because leaders are sanctioned in different years, the data provide staggered shocks to their access to finance; and because the registry records charities, board members, and activity, we can trace how these shocks propagate from sanctioned leaders to affiliated members and connected organizations.

To discipline the empirical analysis, we develop a simple framework in which a sanctioned leader allocates resources within a violent organization and relies on an operative who can work either for the leader or for an independent project. Effort in either activity both raises violent capacity and generates financial resources, for example through the creation or promotion of affiliated charities. Sanctions tighten the leader's budget constraint and reduce the incentives that the leader can offer to retain the operative. Once these incentives fall below the operative's outside return, the operative reallocates effort toward his own charities and violent activities, while the leader increases his own fundraising effort to offset the loss. The model therefore shows how sanctions can increase aggregate charity activity, organizational fragmentation, and violence even as they restrict the leader's formal access to finance, generating the empirical predictions that guide our analysis.

Identifying the organizational effects of financial sanctions requires shocks to leaders' access to finance that are plausibly unrelated to the internal dynamics of their organizations. We address this challenge by combining the staggered timing of individual sanctions with network-based variation from administrative charity records. The registry reports when charities are created, whether they are active, and which individuals sit on their boards, allowing us to reconstruct domestic charity networks around terrorist leaders and match these leaders to the groups they serve. We define a charity as an entity directly exposed from the year in which one of its board members is sanctioned, and as indirectly exposed if it has no sanctioned member but shares a board member with a charity that does. We then compare exposed charities and groups before and after sanctions to units that are either never exposed or not yet exposed, the latter providing a more stringent comparison group. Because treatment occurs at different dates, we estimate effects using the imputation-based estimator of Borusyak et al. (2024), which is robust to staggered adoption and avoids the negative-weight problems of traditional two-way fixed-effects estimators (Goodman-Bacon, 2021). Combining this design with data on charity activity, donations, terrorist attacks, and group splits allows us to trace how sanctions reshape fundraising, organizational structure, and violence.

Our first set of results concerns the charitable sector. We find that sanctions trigger a reorganization of charitable activity within networks rather than a simple collapse of exposed entities. At the charity-year level, the probability that a directly exposed charity is active rises by around 6–22 percentage points after a member is sanctioned, relative to a baseline probability that a charity is active around 35%. The response is, if anything, stronger for charities that are only indirectly exposed through overlapping board members: their probability of being registered and active increases by approximately 15–30 percentage points, and these effects build up over several years after the first sanction, as shown in Table 2.

Second, we show that this organizational response is accompanied by a sizable increase in local fundraising through Zakat donations. The financing of violent groups is typically hard to observe, since fundraising often takes place through informal, opaque, or illicit channels. Pakistan provides a rare setting in which we can measure this margin directly: Zakat is a religiously mandated charitable contribution, paid at the beginning of Ramadan, and prior evidence and official concerns indicate that charitable giving has been used as a channel for terrorism financing when extremist groups operate legally registered charity branches (Limodio, 2022).[1]. Using household survey data, we relate individual donations to the division-level share of charities connected to sanctioned individuals. As more local charities become exposed to sanctions, households become more likely to donate and contribute larger amounts, even after controlling for household characteristics and local and time-varying unobservables. A one-percentage-point increase in the share of exposed charities raises the probability of donating by 0.11 percentage points (Table 3). The response is concentrated in donations to private charities, which may include organizations connected to violent groups, while donations to public, state-administered charities remain flat. This contrast provides a sharp placebo test: it is difficult to rationalize why an unrelated shock would increase giving to private recipients while leaving public giving unchanged.

We next examine whether these changes in charity activity and fundraising translate into terrorist violence. At the group–district–year level, sanctions generate a sizable and persistent increase in attacks: the probability of at least one attack rises by 6–20 percentage points, while the number of attacks increases by 0.5–0.7 incidents per year relative to a mean of 0.27 (Table 4). Event-study estimates show no pre-trends and a growing post-sanction divergence between exposed and unexposed cells. Consistent with the financial-reallocation mechanism, the increase in violence is concentrated among groups with pre-existing charitable infrastructure: groups with a charitable arm experience much larger post-sanction increases in both the probability and number of attacks than groups without charities, even after matching on pre-sanction group size. Finally, we provide evidence that the increase in violence is not uniform across space. Outside Pakistan, attacks decline in the United States and Western Europe, the jurisdictions that impose these sanctions and where enforcement capacity is strongest. This pattern suggests that sanctions limit adaptation where compliance systems are most effective. These results speak to a central concern in financial statecraft:

[1]See Dawn, Pakistan's most widely circulated English-language newspaper, "Zakat must not land in wrong hands: govt," July 13, 2015, reporting remarks by Pervaiz Rashid, then Minister of Information, who "advised people to pay Zakat and charity to institutions which save lives and not to those producing suicide bombers." Available at: `https://www.dawn.com/news/1194098`. For more information on the functioning of Zakat and the Zakat levy, refer to Limodio (2022) and Choudhary and Limodio (2022)

restrictions on access to the dollar-centric system do not simply reduce violent capacity, but reshape where and how targeted organizations operate. The decline in attacks in sanctioning jurisdictions suggests that sanctions bind where enforcement is strongest, while the increase in violence in Pakistan indicates that the resulting financial frictions induce organizational adaptation, reallocating fundraising and violence toward domestic, less monitored, and more fragmented channels. Thus, the increase in violence in Pakistan and the decline in attacks in sanctioning jurisdictions are two sides of the financial friction created by the sanctions.

Moreover, our main novel evidence concerns how sanctions reshape the internal organization of violent groups. We construct a new panel of militant group split-ups by hand-collecting information from newspaper articles and online sources, identifying when new factions emerge and linking each splinter group to its parent organization. Using this dataset, we show that both the number and likelihood of split-ups rise sharply with the cumulative number of sanctioned members in a group (Table 6). The effect is concentrated among groups with a charitable arm and remains large when we restrict the comparison group to not-yet-sanctioned organizations. These patterns suggest that sanctions, by tightening financial constraints at the leadership level, generate internal agency frictions that materialize as organizational fragmentation. More broadly, they imply that the effectiveness of financial statecraft depends on domestic intermediation structures: when charitable and informal channels can substitute for formal cross-border finance, restrictions on the dollar-based system may reallocate funding across internal networks rather than eliminate it, increasing fragmentation and potentially amplifying conflict.

Several mechanism checks and robustness exercises support the financial-frictions interpretation. The effects are stronger for groups with greater cross-border exposure, for whom sanctions are more likely to bind through international compliance and enforcement systems, consistent with Efing et al. (2023). This interpretation is also in line with Dutt et al. (2025), who show that sanctions enforcement depends critically on the ability of third-party intermediaries to identify violators, and that improving information available to market participants can substantially reduce violators' access to finance and trade. The increase in charity activity appears both at cash-based and non-cash based charities that use formal banking instruments, indicating that the response is not simply a retreat into the most opaque financial channels (Limodio, 2022). We also find no evidence that sanctions raise the public salience of targeted individuals, which weighs against a notoriety-based explanation. Finally, the pattern of violence is more consistent with fragmentation and decentralization than with competition alone: attacks rise much more against external targets than against other militant groups, and sanctioned groups expand ties to allies, associates, and supporters more than to rivals (Clayton et al., 2025c). Our findings are also robust across alternative samples, fixed effects, outcomes, and levels of aggregation.

Finally, we complement the causal analysis with a structured, LLM-assisted coding procedure, conceptually related to Clayton and Coppola (2026) and described in Online Appendix A. This is not a second causal estimate: the procedure does not identify the effect of sanctions on any outcome. It is, rather, a transparent and auditable device for mapping heterogeneous qualitative evidence (on financing structures, sanctions listings, charities, front organizations, and post-sanction adaptation) into the language of our model, in the spirit of Bryzgalova et al. (2024). A multi-agent workflow first organizes this evidence into separate reports, and a final agent translates them into model-implied intervals for the unobserved financial friction, modeled as a tax on the wealth of terrorist groups.[2] Sanctions are found to be more binding for organizations with centralized, charity-linked financing and as less binding or more uncertain for groups reliant on local or informal finance. Aggregating across individuals, the midpoint of these intervals reaches 20 percent by the end of the sample: a magnitude comparable to a significant wealth tax on the targeted organizations. The exercise should thus be read as a disciplined way to organize the qualitative record in the terms of the model, complementing rather than substituting for the reduced-form results.

This article contributes to three main streams of the literature. First, this paper con-

[2]We report intervals rather than point values because the underlying record is uneven, with bounds that widen when evidence is group-level, sparse, or compatible with both resilience and fragmentation.

tributes to the growing literature on the geoeconomics of finance and economic coercion by providing micro-level evidence on the organizational consequences of sanctions. Recent work shows that geoeconomic pressure operates through financial and trade networks, affects firms differently depending on the instrument used, and can generate fragmentation in the international monetary and financial system (Clayton et al., 2025a,b,c; Bianchi and Sosa-Padilla, 2024, 2025). We complement this literature by studying how targeted financial sanctions propagate inside non-state organizations. Our evidence shows that sanctions reallocate fundraising across domestic charity networks, shift financial intermediation from leaders to affiliates, create agency frictions that fragment targeted groups, while reducing attacks in the jurisdictions where authorities have stronger enforcement capacity. In doing so, we provide a microeconomic counterpart to work on sanctions, dollar dominance, and financial fragmentation, and document both the intended and unintended consequences of financial coercion for the behavior, organization, and geographic allocation of activity by targeted entities (Keerati, 2022; Mamonov and Pestova, 2022; Efing et al., 2023).

Second, the paper speaks to research in corporate finance and organizational economics showing that external frictions reshape how organizations select, allocate, and motivate people. Closest to our setting, Colonnelli et al. (2020) show that political interference distorts selection inside organizations, while Colonnelli et al. (2025) show that political alignment between owners and workers affects hiring, careers, and firm behavior. Related work documents that social divisions and partisan identity shape productivity, financial intermediation, and regulatory decisions (Hjort, 2014; Kempf and Tsoutsoura, 2021; Limodio, 2021; Engelberg et al., 2023). We extend this organizational view to violent groups with weak formal governance. When sanctions tighten financial constraints at the top of the organization, activity does not contract mechanically; instead, groups reorganize by reallocating authority and resources toward affiliates, charitable fronts, and overlapping networks. In this sense, financial sanctions operate like an external organizational shock: they alter internal incentives, reshape the allocation of people and resources, and ultimately generate broader fundraising, fragmentation, and more violence.

Third, we contribute to the literature on terrorism financing and the organizational economics of violent groups. Prior work documents that shocks to resource availability, through commodity prices, aid flows, or development projects, shape conflict intensity and tactics (Dube and Vargas, 2013; Berman et al., 2017; Battiston et al., 2024). A parallel literature emphasizes agency problems and financial frictions within terrorist organizations, highlighting how constraints on local operatives interact with central funding and monitoring technologies (Shapiro and Siegel, 2007; Bueno de Mesquita, 2013; Shapiro, 2013; Wright, 2016; Limodio, 2022). By treating financial sanctions as shocks to the internal capital market of violent organizations, our analysis provides direct evidence that such frictions matter: groups with access to flexible, charity-based funding adjust their financing and organizational structure in ways that sustain and even intensify attacks. Finally, we relate to work on sanction leakage and evasion in international trade and finance, which shows how targets reroute flows through intermediaries and third countries (Eaton and Engers, 1992; Fisman et al., 2008, 2025; Mamonov et al., 2023). Our contribution is to show that even highly targeted individual sanctions can be undone at the network level, not by simple evasion but through endogenous reallocation of fundraising and the proliferation of competing organizations.

The remainder of the paper is organized as follows. Section 2 presents a simple conceptual framework and the institutional background. Section 3 describes the data and empirical strategy. Section 4 reports the main results on charities, Zakat donations, terrorist activity, and group splits. Section 4.4 discusses mechanisms. Section 5 presents our LLM exercise and results. Section 6 presents robustness checks. Section 7 concludes.

2 Theoretical and Institutional Setting

2.1 Theoretical Framework

To organize the empirical analysis, we develop a simple static model with a leader (principal) and an operative (agent). Both players choose non–negative effort levels in conflict activities, and each unit of conflict effort simultaneously (i) raises the probability or intensity of a terrorist attack and (ii) generates resources by creating or promoting charities that can be used to finance further activity. When the operative works for the leader, his effort increases both the likelihood of an attack attributed to the leader's organization and the leader's wealth, for example through fundraising in a charity aligned with the leader. When the operative works independently, his effort instead raises the attack activity and financial resources of a separate, alternative organization.

Formally, let $e_L \geq 0$ denote the leader's effort on his own project, $e_T \geq 0$ the operative's effort on the leader's project, and $e_O \geq 0$ the operative's effort on an alternative terrorist project (another group, splinter faction, or freelancing). The operative's effort on any project generates both violent output and funding for the corresponding organization. The operative's utility is

$$U_A(e_T, e_O) = qe_T + pe_O - \frac{c}{2}(e_T + e_O)^2,$$

where $q \geq 0$ is the piece rate per unit of e_T paid by the leader, $p > 0$ is the operative's private return per unit of e_O (including wages and access to independent charities), and $c > 0$ governs the convex cost of total effort $e_T + e_O$. The leader's conflict output is $y_L = F(e_L + e_T)$ with $F(z) = Az - (b/2)z^2$, $A > 0$, $b > 0$, so total effective input is $z = e_L + e_T$ and F is strictly concave. Each unit of e_L and e_T raises both the likelihood of an attack by the leader's organization and the amount of funding and charity activity controlled by the leader. Each unit of e_O similarly raises attacks and funding for the alternative organization. The leader's payoff is

$$U_L(e_L, e_T) = F(e_L + e_T) - qe_T - \frac{\gamma}{2}e_L^2,$$

where $\gamma > 0$ captures the (convex) cost of leader effort.

Given q and p, the operative chooses (e_T, e_O) to maximize U_A. Since the cost depends only on the sum $e_T + e_O$, the operative specializes in the activity with the higher effective return. Solving his problem implies that if $q \geq p$ he works only for the leader (so $e_T = q/c$ and $e_O = 0$), whereas if $q < p$ he separates and works only on his own project (so $e_T = 0$ and $e_O = p/c$). Taking e_T as given, the leader chooses e_L to maximize $U_L(e_L, e_T)$. When $e_T < \frac{A}{b}$, the first–order condition $A - b(e_L + e_T) - \gamma e_L = 0$ yields a unique interior solution

$$e_L(e_T) = \frac{A - be_T}{b + \gamma},$$

so that operative effort raises the leader's effective input $z = e_L + e_T$ while allowing him to economize on his own costly effort. In what follows, we focus on the parameter region where $e_T < \frac{A}{b}$, so that the leader's optimal effort is non-negative, $e_L > 0$.

We model sanctions as a tax $\tau \in [0, 1)$ on the leader's non–charity wealth W_0, which tightens the financing constraint for the wage bill qe_T. In particular, if each unit of e_T generates proportional charity–based funding that can be used to pay wages, the effective resource constraint can be written as $qe_T \leq (1-\tau)W_0 + \kappa(e_L + e_T)$, where $\kappa > 0$ captures how conflict effort (including work in charities) raises the leader's usable wealth. This constraint implies an upper bound $\bar{q}(\tau)$ on the feasible incentive rate q. Without sanctions ($\tau = 0$), we assume $\bar{q}(0) \geq p$ and parameter values such that the leader optimally chooses $q^N \geq p$ and employs the operative on his project. In this regime the operative works exclusively for the leader, exerting $e_T^N = q^N/c > 0$ and $e_O^N = 0$, while the leader chooses $e_L^N = e_L(e_T^N) > 0$ according to the best response above. All charity–related fundraising effort by the operative is therefore tied to the leader's organization, and overall funding is concentrated in that group. Overall conflict, defined as the sum of conflict output from the leader's organization and from the alternative project, is $C^N = F(e_L^N + e_T^N)$, since $e_O^N = 0$.

Under sanctions, the tax $\tau > 0$ reduces the non–charity component of the leader's wealth

$(1-\tau)W_0$ and thus lowers the maximal incentive rate $\bar{q}(\tau)$ that he can finance. We focus on the case in which sanctions are sufficiently tight that $\bar{q}(\tau) < p$. In this regime, even if the leader devotes substantial effort to his own activities (including charity–related work that raises $\kappa(e_L + e_T)$), he cannot offer a piece rate q that matches the operative's private return p from working independently. The operative then separates and reallocates all effort to his own project: $e_T^S = 0$ and $e_O^S = p/c$. His effort now raises both the probability and intensity of attacks by the alternative organization and the wealth that he controls through his own charity networks. Anticipating this, the leader optimally sets $e_L^S = e_L(0) = A/(b+\gamma)$, which is strictly higher than e_L^N, to partially compensate for the loss of the operative. Total charity–linked effort and funding in the system increase: the leader devotes more effort to his own organization, while the operative reallocates his effort to an independent project ($e_O^S > 0$), so that the sum of effort devoted to conflict and fundraising across the two organizations is higher than in the no–sanctions benchmark.

The intuition is illustrated in Figure 1. Panel (i) shows that as sanctions increase, the leader's available resources shrink, reducing the maximum feasible incentive $\bar{q}(\tau)$. For low levels of sanctions, the leader can still offer $\bar{q}(\tau) \geq q^*$ and retain the operative. As sanctions intensify, however, $\bar{q}(\tau)$ declines until it reaches q^*, beyond which retention becomes infeasible and the operative exits. Panels (ii) and (iii) illustrate the behavioral and aggregate consequences of this constraint. For $0 < \tau < \tau^E$, weaker incentives reduce the operative's effort $e_T(\tau)$, leading the leader to partially compensate by increasing his own effort $e_L(\tau)$. When $\tau \geq \tau^E$, the operative exits and reallocates effort to outside opportunities $e_O(\tau)$, causing a sharp decline in incumbent activity. This reallocated effort gives rise to activity outside the organization, while the leader of the incumbent organization further increases his effort to compensate for the exit, so that total activity increases. Panel (iv) summarizes this reallocation through a measure of fragmentation, defined as the share of activity taking place outside the organization. Fragmentation is zero for $\tau < \tau^E$ and rises discontinuously once the operative exits.

[Insert Figure 1 About Here]

The following proposition summarizes the main implications of the model.

Proposition 1. *When financial sanctions reduce the leader's usable non–charity wealth to the point that he can no longer offer incentives strong enough to retain the operative ($\bar{q}(\tau) < p$), despite otherwise wishing to do so, an equilibrium emerges with the following characteristics. First, the operative separates from the leader and devotes all effort to an alternative terrorist project. Second, both the leader and the operative increase their efforts independently, resulting in a higher overall level of effort. Finally, because effort generates both conflict and funding through charities, total financial resources rise, and aggregate violence exceeds the level observed in the absence of sanctions.*

2.2 Institutional Setting

Pakistan offers a unique institutional and social environment in which charitable donations, religious obligations, and militant organizations are deeply intertwined. Terrorist groups frequently operate through dual structures: formal charitable fronts that collect donations, and covert militant wings that use these resources to finance attacks. This duality has been widely documented, including in recent empirical work showing that religious charities can act as intermediaries for terrorism financing by exploiting legal frameworks and social trust (Limodio, 2022).

Zakat donations play an important role in this system. As one of the core pillars of Islamic giving, Zakat provides a predictable annual flow of funds that can be mobilized by local charities, including those with opaque or militant affiliations. These donations, which are often delivered in cash or through informal channels, are difficult to monitor and can be redirected for operational purposes. The liquidity and periodicity of Zakat funding make it a flexible financial instrument for organizations seeking to quickly ramp up or reallocate resources in response to external shocks.

The institutional landscape also reflects systemic weaknesses in oversight. Prominent militant outfits, such as Lashkar-e-Taiba (LeT), have operated registered charities under different names, blurring the distinction between philanthropy and militancy. Regulatory capacity remains limited, and Pakistan has faced repeated scrutiny from the Financial Action Task Force (FATF) for deficiencies in anti-money laundering and counter-terror finance enforcement.

To explore these institutional dynamics at scale, we construct a rich dataset linking individual charity participants to formal sanctions across time.[3] Using administrative records from the Nonprofit Organizations Central Registry, we observe the full universe of registered charities and their affiliated individuals. We then merge these with global sanctions data—to identify sanctioned individuals within the charity network. Our data show that sanctioned individuals frequently sit at the center of densely connected networks, often bridging multiple organizations.Figure 3 and Figure 2 illustrate the close relationship between sanctioned terrorist leaders and charitable networks. Figure 3 reports the UN sanction listing for Zafar Iqbal, a senior LeT leader, while Figure 2 maps charity affiliations in our sample and shows him as a central node connecting several organizations. These figures highlight that charitable structures operate not only as financial channels, but also as personnel coordination platforms for sanctioned actors.

In parallel, Pakistan has experienced widespread organizational fragmentation among armed groups. Internal leadership disputes and succession struggles frequently lead to splintering. Gassebner et al. (2023) show that such splits significantly increase violence, as newly formed groups compete for visibility, recruits, and financial support. Importantly, the rise in violence is not due to infighting but to strategic signaling under competitive pressure. In our context, the decentralization of financing, triggered by sanctions disrupting central figures in charity networks, can further amplify these dynamics. As financial flows are restructured and redistributed across more organizations or individuals, they may lower barriers to en-

[3]For more details, see Section 3.

try, intensify rivalry among splinter factions, and elevate incentives for attacks as a form of strategic differentiation.

Overall, these features (voluntary religious donations, fragmented oversight, liquidity-sensitive financing, and fluid organizational structures) make Pakistan a compelling setting to study the unintended consequences of financial sanctions. Our study focuses on how sanctions targeted at key individuals within charitable networks affect group behavior, operational strategies, and the broader ecology of violence.

3 Data and Empirical Strategy

3.1 Data

Pakistan provides a high-incidence setting of terrorism and charity-based donations, where many extremist groups operate dual structures: a formal charity front and a covert militant wing. To study the effect of sanctions on terrorist financing, we compile a novel dataset that links information on charity networks, targeted individuals, donations, and attacks. Our data construction builds on and extends sources from previous research (Limodio, 2022; Gassebner et al., 2023):

- **Charity Registry and Participation**: We use administrative records from Pakistan's Nonprofit Organizations Central Registry, maintained by the Federal Board of Revenue. These data include the universe of registered charities, along with information on founding dates, geographic location, and payment instruments (e.g., cash, bank, check). Crucially, the registry also lists individuals affiliated with each charity, allowing us to reconstruct a panel of individual–charity links. These links form the basis for our network-level analysis and sanction exposure measures.

- **Sanctioned Individuals and Group Affiliation**: We obtain data on individual sanctions from SanctionsExplorer.org, a centralized database curated by C4ADS that compiles sanctions issued by the UN, OFAC (U.S.), EU, UK, and Canada. For each sanctioned individual, we observe names, aliases, dates of designation, known affiliations, and issuing authority. We use this information to infer the terrorist group affiliation of each individual, based on descriptive fields and the sanctioning body's justification. We then match sanctioned individuals to the charity registry using fuzzy string matching and manual validation. This allows us to identify both direct and network-based exposure to sanctions, and to link charities to specific militant groups.

- **Terrorist Attacks**: Terrorist incidents are sourced from the Global Terrorism Database (GTD), which includes detailed information on the date, location, responsible group, attack type, and casualties of each event. We restrict the sample to attacks in Pakistan and harmonize group identifiers over time. We construct a panel at the terrorist group–district–year level for our main analysis of violence.

- **Organizational Splits**: To track group-level adaptation, we hand-collected data on organizational splits from media reports. Using group names in the GTD, we identified instances in which new groups emerged from existing ones (e.g., through leadership disputes or factional breakaways). These splits are coded by year and parent group based on consistent naming patterns and confirmed through contemporaneous news sources.

- **Zakat Donations**: Household-level data on charitable donations come from the Pakistan Social and Living Standards Measurement Survey (PSLM), a nationally representative survey administered by the Pakistan Bureau of Statistics. The PSLM reports the amount and channel of Zakat donations, excluding mandatory deductions. We aggregate donation amounts at the division-year level to capture variation in local financing flows.

- **Militant Group Alliances and Rivalries (MGAR):** This database provides global time-series data on relationships among militant groups from 1950 to 2016. In our setting, we use MGAR to measure changes in group relationships, including alliances, associations, rivalries, and competition, as a mechanism check on whether sanctions induce organizational fragmentation.

[Insert Table 1 About Here]

Table 1 reports descriptive statistics for key outcomes. Panel A shows district-year variation in terrorist activity and charity presence. On average, there are 0.27 attacks per district-year, though the distribution is highly skewed, with a maximum of 92 attacks in a single district-year. About 9% of district-years report active charity presence, and 12% have at least one charity. The average number of active terrorist groups per district-year is 0.78, and roughly 1.19 groups per district-year are associated with sanctioned members.

Panel B presents household-level statistics on Zakat donations. The average share of sanctioned charities over total charities at the division-year level is 9.3%, with substantial variation (ranging from 0 to over 50%). The mean donation per household is PKR 1,613, with donations heavily skewed (with some households report giving over PKR 600,000). Most donations are directed toward private sector recipients, such as friends, relatives, or mosques, with very limited public-sector giving.

These patterns highlight substantial heterogeneity in both charity activity and terrorist group exposure across time and space, underscoring the importance of flexible empirical strategies in identifying the causal effects of sanctions on organizational behavior.

3.2 Empirical Strategy

We estimate the effects of exposure to individual sanctions on charity activity, Zakat donations, and terrorist incidents using a combination of difference-in-differences (DID) and event-study estimators. Our strategy exploits variation in the timing of exposure across individuals and the organizations they are affiliated with, using rich panel data tracking outcomes over time (see Figure 4).

Recent research has highlighted that traditional two-way fixed effects (TWFE) models can produce misleading estimates when treatments occur at different times.[4] To address these concerns, we apply the imputation-based estimator proposed by Borusyak et al. (2024), which provides consistent estimates of average treatment effects under staggered treatment and avoids issues related to negative weighting or implicit extrapolation.

We further account for potential differences between exposed and non-exposed units by employing two complementary control group strategies. First, we use the full sample of observations, combining treated and untreated units over the full panel ("All" sample). Second, we restrict the control group to only those units that have not yet been exposed by time t but will be treated later in the sample ("Not-yet-treated" sample). This latter approach improves internal validity by ensuring that the treatment and control groups are more comparable.

We implement this design in a series of regressions across our main outcomes.

First, to assess whether exposure to an individual sanction in the charity personnel increases the likelihood that a charity becomes active, we estimate:

$$\text{Active}_{it} = \alpha_i + \alpha_{dt} + \beta_S \times \text{PostExposure}_{it} + \epsilon_{it}, \tag{1}$$

where Active_{it} is an indicator that takes value one if charity i is active in year t, and zero otherwise; and PostExposure_{it} equals one if any member of charity i has been sanctioned at or before time t and zero otherwise. Charity fixed effects α_i absorb time-invariant heterogeneity; district-year fixed effects α_{dt} control for location-specific shocks.[5]

Next, we examine charities that are not directly sanctioned but are linked to sanctioned individuals through shared personnel ties. This approach allows us to distinguish the direct effect of sanctions on targeted charities from broader patterns of network-based adaptation.

[4] See, e.g., Goodman-Bacon (2021); Callaway and Sant'Anna (2021); de Chaisemartin and d'Haultfœuille (2020). Goodman-Bacon (2021) shows that TWFE estimators produce a weighted average of unit-time treatment effects, where weights can be negative depending on the structure of treatment timing (de Chaisemartin and d'Haultfœuille, 2020).

[5] See Figure A.4 for the spatial distribution of sanction exposure and terror activity.

If indirectly exposed charities also respond after a connected individual is sanctioned, this would suggest organizational reallocation within the charity network:

$$\text{Active}_{it} = \alpha_i + \alpha_{dt} + \beta_S \times \text{ExposedNetwork}_{it} + \epsilon_{it}, \tag{2}$$

where $\text{ExposedNetwork}_{it}$ equals one if charity i has at least one unsanctioned member connected to an individual exposed to a sanction.

To analyze local fundraising responses, we use a continuous DID specification:

$$\text{ZakatDonations}_{dt} = \alpha_d + \alpha_t + \beta_S \times \frac{\text{ExposedCharities}}{\text{TotalCharities}}_{dt} + \mathbf{X}'_{hdt}\gamma + \epsilon_{dt}, \tag{3}$$

where the key regressor is the share of charities in division d and year t exposed to a sanction. Because nearly all divisions become exposed around the same time, staggered treatment is not a concern in this setting. The specification includes division fixed effects α_d and year fixed effects α_t, as well as a vector of household-level controls $\mathbf{X}_{hdt}$: total number of children, total family members, annual income, and the educational level of the household head. These controls account for observable differences in household donation behavior that may be correlated with exposure to affected charities.

Next, we analyze whether the effects of individual sanctions and the potential funding responses through charities translate into changes in terrorist activity. To do that, we estimate the effects of such a exposure on terrorist activity:

$$\text{Terror}_{dgt} = \alpha_{gd} + \alpha_{dt} + \beta_S \times \text{PostSanction}_{gt} + \epsilon_{dgt}, \tag{4}$$

where Terror_{dgt} is either the number of attacks or an indicator for any attack by group g in district d and year t. We include group-district fixed effects α_{gd} and district-year fixed effects α_{dt}. As with the charity regressions, we apply the Borusyak et al. (2024) estimator to address staggered adoption.

Across specifications, we test the identifying parallel trends assumption using event-study plots that display dynamic treatment effects and confirm the absence of systematic pre-trends. Standard errors are clustered at the appropriate level—charity, district, or group—depending on the outcome of interest.

4 Results

4.1 Effect of Sanctions on Charities

This section analyzes how financial sanctions imposed on individuals affect the behavior of charitable organizations with which they are affiliated. The key empirical challenge is identifying the causal effect of sanctions on charity activity, disentangled from confounding shifts in enforcement, local conditions, or endogenous selection. To address this, we exploit both direct exposure—charities with a sanctioned member—and a cleaner, more plausibly exogenous form of network exposure—charities indirectly linked through shared personnel affiliations.

Panel A of Table 2 presents difference-in-differences estimates where treatment is defined by the presence of at least one sanctioned individual within a charity. Across specifications, we find that sanctions lead to a sizable increase in the probability that a charity becomes active. In the full sample, sanctions are associated with a 6.2 percentage point increase in activation (column 1), growing to 9.7 percentage points when district-by-year fixed effects are included (column 3). Notably, column (4) restricts the comparison group to charities that are not treated yet but will be sanctioned in the future—effectively controlling for potential time-invariant differences across charities and isolating the impact of timing. Under this "not-yet-treated" design, the effect rises to 21.7 percentage points, indicating a strong behavioral response to sanctions even among observably similar organizations.

Panel B shifts focus to charities that are not directly linked to any sanctioned individual but are exposed via second-degree network ties: at least one of their members is affiliated with another charity that includes a sanctioned individual. These organizations are legally untouched but experience indirect exposure through personnel overlap. The estimates show that even this more distal form of network exposure substantially increases activity. The effect ranges from 14.4 to 19.3 percentage points across specifications when non-treated charities are included in the control group. In columns (2) and (4), which again use only not-yet-treated charities as controls, the estimates rise to 35.2 and 28.8 percentage points, respectively. Since these charities are not themselves sanctioned and do not have any sanctioned members, this pattern is consistent with a structural adaptation to external enforcement shocks propagating through organizational networks.

[Insert Table 2 About Here]

The dynamics of these effects are presented in Figure 5, which shows event-time estimates centered around the year of first sanction exposure. The pre-treatment coefficients are flat and indistinguishable from zero, supporting the assumption of parallel trends. Following the sanction year, the probability that a charity is active increases persistently, reaching 10–12 percentage points above baseline by year four. This gradual and sustained rise suggests that the operational response to sanctions unfolds over time, consistent with strategic reorganization and substitution behavior within the charitable network.

[Insert Figure 5 About Here]

Together, these results provide strong evidence that sanctions on individuals—both directly and indirectly—activate organizational responses among affiliated charities. Importantly, the effects estimated in Panel (ii) are not simply spillovers: they exploit more exogenous variation in exposure, as the focal organizations are not targeted and are treated only through network connections. The use of not-yet-treated organizations as controls further reinforces the credibility of the identification. These findings point to a broader organizational resilience and adaptability in response to targeted financial regulation, suggesting that enforcement strategies need to consider the role of personnel networks in mediating policy impact.

4.2 Sanctions and Zakat Donations

This section investigates a potential mechanism behind the observed increase in charity activity following individual sanctions: the mobilization of Zakat donations. Zakat, a religiously mandated form of almsgiving, plays a central role in financing both philanthropic and, in some cases, militant organizational infrastructures. When a member of a charitable network is sanctioned, affiliated groups may face a sudden financial shock. In response, they may strategically intensify Zakat-based fundraising, particularly during the Ramadan period, when religious giving peaks.

Table 3 presents evidence consistent with this interpretation. Following the sanctioning of an affiliated individual, reported Zakat donations increase significantly. This result suggests that charities may not only become operationally active after sanctions, but also seek to re-stabilize their funding base. This interpretation aligns with prior evidence that extremist networks systematically use charitable institutions to mobilize religious donations in support of organizational activities (Limodio, 2022).

To distinguish this mechanism from alternative explanations, we also examine the effect of sanctions on public sector charity donations. The estimated coefficients are statistically indistinguishable from zero. These null results serve as a falsification test: the observed increase in Zakat is not simply due to broader shifts in individual generosity, economic trends, or seasonal giving. Rather, the response appears organizationally mediated and targeted—specific to charitable structures activated in response to individual sanctions.

[Insert Table 3 About Here]

These results support the view that increased charity activity is not a passive byproduct of sanctions but part of a deliberate financial adjustment process. Charities, particularly those embedded in personnel networks affected by sanctions, act as flexible funding conduits. The surge in Zakat collections reflects an adaptive response designed to offset the economic impact of individual financial restrictions, illustrating the financial resilience of such networks.

4.3 Sanctions and Terrorism

We now examine how sanctions affect terrorist violence. Table 4 reports estimates from a difference-in-differences design measuring the impact of individual-level sanctions on the intensity of terrorist activity. Across specifications, we find that sanctions lead to a statistically and economically significant increase in attacks. The baseline estimate indicates an increase in the probability of a terrorist incident, as well as in the number of attacks and associated casualties, in the years following a sanction. These effects are not only immediate but persist for several years, highlighting the potential for sanctions to escalate rather than contain violence.

[Insert Table 4 About Here]

The dynamic response is further illustrated in Figure 6. The event-study estimates show no evidence of pre-trends, followed by a sharp increase in violence beginning in the year of the sanction. The effect intensifies over time, suggesting that the organizational and strategic adjustments by terrorist actors in response to sanctions take time to materialize but then persist.

[Insert Figure 6 About Here]

The effect is particularly strong for groups with an affiliated charitable organization. As shown in Table 5, terrorist groups that also operate a charity arm exhibit significantly larger post-sanction increases in violence. This finding reinforces the idea that charities serve as operational infrastructure and funding vehicles. Their presence enables sanctioned groups to more effectively absorb financial shocks, mobilize resources, and reconfigure their strategic posture following disruptions.

[Insert Table 5 About Here]

We also find evidence that sanctions increase the likelihood of organizational fragmentation within terrorist networks. Table 6 shows a significant rise in group splits following sanctions. This is consistent with the theory that sanctions exacerbate internal frictions—such as leadership disputes or competition over scarce resources—which in turn lead to the proliferation of armed actors. Recent empirical work by Gassebner et al. (2023) shows that such proliferation increases organized political violence, as new splinter groups compete for funding, recruits, and visibility. Our results support this channel: the increase in violence post-sanction is not only due to the intensified activity of existing groups, but also the emergence of new, competitive ones.

[Insert Table 6 About Here]

Finally, Table 7 shows that the effects are geographically concentrated in a way that connects our findings to the geoeconomics literature. While sanctions increase violence in Pakistan, attacks outside Pakistan decline in the jurisdictions that impose and more strongly enforce these restrictions, suggesting that sanctions limit adaptation where enforcement capacity is strongest: the United States and Western Europe experience a significant reduction in both the probability and number of attacks after sanctions. Consistent with Efing et al. (2023), this pattern suggests that sanctions operate through financial frictions whose bite depends on enforcement capacity and exposure to the international financial architecture. The fragmentation documented above may also help explain these results: by weakening central coordination and reallocating resources toward local or competing factions, sanctions can reduce groups' ability to plan, finance, and execute attacks in highly monitored foreign jurisdictions. Thus, financial coercion can be effective where enforcement is strongest while simultaneously reshaping the internal organization and geographic allocation of violence by targeted actors.

[Insert Table 7 About Here]

In sum, sanctions intended to suppress terrorist capacity may trigger adaptation along two key dimensions: (i) financial substitution through affiliated charities, and (ii) organizational restructuring through group splits. These adjustments—rather than reducing violence—may instead contribute to its escalation and diffusion, particularly in settings where institutional infrastructure allows for flexible responses.

4.4 Potential and Complementary Mechanisms

Cash and Informal Financial Networks A natural mechanism is that sanctions may induce substitution toward charities that are harder to monitor financially, especially organizations relying on cash or other non-bank payment instruments. If the post-sanction rise in charity activity were driven primarily by increased opacity, we would expect the effect to be concentrated among cash-based charities rather than among charities that also operate through formal banking channels.

To evaluate this mechanism, Table A.1 splits charities by payment mode. The evidence does not support a purely opacity-based interpretation. Among directly exposed charities, post-sanction activity rises for both non-bank and bank-using organizations. Among indirectly exposed charities in the sanction network, the increase is again present for both payment types, with economically meaningful estimates in each case. This pattern suggests that sanctions activate a broader reallocation of fundraising and organizational effort across the charitable network, rather than merely shifting activity toward the most opaque cash-intensive entities.

This evidence is informative for the mechanism in two ways. First, it is consistent with the paper's argument that sanctions induce network-wide organizational adaptation. Second, it indicates that the adjustment is not confined to the subset of charities least connected to formal financial infrastructure. In other words, the mechanism appears to be broader charitable reorganization and fundraising substitution, not simply a retreat into cash.

Public Salience versus Financial Frictions An alternative mechanism is that sanctions may affect behavior by raising the public profile of sanctioned individuals rather than by tightening financial constraints. For example, if designation increases visibility or notoriety, the observed responses could reflect publicity effects instead of changes in access to finance.

We assess this possibility in Table A.2, which examines whether sanctions increase Google search interest for sanctioned individuals. Across specifications, the estimated effects on both the continuous Google Trends measure and an indicator for above-median search intensity are small and statistically insignificant. The absence of any systematic increase in search interest cuts against a salience-based interpretation of the results.

This placebo-style mechanism check strengthens the financial-frictions interpretation of the paper. If sanctions were primarily working by increasing public attention, we should observe detectable shifts in search behavior. Instead, the null results suggest that the main effects are unlikely to be driven by changes in popularity or visibility and are more consistent with sanctions altering the financing environment faced by these organizations.

Competition, fragmentation, and decentralization. One possible mechanism is that sanctions increase violence by intensifying competition across militant organizations. If sanctions mainly operated through greater inter-group rivalry, we would expect a broad rise in conflict directed at other militant groups and a deterioration in external group relationships. The evidence points instead to a broader process of fragmentation and decentralization.

Table A.3 shows only a modest increase in attacks against other terrorist groups, whereas the rise in attacks against other targets is substantially larger. At the same time, Table A.4 shows that sanctions are associated with an increase in the number of allies, associates, and supporters. The estimated effects are positive and statistically significant across these margins, while the effects on rivals are small and statistically insignificant. The number of competitors does increase after sanctions, but the magnitude of this effect is more limited than the increase in cooperative or affiliated ties.

Taken together, these patterns are difficult to reconcile with a mechanism based on increased competition alone. Instead, they are more consistent with sanctions inducing organizational fragmentation and decentralization, whereby sanctioned groups rely more heavily on a broader set of allies, associates, and supporters, while violence expands primarily against external targets rather than through direct inter-group conflict.

5 Mapping Qualitative Info to Analytical Framework: An LLM Approach

The analytical framework, presented in Section 2.1, highlights a measurement challenge: the sanction-induced financial friction, τ, is not directly observed. We therefore use a structured LLM-assisted coding procedure, described in Online Appendix A, to map qualitative evidence on organizational financing, sanctions listings, front organizations, charities, and post-sanction adaptation into model-implied ranges for τ. The LLM is not used to estimate causal effects; it serves as a disciplined coding tool that organizes heterogeneous historical evidence in the language of the model. Following the model's logic, sanctions are coded as more binding when organizations rely on centralized financing, identifiable transfer channels, foreign donors, charities, or front organizations, and as less binding or more uncertain when financing is local, informal, coercive, or already decentralized.

The procedure separates evidence collection from model mapping. Specialized agents summarize evidence on fundraising structures, sanction responses, fragmentation, and individual sanctions, while a final agent maps these inputs into intervals for τ. This division makes the coding auditable and limits discretion: the final agent does not conduct new research, but assigns wider intervals when evidence is indirect or thin and tighter intervals when evidence is direct and consistent. The resulting individual-level intervals are then aggregated mechanically. At the group level, the coding shows meaningful heterogeneity: organizations linked to centralized financing, charities, or identifiable fronts receive higher sanction-friction intervals, while decentralized or locally financed groups receive lower or wider intervals, as shown in Figure A.2. Over time, the aggregation rises as more sanctioned individuals are sanctioned and as active sanctions increasingly apply to groups with stronger model-implied financial frictions; the midpoint reaches about 20 percent by the end of the period, as shown in Figure 7. Overall, the LLM-assisted procedure provides a transparent bridge between the model and historical evidence by creating a micro-level coding layer that captures when sanctions are more likely to bind through centralized or externally exposed financial channels.

[Insert Figure 7 About Here]

6 Robustness Checks

6.1 Number of Charities per Individual

We further assess the robustness of our results by using a coarser measure of charity activity: the number of active charities per individual in a given district. While this specification is less granular than our baseline, which measures activation at the charity-year level, it offers a useful aggregate perspective on organizational engagement.

As reported in Table A.5, we continue to find a significant increase in activity in the post-sanction period. This confirms that our baseline findings are not an artifact of how the charity-level panel is constructed, and that the rise in participation is robust even when using individual-level aggregates.

6.2 Sanctions and Terror Casualties

Table A.6 tests whether the increase in terrorist activity following sanctions also translates into higher human costs. We examine both the number of casualties and an indicator for any casualties as dependent variables. Across specifications, sanctions significantly increase total casualties and the probability of any casualty, with effects persisting when restricting the control group to not-yet-sanctioned entities. This confirms that sanctions intensify the lethality—not just the frequency—of terrorist operations.

These results complement the baseline findings by demonstrating that organizational adaptation after sanctions has substantive operational consequences: sanctioned and network-linked groups escalate both attack intensity and destructive capacity. The consistency of these results across specifications reinforces the interpretation that sanctions trigger organizational fragmentation and resource reallocation that ultimately heighten the human toll of violence.

6.3 Sanctions and the Capital Intensity of Attacks

Table A.7 explores whether sanctions shift the composition of violence toward more or less resource-intensive operations. We distinguish between capital-intensive (e.g., bombings, coordinated assaults) and non-capital-intensive (e.g., shootings, kidnappings) attacks. The estimates show a pronounced post-sanction increase in the likelihood and number of capital-intensive attacks, while non-capital-intensive attacks also rise but to a lesser extent.

These findings align with the mechanism proposed in Limodio (2022): access to flexible, charity-based funding allows sanctioned organizations to finance costly, capital-heavy attacks despite formal financial restrictions. In this sense, the robustness check strengthens the causal link between financial adaptation and the escalation of organized violence.

6.4 Charities or Group Size?

Table A.8 addresses the concern that our findings on terrorist activity could be mechanically driven by group size, as larger organizations might both operate charitable arms and be more likely to conduct attacks. To account for this, we implement a coarsened exact matching procedure based on the number of districts in which each group was active prior to any sanction in our sample. This procedure ensures that treated groups are compared only with untreated groups of similar pre-treatment size, rather than with organizations that were systematically different.

The results confirm that our main effects are not driven by size differences. Groups with pre-existing charitable structures continue to display a significantly larger increase in both the probability and number of attacks after sanctions, while the effects for groups without charities remain small and statistically insignificant.[6] Overall, the findings reinforce that the post-sanction escalation in violence is linked to the presence of charity-based financing networks rather than to pre-existing group scale.

7 Conclusion

Sanctions are a central instrument for disrupting terrorist financing networks, particularly through designations of individuals and organizations believed to channel resources to violent actors. Yet our findings show that these interventions can generate significant and persistent unintended consequences.

We begin by documenting that individual financial sanctions, especially those imposed on actors embedded within charitable networks, induce strategic adaptation across multiple organizational layers. Sanctioned individuals increase their participation in charities, deepening their involvement in existing fronts. Strikingly, these adjustments are not confined to sanctioned actors. Using a clean network-exposure design, we show that individuals who are not sanctioned but are indirectly connected to sanctioned leaders through overlapping charity affiliations also increase their charitable participation once their peers are designated. Because these individuals face no legal restrictions, their behavioral responses provide compelling evidence that enforcement propagates through personnel networks. This design strengthens causal interpretation and highlights how organizational inter-dependencies mediate the effects of financial restrictions.

[6] Because the matching procedure substantially reduces the effective sample size of not yet treated units, using these units as the control group cannot be implemented in this setting.

We then examine whether increased charity participation translates into changes in fundraising. Zakat donations rise sharply following sanctions, especially in districts with a larger share of sanctioned charities. This increase is specific to charity-linked giving and does not extend to donations routed through public channels, reinforcing the view that organizations strategically mobilize private resources to buffer against financial disruptions.

Sanctions also heighten political violence. Attacks and casualties increase, particularly for groups with charitable arms, and these effects persist for several years. We further show that sanctions are associated with a greater likelihood of group splits—hand-coded from media reports—with new factions contributing to the diffusion of violence as they compete for visibility, recruits, and funding. This dynamic echoes recent evidence that proliferation of armed groups intensifies conflict (Gassebner et al., 2023).

Our evidence on the proliferation of splinter groups mirrors, at the organizational level, macro patterns of fragmentation in global financial markets emphasized in recent work on the geoeconomics of finance. When leaders lose access to formal dollar-based channels, fundraising is reallocated toward more local, decentralized, and opaque structures, often accompanied by the emergence of rival factions. This suggests that the strategic use of financial sanctions can induce not only cross-border rerouting of capital flows but also internal fragmentation of targeted organizations, complicating both monitoring and deterrence.

Taken together, these results challenge the effects, design and scope of financial sanctions, since while they may successfully target known nodes in financing networks, they also activate endogenous responses that reshape the broader financial and organizational architecture of extremist groups. Effective financial statecraft requires acknowledging the networked nature of terrorist financing, monitoring indirect exposure through personnel ties, and anticipating reorganization strategies that can blunt enforcement and amplify violence.

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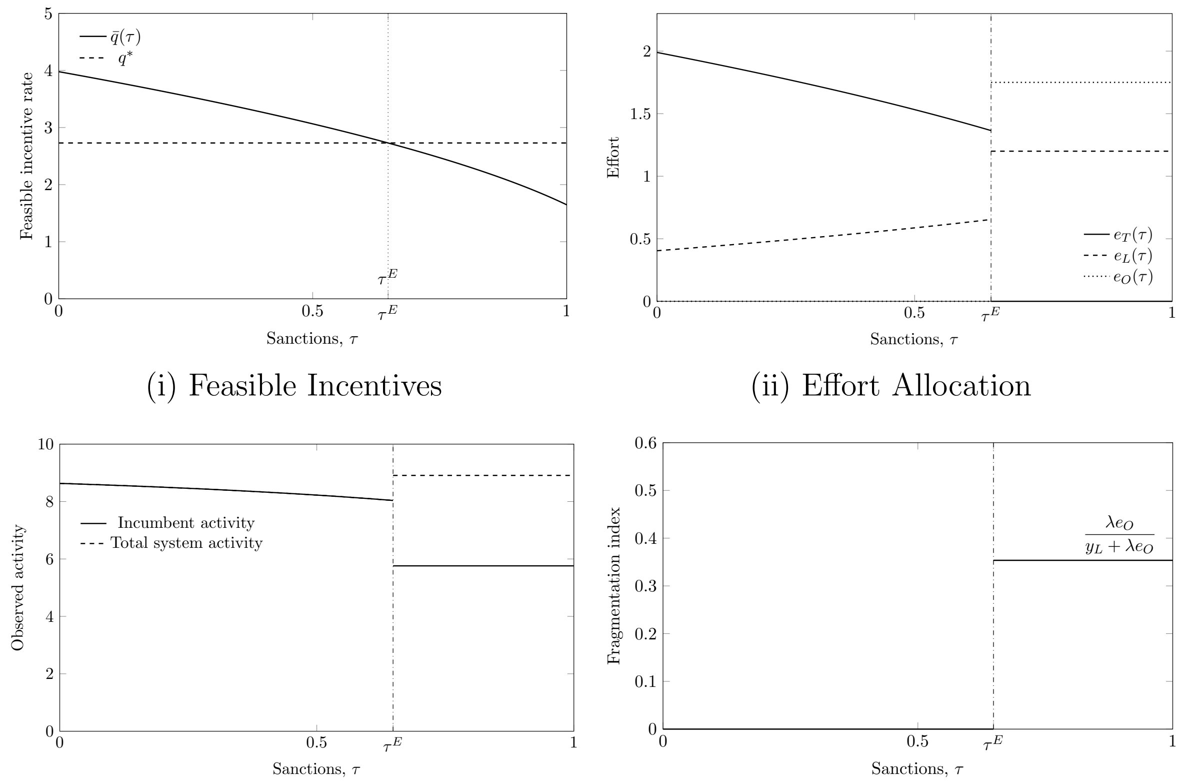
Figures

Figure 1: Sanctions and Organizational Outcomes



(i) Feasible Incentives

(ii) Effort Allocation

(iii) Activity

(iv) Fragmentation

Notes: The figure illustrates the model-implied effects of sanctions τ on incentives, effort allocation, activity, and fragmentation. Panel (i) shows the maximum feasible incentive $\bar{q}(\tau)$ and the participation threshold q^*, with τ^E denoting the retention cutoff where $\bar{q}(\tau) = q^*$. Panel (ii) depicts equilibrium effort levels of the operative (e_T), the leader (e_L), and outside activity (e_O). Panel (iii) reports incumbent activity and total system activity. Panel (iv) shows fragmentation, measured as the share of total activity conducted outside the organization. The vertical line indicates the threshold τ^E at which the operative exits and activity is reallocated outside the organization.

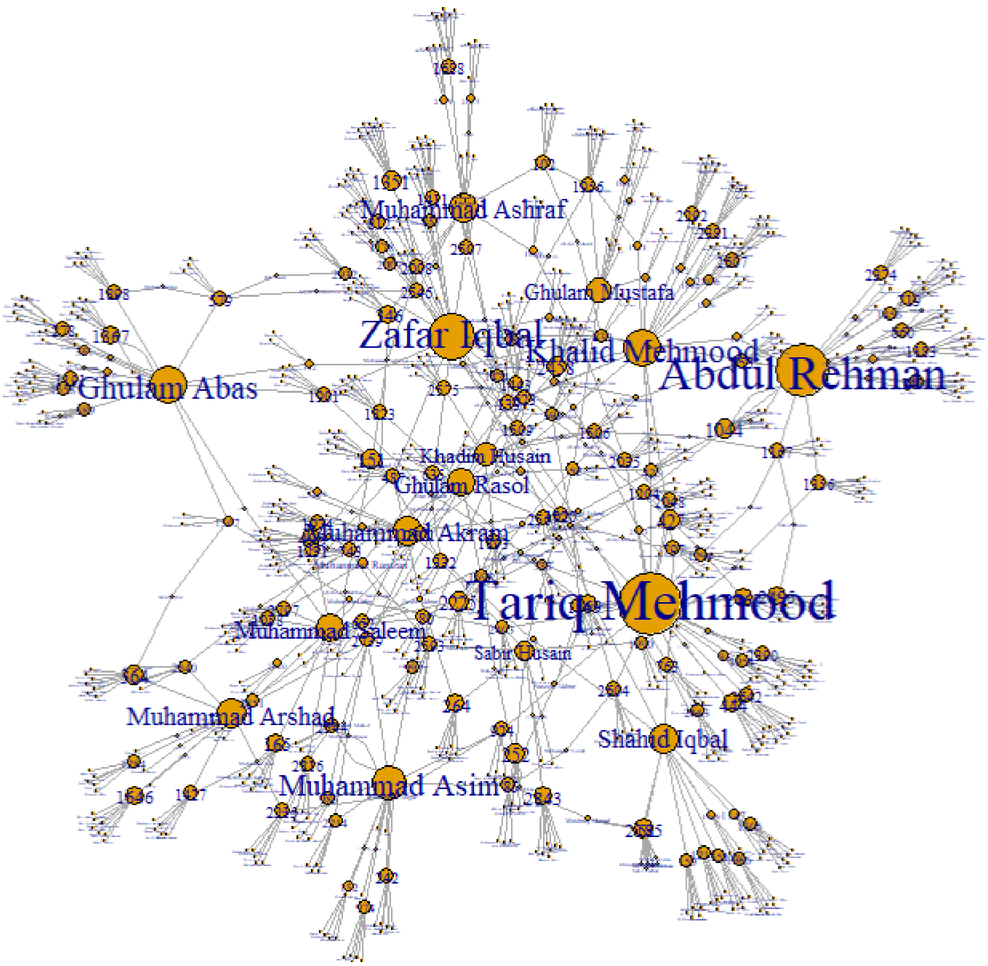


Figure 2: Charity Members Network

United Nations | Security Council

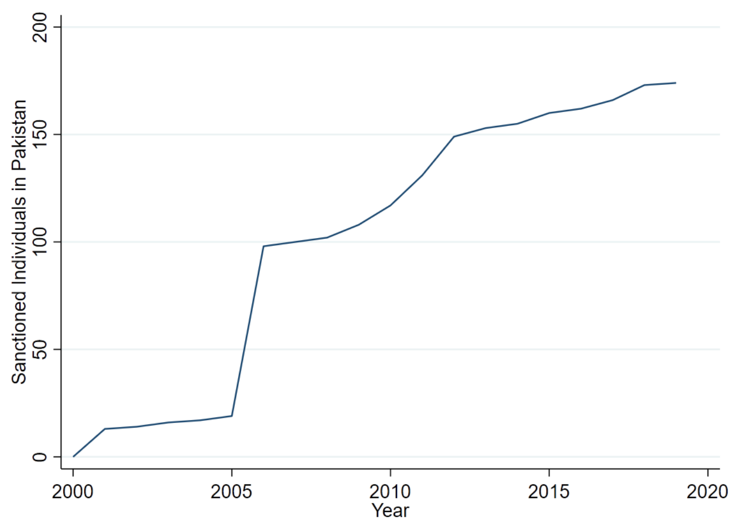
/ Sanctions List Materials / Narrative Summaries of Reasons for Listing

ZAFAR IQBAL

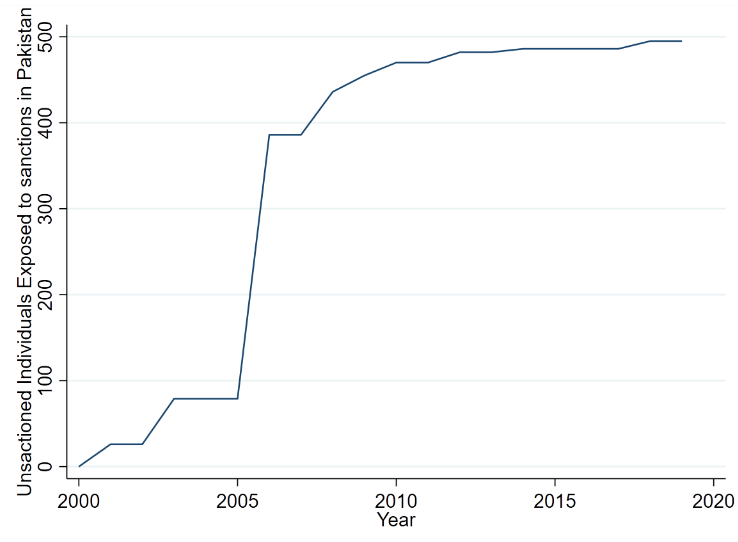
In accordance with paragraph 13 of resolution 1822 (2008) and subsequent related resolutions, the ISIL (Da'esh) and Al-Qaida Sanctions Committee makes accessible a narrative summary of reasons for the listing for individuals, groups, undertakings and entities included in the ISIL (Da'esh) and Al-Qaida Sanctions List.

QDi.308
ZAFAR IQBAL
Date on which the narrative summary became available on the Committee's website
14 March 2012 - 12:00pm
Reason for listing
Zafar Iqbal was listed on **14 March 2012** pursuant to paragraph 4 of resolution 1989 (2011) as being associated with Al-Qaida for "participating in the financing, planning, facilitating, preparing, or perpetrating of acts or activities by, in conjunction with, under the name of, on behalf of, or in support of" and "recruiting for" Lashkar-e-Tayyiba (QDe.118).

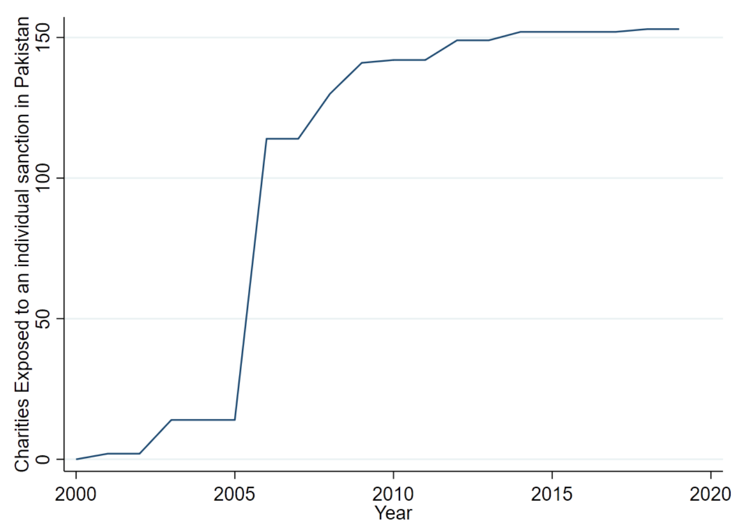
Figure 3: Zafar Iqbal's UN Sanction



(i) Sanctioned Individuals in Pakistan



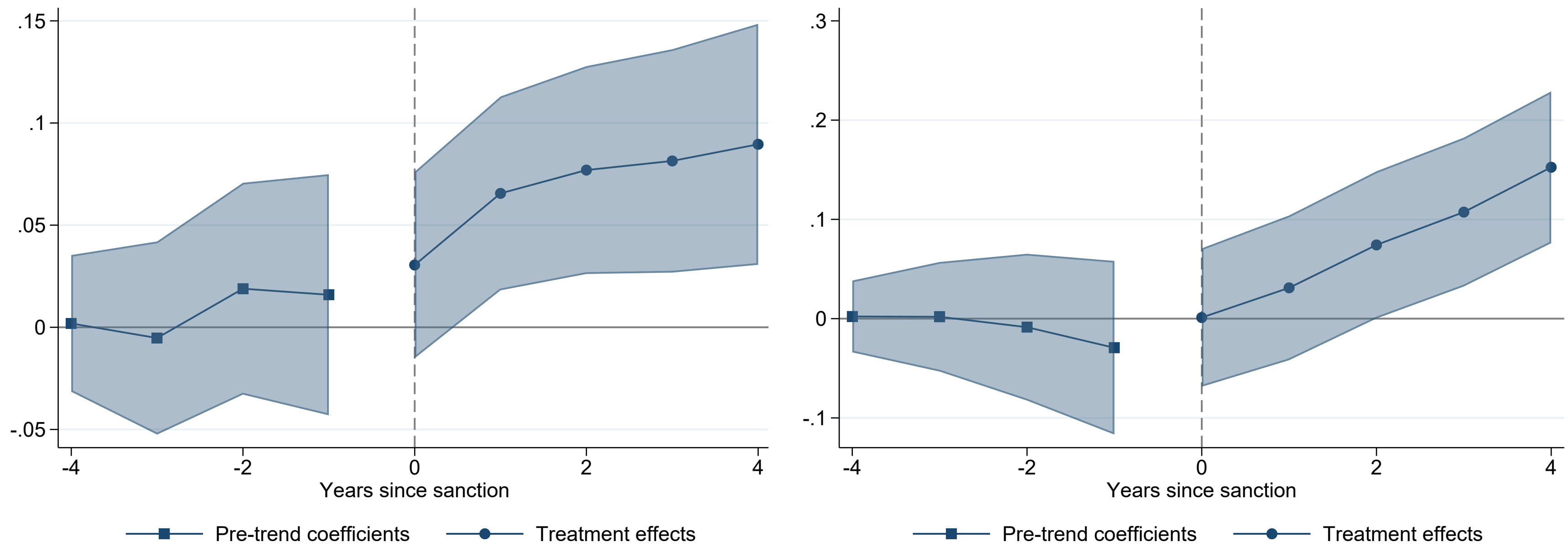
(ii) Individuals exposed to sanctions only through network



(iii) Charities exposed to sanctions through board members

Figure 4: Sanctions over time

Notes: We obtain data on individual sanctions from SanctionsExplorer.org, a centralized database curated by C4ADS that compiles sanctions issued by the UN, OFAC (U.S.), EU, UK, and Canada.

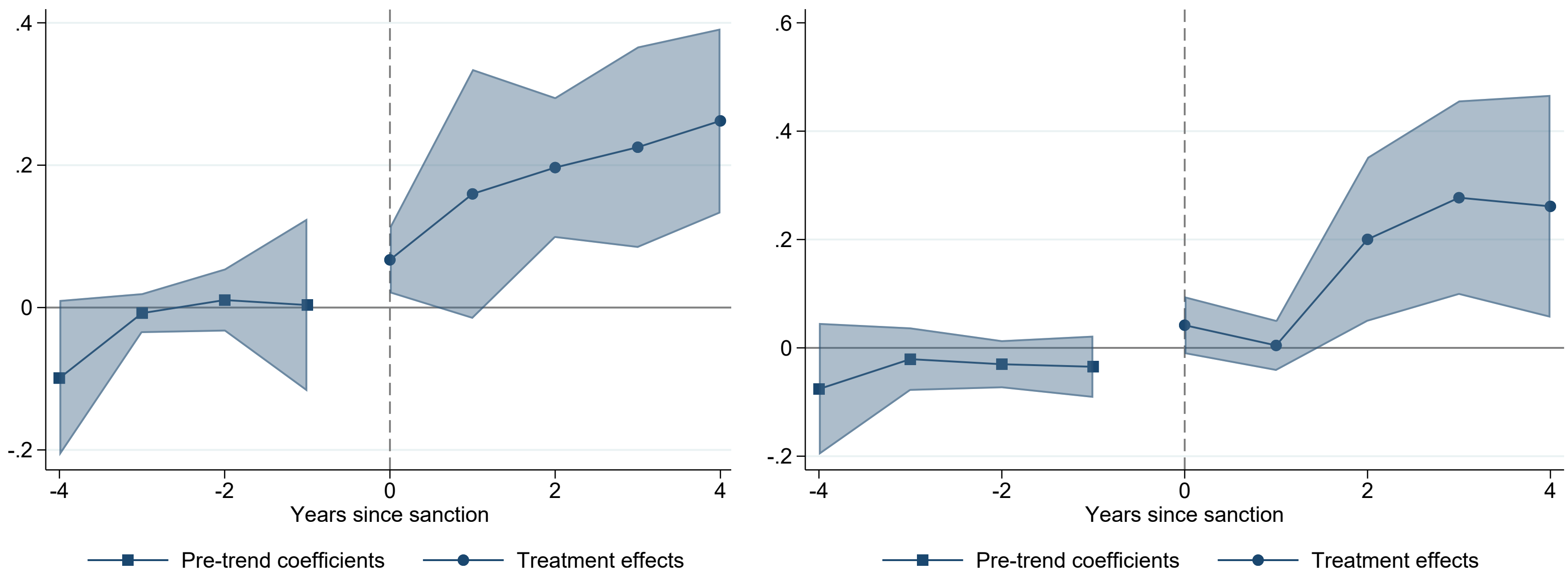


(i) Individuals Sanctioned in Charity

(ii) Individuals Sanctioned in Charity Network

Figure 5: Dynamic Effects of Sanctions on Charity Activity

Notes: Event-study coefficients relative to the first year of sanction exposure. Panel (i) shows effects for charities with a sanctioned member (*Post-Sanction*); Panel (ii) shows effects for charities indirectly exposed via personnel ties (*Sanctioned Network*). Outcome is the probability a charity is active (*Active Charity*). Shaded areas denote 95% confidence intervals. Specifications include charity fixed effects and common time effects; some variants include richer time-by-area fixed effects.



(i) Active at District

(ii) Number of Attacks

Figure 6: Dynamic Effects of Sanctions on Terror

Notes: Event-study estimates at the group×district level around the first sanction affecting group g. Panel (i) outcome: indicator for any attack in district d; Panel (ii) outcome: number of attacks (levels or IHS, depending on specification). Models include group×district fixed effects and common time effects; some variants add group×year or district×year fixed effects. Shaded areas denote 95% confidence intervals.

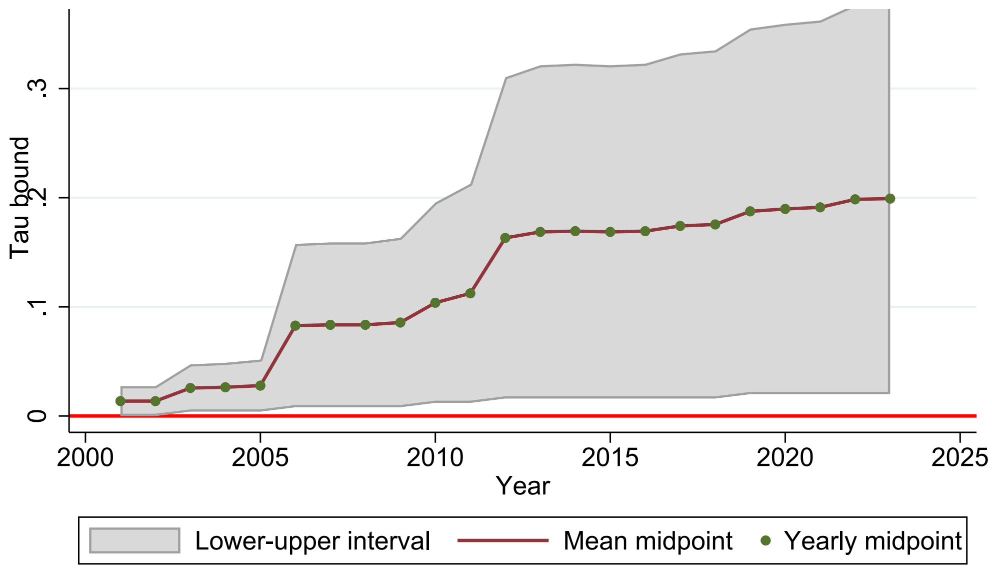


Figure 7: Model-implied τ intervals over time. Inactive, not-yet-sanctioned, and no-longer-active individuals are imputed as zero. Individual-year observations are aggregated first to group-year cells and then to the year level.

Tables

Table 1: Summary Statistics

Panel A: District Level

Variable	Mean	Median	Min	Max
# of Attacks	0.27	0	0	92
Active at District	0.09	0	0	1
Have Charities at District	0.12	0	0	1
# of Active Groups	0.78	0	0	12
# of Sanctioned Groups	1.19	0	0	6
# of Groups with Charities	0.86	1	0	2
Observations				13,981

Panel B: Individual Zakat Donations

Variable	Mean	Median	Min	Max
$\frac{SanctionedCharities}{TotalCharities}$	0.09	0.05	0	0.53
Total Charities	150	161	0	478
Amount of Zakat paid	1613	0	0	666,000
Private Sector Zakat paid	1493	0	0	666,000
Public Sector Zakat paid	121	0	0	300,000
Observations				54,988

Notes: This table reports summary statistics for the main variables used in the analysis. Panel A presents district-year measures of terrorist activity and charity presence. # of Attacks is the number of terrorist incidents in a district-year; Active at District is an indicator equal to 1 if there is at least one attack in the district-year; Have Charities at District indicates whether terrorist organizations have at least one charity present in the district-year; # of Active Groups is the number of terrorist groups active in the district-year; # of Sanctioned Groups is the number of groups in the district-year linked to sanctioned members; and # of Groups with Charities is the number of groups in the district-year with a charitable arm. Panel B presents household-level Zakat donation outcomes from the PSLM. Sanctioned Charities / Total Charities is the division-year share of charities connected to sanctioned individuals; Total Charities is the total number of registered charities in the division-year; Amount of Zakat paid is annual household Zakat giving; Private Sector Zakat paid and Public Sector Zakat paid split donations by recipient type. District-year variables are constructed from the charity registry, sanctions data, and terrorist incident records; donation variables are constructed from household survey data.

Table 2: Sanctions and Active Charities

Panel A: Individuals Sanctioned in Charity

	Active Charity			
	(1)	(2)	(3)	(4)
Post-Sanction	0.062***	0.161***	0.097***	0.217***
	(0.011)	(0.034)	(0.010)	(0.027)
Observations	51996	3381	51983	2201
Charity FE	✓	✓	✓	✓
Year FE	✓	✓		
District X Year FE			✓	✓
MDV	0.369	0.362	0.369	0.436
Control Group	All	Not yet	All	Not yet

Panel B: Individuals Sanctioned in Charity Network

	Active Charity			
	(1)	(2)	(3)	(4)
Sanctioned Network	0.144***	0.352***	0.193***	0.288***
	(0.014)	(0.051)	(0.013)	(0.038)
Observations	46074	1680	46074	948
Charity FE	✓	✓	✓	✓
Year FE	✓	✓		
District X Year FE			✓	✓
MDV	0.380	0.158	0.380	0.222
Control Group	All	Not yet	All	Not yet

Notes: Each panel reports estimates using the sanctioned sample (Panel A) or the unsanctioned but network-exposed sample (Panel B). The dependent variable *Active Charity* equals 1 if charity i has any recorded activity in year t. *Post-Sanction* equals 1 in years $\geq$ the first designation date of any individual affiliated with charity i. *Sanctioned Network* equals 1 if charity i has no sanctioned member but at least one member is also affiliated with another charity that has a sanctioned individual (indirect exposure via personnel ties). Some specifications restrict controls to "not-yet treated" units. Standard errors clustered at the charity level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Sanctions and Zakat Donations

Panel A: Intensive Margin

	Zakat Donations		Private Zakat Donations		Public Zakat Donations	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{ExposedCharities}{TotalCharities}$	0.815**	0.883***	0.885***	0.967***	0.042	-0.062
	(0.342)	(0.317)	(0.336)	(0.312)	(0.110)	(0.106)
Observations	54988	53986	54988	53986	54988	53986
Division FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
HH Characteristics Controls		✓		✓		✓
MDV	1.474	1.334	1.416	1.281	0.084	0.075

Panel B: Extensive Margin

	Zakat Donations		Private Zakat Donations		Public Zakat Donations	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{ExposedCharities}{TotalCharities}$	0.110***	0.115***	0.119***	0.125***	0.001	-0.009
	(0.039)	(0.036)	(0.038)	(0.036)	(0.012)	(0.012)
Observations	54988	53986	54988	53986	54988	53986
Division FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
HH Characteristics Controls		✓		✓		✓
MDV	0.163	0.148	0.157	0.142	0.009	0.008

Notes: Panel A reports intensive-margin results where outcomes are the inverse hyperbolic sine (IHS) of donation amounts; Panel B reports extensive-margin indicators (= 1 if amount > 0). *Zakat Donations* are household-reported annual charitable transfers; where applicable, results may be shown separately by destination type (e.g., private vs. public channels). The key exposure regressor is the local sanction intensity (e.g., share or presence of sanctioned charities in the administrative unit and year). All columns include area and year fixed effects; some add household covariates. Standard errors clustered at the administrative-division level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Sanctions and Terror

	Prob. of Attack				Num. of Attacks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Sanction	0.064***	0.111***	0.192***	0.151***	0.454***	0.649***	0.671***	0.594**
	(0.019)	(0.021)	(0.019)	(0.034)	(0.148)	(0.172)	(0.130)	(0.256)
Observations	13981	13393	3784	2956	13981	13393	3784	2956
Terror Group X District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year X District FE		✓		✓		✓		✓
MDV	0.088	0.085	0.056	0.021	0.271	0.267	0.191	0.059
Control Group	All	All	Not yet	Not yet	All	All	Not yet	Not yet

Notes: Outcomes include *Number of Attacks* (count of incidents by group g in district d, year t) and *Active at District* (indicator for any attack). *Post-Sanction* equals 1 in years $\geq$ the first designation date of any sanctioned individual affiliated with group g. Specifications include group$\times$district fixed effects and common time effects; some columns add district$\times$year fixed effects or "not-yet treated" comparisons. Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Sanctions, Terror, and Charity Involvement

	Prob. of Attack			Num. of Attacks		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Sanction X No Charities	-0.006	0.111**		0.079	0.192	
	(0.025)	(0.047)		(0.162)	(0.135)	
Post-Sanction X Had Charities	0.153***	0.166***	0.128***	0.859***	0.746**	0.606***
	(0.026)	(0.043)	(0.030)	(0.220)	(0.338)	(0.231)
Observations	13393	2956	5332	13393	2956	5332
Terror Group X District FE	✓	✓	✓	✓	✓	✓
Year X District FE	✓	✓	✓	✓	✓	✓
Sanction Year X Year FE			✓			✓
MDV	0.085	0.021	0.105	0.267	0.059	0.385
Control Group	All	Not yet	Sanctioned w/o Charities	All	Not yet	Sanctioned w/o Charities

Notes: Outcomes include *Number of Attacks* and *Probability of Attack*. Interactions of *Post-Sanction* with pre-sanction charity involvement indicators compare groups that operated a charity arm (*Had Charities*) versus those that did not (*No Charities*). Some specifications include group×district and district×year fixed effects, and flexible *Year*×*Sanction-Year* controls. Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Sanctions and Terrorist Group Split-ups

	# of Split-ups				Any Split-up			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# of Sanctioned Members	0.085***		0.083***		0.010***		0.005**	
	(0.011)		(0.014)		(0.002)		(0.002)	
# of Sanctioned Members × No Charities		0.020***		-0.007		0.007**		-0.003
		(0.006)		(0.006)		(0.003)		(0.003)
# of Sanctioned Members × Had Charities		0.124***		0.111***		0.012***		0.008***
		(0.009)		(0.009)		(0.002)		(0.002)
Observations	1541	1541	184	184	1541	1541	184	184
Terrorist Group FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
MDV	0.302	0.302	1.511	1.511	0.187	0.187	0.598	0.598
Control Group	All	All	Not yet	Not yet	All	All	Not yet	Not yet

Notes: Outcomes are *Number of Split-ups* (count of new factions emerging from a parent group in year t) and *Any Split-up* (indicator). *Number of Sanctioned Members* is the cumulative count of sanctioned individuals affiliated with the parent group by year t. Models include group and year fixed effects; some columns use "not-yet treated" comparisons. Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Sanctions and Terror Outside Pakistan

	Prob. of Attack			Num. of Attacks		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Sanction	-0.003			-0.100		
	(0.053)			(0.216)		
Post-Sanction X Other Countries		0.014			-0.052	
		(0.055)			(0.229)	
Post-Sanction X US/Western EU		-0.114**	-0.174***		-0.406**	-0.226***
		(0.050)	(0.026)		(0.183)	(0.049)
Observations	2856	2856	2856	2856	2856	2856
Group X Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓		✓	✓	
Group X Year FE			✓			✓
MDV	0.081	0.081	0.081	0.218	0.218	0.218
Control Group	All	All	Sanctioned Group in Other Countries	All	All	Sanctioned Group in Other Countries

Notes: Outcomes are *Number of Attacks* and *Probability of Attack* at the group-country level. Interactions compare the US and Western EU with versus Other Countries. Standard errors clustered at the group-country level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendices

A LLM Approach

A.1 Purpose and Empirical Object

This appendix explains how we convert qualitative evidence on sanctions and terrorist financing into a quantitative object that can be used in the model and plotted in the paper. The goal is not to estimate a causal treatment effect of sanctions in the usual econometric sense. Instead, the goal is to construct a disciplined measure of the model-relevant financial friction faced by sanctioned individuals and the organizations to which they are connected. We denote this friction by τ.

The empirical problem is that τ is not observed directly. Official sanctions lists tell us who was listed and often report organizational links, aliases, roles, and reasons for designation. Historical and policy sources describe how organizations raised funds, moved money, adapted to sanctions, used charities or fronts, decentralized operations, or fragmented. None of these sources reports a number called τ. The exercise in this appendix therefore translates heterogeneous qualitative evidence into a structured coding object that is consistent with the model.

What we code. The unit of observation is a sanctioned individual i. For each individual, we consider a grid of externally imposed threshold values

$$\tau_E \in \{0.0, 0.1, \ldots, 0.9\}.$$

For each pair (i, e), where e indexes a value of τ_E, the coding procedure assigns an interval

$$[\underline{\tau}_{i,e}, \overline{\tau}_{i,e}].$$

The interval summarizes the range of sanction-induced financial frictions that is consistent with the upstream evidence. A higher interval means that the available evidence points to stronger disruption of the channels through which the organization can transfer resources, maintain central control, or support the sanctioned individual. A lower interval means that the evidence points to weaker disruption, greater pre-sanction local financial autonomy, or financing channels that are less exposed to formal sanctions.

Why intervals rather than point estimates. We use intervals because the underlying historical evidence is uneven. For some organizations, the record is relatively detailed: there is evidence on charities, public fundraising, offices, formal assets, front organizations, or repeated reconstitution after bans. For other groups, financing is more informal and person-level evidence is sparse. In those cases, assigning a single value would create false precision. The lower bound records the minimum disruption consistent with the evidence, while the upper bound records the maximum plausible disruption without assuming facts that are not in the record. Midpoints are used only to summarize figures visually; they are not treated as separate estimates.

How the coding is produced. The coding is produced in two steps. First, a multi-agent workflow organizes the evidence into separate artifacts: group financing structure, reactions to sanctions, fragmentation and reorganization, and individual sanctions information. Second, a final mapping agent uses only those upstream artifacts and the model logic to assign the interval $[\underline{\tau}_{i,e}, \overline{\tau}_{i,e}]$. The final agent is therefore not an independent source of facts. It is a structured coding device that maps the assembled record into the notation of the model.

How to interpret the empirical object. The resulting object is an individual-by-threshold table. It should be read as a model-based coding of qualitative evidence, not as a directly observed outcome. The table is useful because it makes the qualitative evidence comparable across individuals, groups, years, and threshold values. Once this table is created, all aggregations in the appendix are mechanical: group averages, time-series exposure measures, and threshold-grid summaries are computed from the same set of lower and upper bounds.

A.2 Multi-Agent Evidence Pipeline

The workflow separates upstream evidence collection from the final theoretical mapping. Four upstream agents produce independent evidence objects. A final agent then combines those inputs with the model structure to create the individual-by-τ_E interval table. Figure A.1 presents the structure.

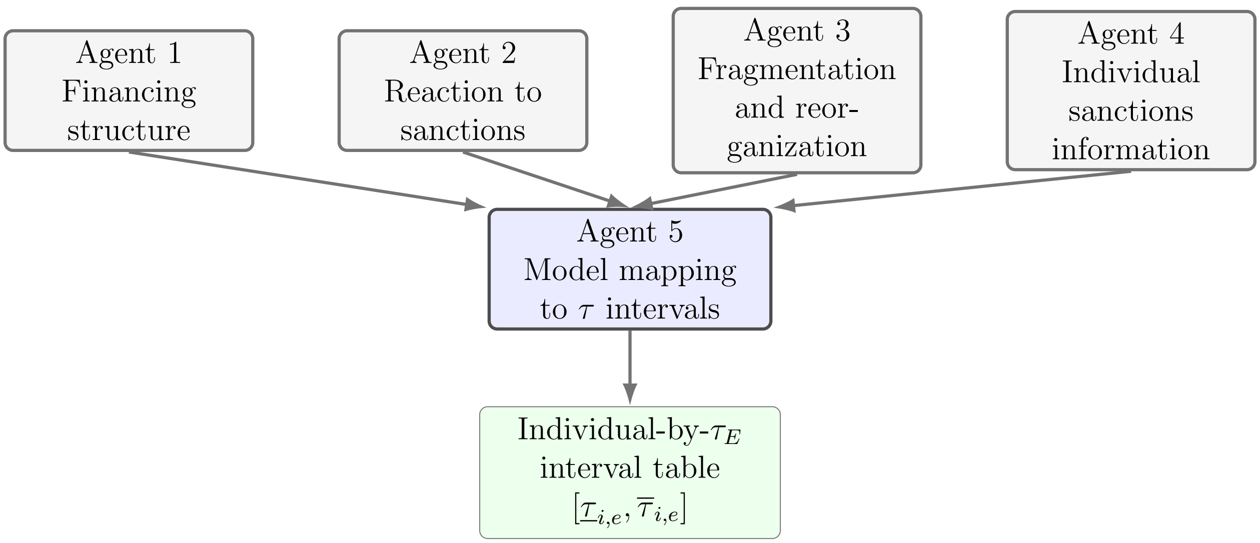


Figure A.1: Evidence pipeline. The first four agents produce upstream artifacts. The final agent uses only these artifacts and the model logic to generate the individual-by-threshold interval table.

Why use several agents? The use of several agents is a design choice for structuring a difficult qualitative coding problem, not a claim that more LLM calls mechanically make the answer correct. The object we need to code combines different types of evidence: how groups raise and move funds, how they adapt after sanctions, whether they fragment or reorganize, and which individuals are listed under official sanctions regimes. These tasks require different source disciplines and different forms of judgment. A single prompt would have to do all of them at once, which would make the output harder to audit. The LLM literature makes a similar point in more technical settings: complex tasks are often more reliable when the problem is first decomposed into smaller components and then solved using the resulting structured inputs Wu et al. (2024). Recent multi-agent applications also emphasize that agents should be assigned focused roles that reflect the structure of the information problem, rather than being treated as interchangeable voters Fernandez-Fuertes (2025); Tillmann (2025).

Why a fixed workflow rather than an open debate? The workflow is intentionally static. The first four agents produce evidence files, and the final agent maps those files into model-implied intervals. The upstream agents do not debate with each other, and the final agent does not conduct new research. This choice is important for an economics or finance application because it makes the procedure auditable: each output can be traced to a specific input file, and the final table can be reproduced from the same upstream artifacts. This follows the logic of decomposition-based LLM systems, where separating the "planning" or evidence-organization stage from the final "solving" stage improves transparency and can reduce the scope for error propagation Wu et al. (2024). Evidence from static versus dynamic decomposition also suggests that a fixed two-stage procedure can be preferable when the subtasks are sufficiently separable, because dynamic procedures may compound errors from intermediate steps and increase computational cost Wu et al. (2024).

How the LLM enters the measurement exercise. The LLM is not a primary source of facts and does not estimate a structural parameter in the econometric sense. It is used as a structured coding device. The first four agents organize qualitative and official information into comparable evidence objects. The last agent applies the model logic to those objects and reports intervals. This is why the final output is an interval rather than a point estimate. In this setting, evidence is often strong at the group level but incomplete at the person level; forcing a single number would create false precision. The interval design preserves uncertainty while still producing a machine-readable object that can be aggregated.

Agent 1: financing structure. The first agent characterizes the financing ecology of terrorist groups in Pakistan. It distinguishes central finance, local fundraising, charity-linked finance, and internal redistribution. Its country-level conclusion is that Pakistan is best described as a mixed financing environment: LeT/JuD/FIF display centralized and charity-linked fundraising, TTP and some sectarian actors rely more heavily on local coercive extraction, while the Haqqani network and Al-Qaida-linked facilitators combine local, cross-border, and donor-based channels. The downstream coding uses this output to assess whether sanctions are likely to bite through central transfers, charity fronts, formal organizations, or local financial autonomy.

Agent 2: reaction to sanctions. The second agent codes how leaders and organizations responded to domestic and international sanctions. Its central finding is that sanctions were present and meaningful but unevenly enforced. Effects were strongest for internationally exposed organizations with visible charities, offices, welfare bodies, bankable assets, or named front organizations. Effects were weaker for cash-based insurgent factions whose revenue sources included extortion, kidnapping, hawala, family intermediaries, and local trusted operators. The agent also documents substitution through renamed entities, informal transfers, leadership insulation, and partial decentralization. These responses matter for the model because they identify whether sanctions increased transfer frictions and uncertainty without necessarily eliminating group resources.

Agent 3: fragmentation and reorganization. The third agent studies organizational split-ups, reorganization, successor entities, and the timing of fragmentation relative to sanctions. Its main conclusion is deliberately cautious. Fragmentation is most visible for TTP, but sources usually emphasize leadership disputes, military pressure, local autonomy, and leadership decapitation rather than sanctions as the proximate cause. For LeT/JuD/FIF and JeM, the stronger pattern is reorganization through fronts and aliases rather than clear splintering. For the Haqqani network, the public record shows resilience and family-centered continuity rather than sanction-linked fragmentation. The mapping agent treats these distinctions as model-relevant: reorganization and decentralization can indicate adaptation, but they can also signal weakened central allocation or a shift toward local financial control.

Agent 4: individual sanctions information. The fourth agent constructs the person-level sanctions file. It uses official sanctions sources to record, for each input individual, the sanctioning authority, regime, sanction date, sanction type, listing status, linked group or network, role or function, reason for listing, and source information. This file defines the individual universe. It also supplies the group or network assignment that links person-level sanctions records to group-level financing and reaction evidence. When the sanctions record identifies a group association but not an individual-specific financial consequence, the interval coding remains anchored in group-level evidence and is kept appropriately wide.

Agent 5: model mapping and final interval construction. The fifth agent maps the four upstream evidence objects into the model. The model summarizes sanctions by $\tau \in [0, 1)$, a friction on transferable non-charity resources. A higher τ lowers the maximal incentive rate $\bar{q}(\tau)$ that central leadership can offer. The operative remains attached when

$$\bar{q}(\tau) \geq q^*,$$

and separates when

$$\bar{q}(\tau) < q^*.$$

The threshold τ_E is defined by $\bar{q}(\tau_E) = q^*$. The grid over τ_E is not estimated; it is imposed to evaluate how the same historical evidence maps into the model under alternative separation thresholds.

For each individual and each grid value, the final agent assigns a lower bound, an upper bound, and a regime code. A low regime indicates little model-relevant financial disruption. A moderate regime indicates meaningful pressure that does not clearly exceed the threshold. A severe regime is allowed when the evidence is consistent with sanctions exceeding the threshold, especially where there is central-channel disruption, charity disruption, weakened internal redistribution, fragmentation, successor formation, or post-sanction local financial autonomy arising from disrupted central transfers. The agent distinguishes pre-sanction structural autonomy, which softens sanction bite (lower τ), from post-sanction decentralization, which signals weakened central allocation under enforcement pressure (higher τ). The final output is the individual-by-τ_E table used in the aggregations below.

A.3 Aggregation Procedures

This section defines the aggregations. Results are shown only in Section A.4. The key point is that aggregation is not another LLM judgment. Once the individual-by-τ_E table has been produced, all group, time, and threshold-grid results are mechanical calculations. This separation is useful because it makes the empirical object transparent: readers can distinguish the qualitative coding step from the statistical summarization step. This separation also follows a simple lesson from recent work on LLM-assisted reasoning: when a task has several logically distinct parts, the researcher should separate the organization of the evidence from the final computation, rather than asking a single prompt to do everything at once Wei et al. (2022); Wu et al. (2024). In multi-agent settings, this corresponds to keeping agent roles, information flow, and decision rules explicit Tillmann (2025).

The aggregation step is also where we deliberately depart from the LLM. The model helps construct a structured table, but it does not choose the plotted group averages, the yearly series, or the threshold-grid summaries. Those objects are produced by deterministic rules. This is analogous to the way self-consistency and agent-ensemble methods emphasize explicit aggregation rules after individual reasoning paths have been produced, except that here the aggregation is not a vote over competing answers; it is a transparent statistical summary of a fixed coding table Wang et al. (2023); Li et al. (2024).

Individual-level intervals. The base table contains one observation for each individual i and grid value e. Each row records $\underline{\tau}_{i,e}$ and $\overline{\tau}_{i,e}$. Keeping the lower bound, upper bound, midpoint, and width as separate objects makes the mapping auditable: the reader can see whether a result is driven by the level of the interval or by uncertainty around it. This mirrors the broader logic of using intermediate structured outputs to make complex reasoning easier to inspect Wei et al. (2022); Wang et al. (2023). The midpoint

$$m_{i,e} = \frac{\underline{\tau}_{i,e} + \overline{\tau}_{i,e}}{2}$$

is a plotting device, not an additional estimate. The width

$$w_{i,e} = \overline{\tau}_{i,e} - \underline{\tau}_{i,e}$$

records uncertainty in the mapping. Wider intervals arise when the upstream evidence is group-level, incomplete, or compatible with both resilience and fragmentation.

Group assignment. Each individual is assigned to a group or network using the sanctions information and the upstream coding. The plotted group aggregation treats the group labels in the analytical file as the relevant categories. In the attached group plot, LeT/JuD is displayed jointly, reflecting the combined coding in that aggregation. The substantive interpretation distinguishes, where possible, between central LeT structures and JuD/FIF-style charity or welfare fronts.

Aggregation by group. The group-level summary first collapses each individual across the τ_E grid. We do this outside the LLM because the group figure is meant to be a descriptive summary of the coded table, not a new qualitative judgment. This keeps the aggregation rule separate from the evidence-mapping step, a distinction emphasized in decomposition-based

LLM workflows Wu et al. (2024). For each individual, define

$$\underline{\tau}_i = \min_e \underline{\tau}_{i,e}, \qquad \overline{\tau}_i = \max_e \overline{\tau}_{i,e}, \qquad m_i = \frac{\underline{\tau}_i + \overline{\tau}_i}{2}.$$

This preserves the widest interval implied by the threshold-grid exercise for that individual. Group-level bounds are then calculated as means over individuals in group g:

$$\underline{\tau}_g = \frac{1}{N_g}\sum_{i\in g}\underline{\tau}_i, \qquad \overline{\tau}_g = \frac{1}{N_g}\sum_{i\in g}\overline{\tau}_i, \qquad m_g = \frac{1}{N_g}\sum_{i\in g} m_i.$$

Thus the group figure reports the mean individual lower bound and the mean individual upper bound. It does not report the lowest and highest individual values within the group.

Aggregation over calendar time. The time-series aggregation combines the sanctions dates with the group-level intervals. This step is again a mechanical panel construction rather than an LLM decision. Let A_{it} equal one if individual i is sanctioned in year t, and zero otherwise. Individuals who are not yet sanctioned are assigned zero:

$$\underline{\tau}_{it} = A_{it}\underline{\tau}_{g(i)}, \qquad \overline{\tau}_{it} = A_{it}\overline{\tau}_{g(i)}, \qquad m_{it} = A_{it}m_{g(i)}.$$

This zero imputation changes the interpretation of the time series. The plotted series is not the average among sanctioned individuals only. It is a measure of active coded sanctions exposure after inactive individuals are assigned no contemporaneous effect.

The annual aggregation is performed in two steps. First, individual-year observations are averaged within group-year cells:

$$\underline{\tau}_{gt} = \frac{1}{N_g}\sum_{i\in g}\underline{\tau}_{it}, \qquad \overline{\tau}_{gt} = \frac{1}{N_g}\sum_{i\in g}\overline{\tau}_{it}, \qquad m_{gt} = \frac{1}{N_g}\sum_{i\in g} m_{it}.$$

Second, the group-year values are averaged across groups:

$$\underline{\tau}_t = \frac{1}{G_t}\sum_g \underline{\tau}_{gt}, \qquad \overline{\tau}_t = \frac{1}{G_t}\sum_g \overline{\tau}_{gt}, \qquad m_t = \frac{1}{G_t}\sum_g m_{gt}.$$

This equal group-year aggregation avoids allowing the largest group in the sanctions file to mechanically dominate the year-level series.

Aggregation over the threshold grid. The threshold-grid aggregation keeps τ_E fixed and averages over individuals. This is the sensitivity-analysis counterpart of the group and time aggregations: the coding table is fixed, but we ask how the same evidence maps into intervals as the theoretical threshold changes. Presenting this grid separately also makes the workflow easier to audit, because the reader can distinguish the substantive group patterns from the sensitivity of the mapping rule Wu et al. (2024).

$$\underline{\tau}_e = \frac{1}{N}\sum_i \underline{\tau}_{i,e}, \qquad \overline{\tau}_e = \frac{1}{N}\sum_i \overline{\tau}_{i,e}, \qquad m_e = \frac{\underline{\tau}_e + \overline{\tau}_e}{2}.$$

This aggregation is a sensitivity exercise. It asks how the same upstream evidence translates into average model-implied intervals as the theoretical separation threshold varies from low to high values.

A.4 Aggregation Results and Interpretation

Group-level heterogeneity. Figure A.2 displays group-level mean intervals. LeT/JuD has the largest plotted mean midpoint and upper bound. This is consistent with the upstream financing report, which identifies central organization, charity-linked fundraising, internal redistribution, and broad public welfare structures for LeT/JuD/FIF. It is also consistent with the sanctions-reaction report, which shows that formal and semi-formal assets, offices, charities, schools, clinics, and public fundraising channels were the most visible targets of sanctions and domestic enforcement. The interpretation is not that LeT/JuD necessarily fragmented more than all other groups. Rather, the model-relevant sanction channel is stronger because central and charity-linked channels are more exposed to formal financial restrictions.

JeM also receives a relatively high mean interval. The upstream record links JeM to charity and support bodies and to recurrent reconstitution after bans. Compared with LeT/JuD, the evidence is less precise and more mixed, so the interval is lower and remains uncertain. TTP has a positive midpoint for a different reason. Its financing is more local and coercive, which reduces the direct bite of formal asset freezes, but the fragmentation report identifies TTP as the clearest case of post-sanction factionalization and local command autonomy. In the model, local autonomy can signal weaker central allocation, so it can still imply a meaningful τ interval.

Haqqani, AQ-linked, IS-linked, and sectarian cases have lower mean intervals in the plotted aggregation. This should not be read as evidence of no sanction effect. It reflects weaker person-level evidence, more informal or cash-based channels, and less direct documentation of central-channel disruption. For the Haqqani network, the upstream reports emphasize family-centered resilience and mixed cross-border finance rather than clear sanction-induced fragmentation. For AQ-linked facilitators, the evidence supports mixed facilitation and courier/hawala channels, but the Pakistan-specific individual-level mapping is less precise. For sectarian and IS-linked cases, the evidence base is thinner and more local, which keeps lower bounds close to zero.

Time-series aggregation. Figure 7 reports the zero-imputed time-series aggregation. The midpoint is close to zero in the early years and rises as the sanctions panel expands. This pattern follows from the construction of the series: individuals contribute zero before they enter the active sanctions panel, and their group-level interval only contributes once the sanction is active. The upward movement therefore reflects the changing composition of active sanctions exposure rather than an event-study estimate of sanction effects.

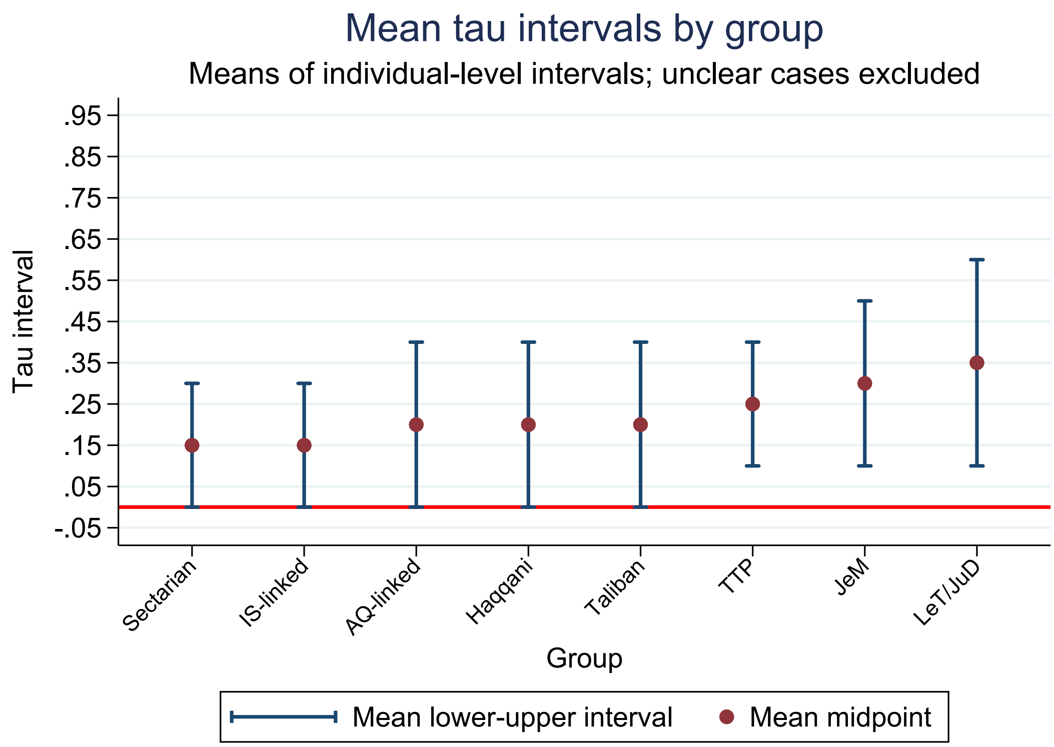


Figure A.2: Mean model-implied τ intervals by group. The vertical caps show the mean individual lower and upper bounds within each group; points show the mean midpoint. Unclear cases are excluded from the plotted aggregation.

The interval widens over time because later years include more active individuals and a more heterogeneous set of groups. Some groups have central or charity-linked structures that generate higher upper bounds; others have local or informal financing that keeps lower bounds near zero. The time-series graph is therefore best interpreted as a descriptive aggregation of coded exposure. It shows when the sanctions panel becomes populated by individuals attached to groups with positive model-implied sanction intervals, but it does not identify whether sanctions caused subsequent organizational outcomes.

Threshold-grid patterns. Figure A.3 shows the average interval by assumed threshold τ_E. This result should be read last because it is a sensitivity analysis rather than an empirical time or group comparison. The midpoint remains in a moderate range across the grid. The lower bound is relatively stable at low values, while the upper bound increases with higher values of τ_E. This pattern reflects the mapping rule: when τ_E is low, moderate evidence can already place cases near or above the threshold; when τ_E is high, the mapping preserves wider uncertainty about whether the same historical evidence is sufficient to exceed a more demanding separation threshold.

The figure therefore does not estimate the true threshold. Instead, it shows that the aggregate conclusions are not driven by a single value of τ_E. Across the grid, the average evidence supports nonzero model-implied sanction effects, but the intervals remain wide enough to preserve ambiguity about whether effects are moderate or severe in any particular threshold environment.

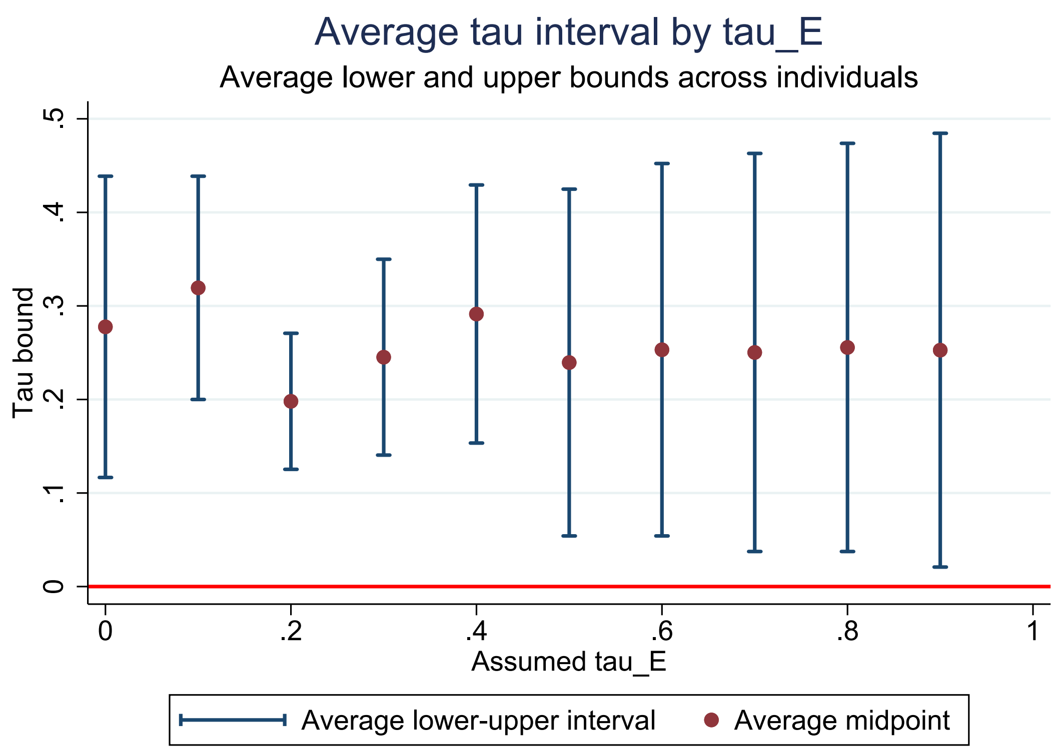


Figure A.3: Average model-implied τ interval by assumed τ_E. Each cap shows the average lower and upper bound across individuals for a fixed threshold value; the point shows the average midpoint.

A.5 Interpretation, Weighting Choices, and Uncertainty

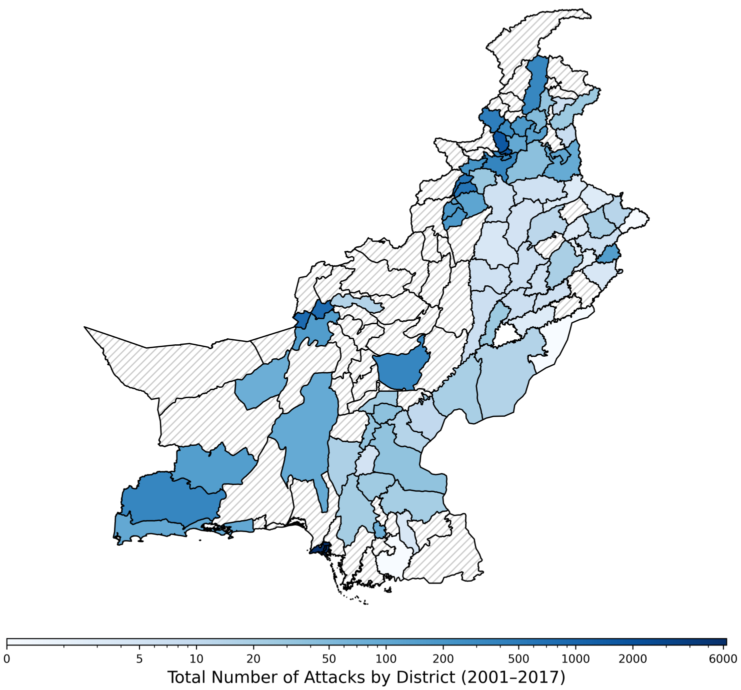
The three aggregation exercises answer different questions. The group graph identifies cross-group heterogeneity in model-implied sanction exposure. The time graph describes how active coded exposure changes over calendar time once inactive individuals are imputed as zero. The threshold-grid graph evaluates sensitivity to alternative theoretical thresholds. The results are consistent with a mixed interpretation: sanctions do not appear uniformly negligible, because several groups have positive midpoints and meaningful upper bounds; but they also do not appear uniformly severe, because many lower bounds remain close to zero and the evidence remains incomplete at the person level.

The methodological choices are deliberately conservative. We do not use many agents as a voting ensemble, even though ensemble and self-consistency methods can improve performance in some benchmark reasoning tasks Wang et al. (2023); Li et al. (2024). That literature is useful because it shows why repeated or multiple reasoning paths can reduce reliance on a single fragile output. But our application is different: we need transparent historical coding, not a contest among several answers. We therefore use specialization rather than voting. The first four agents organize different bodies of evidence, the final agent applies the model mapping, and the remaining aggregation is done mechanically outside the LLM.

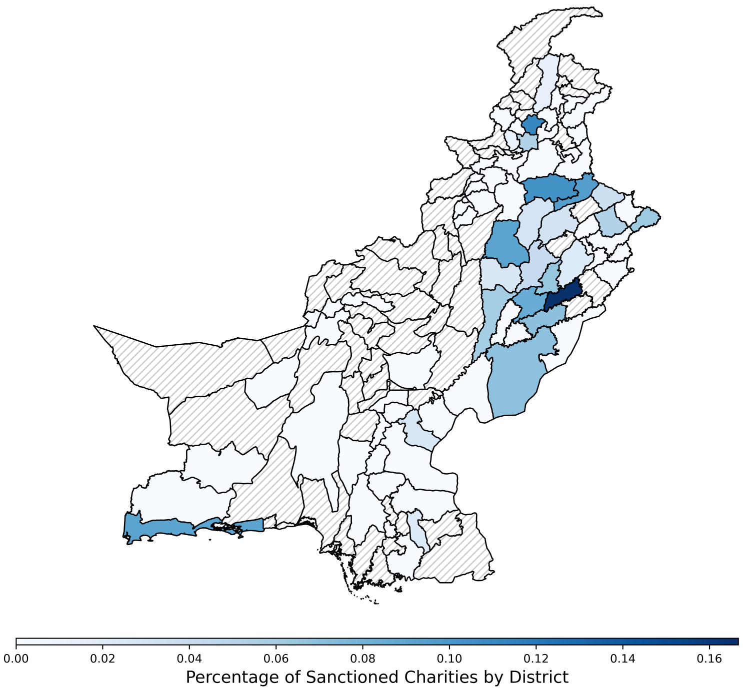
The strongest model-implied effects arise where upstream evidence identifies central organization, charity-linked fundraising, institutional fronts, or formal assets that can be targeted by sanctions and domestic enforcement. This explains the high position of LeT/JuD in the group aggregation and the positive interval for JeM. For TTP, the mechanism is different. The upstream evidence emphasizes local financing, fragmentation, and factional autonomy. These features reduce direct exposure to formal asset freezes but increase the relevance of the model channel in which weakened central allocation and local autonomy can push units away from central control.

Several choices should be kept in mind. First, the intervals are structured codings, not observed parameters. Second, the group aggregation uses means of individual intervals, not the most extreme members of a group. Third, the time-series aggregation uses zero imputation and equal group-year weighting; a person-weighted or attack-weighted aggregation would answer a different question. Fourth, the final mapping intentionally keeps uncertainty visible. A wide interval should be interpreted as a sign of ambiguous or heterogeneous evidence, not as direct evidence that sanctions had a large effect.

B Other Figures



(i) Terrorist attacks across districts (log scale)



(ii) Charities with sanctioned board members across districts

Figure A.4: Spatial Distribution of Terror Activity and Sanctions

Notes: Dashed polygons represent districts without any charity registration between 2001 and 2017.

C Other Tables

Table A.1: Sanctions, Charities, and Banking

Panel A: Individuals Sanctioned in Charity

	Active Charity			
	(1)	(2)	(3)	(4)
Post-Sanction X Non-bank Donations	0.085***	0.021	0.116***	0.046
	(0.015)	(0.032)	(0.014)	(0.035)
Post-Sanction X Bank Donations	0.059***	0.240***	0.090***	0.271***
	(0.014)	(0.041)	(0.013)	(0.027)
Observations	51996	3381	51983	2201
Charity FE	✓	✓	✓	✓
Year FE	✓	✓		
District X Year FE			✓	✓
MDV	0.369	0.362	0.369	0.436
Control Group	All	Not yet	All	Not yet

Panel B: Individuals Sanctioned in Charity Network

	Active Charity			
	(1)	(2)	(3)	(4)
Sanctioned Network X Non-bank Donations	0.188***	0.396***	0.211***	0.337***
	(0.023)	(0.053)	(0.022)	(0.067)
Sanctioned Network X Bank Donations	0.116***	0.324***	0.182***	0.281***
	(0.017)	(0.052)	(0.016)	(0.037)
Observations	46074	1680	46074	948
Charity FE	✓	✓	✓	✓
Year FE	✓	✓		
District X Year FE			✓	✓
MDV	0.380	0.158	0.380	0.222
Control Group	All	Not yet	All	Not yet

Notes: The dependent variable *Active Charity* equals 1 if charity i is active in year t. Samples are split by payment instrument (e.g., bank-based versus charities that do not accept bank transfers or checks). *Post-Sanction* and *Sanctioned Network* are defined as in the main text. Standard errors clustered at the charity level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.2: Sanctions and Public Salience

	Google Trends Score		Google Trends Above Median	
	(1) Worldwide	(2) Pakistan	(3) Worldwide	(4) Pakistan
Post-Sanction	-0.183	0.135	0.034	-0.043
	(0.279)	(0.209)	(0.026)	(0.029)
Observations	4531	4439	4531	4439
Sanctioned Individual FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
MDV	2.192	0.874	0.461	0.386

Notes: Outcomes are *Google Trends score* and *Google Trends score above the median*. Standard errors clustered at the sanctioned individual level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3: Sanctions and Conflict Against Other Terrorist Groups

	Attacks Against Terrorist Groups		Other Attacks	
	(1)	(2)	(3)	(4)
Post-Sanction X No Charity	-0.013		0.092	
	(0.011)		(0.159)	
Post-Sanction X Charity Presence	0.038^{**}	0.044^{***}	0.821^{***}	0.563^{**}
	(0.016)	(0.013)	(0.210)	(0.224)
Observations	13393	5332	13393	5332
Terror Group X District FE	✓	✓	✓	✓
Year X District FE	✓	✓	✓	✓
Sanction Year X Year FE		✓		✓
MDV	0.008	0.016	0.258	0.369
Control Group	All	Sanctioned w/o Charities	All	Sanctioned w/o Charities

Notes: *Attacks Against Terrorist Groups* counts incidents where the target is another terrorist group; *Other Attacks* covers remaining targets (government, civilian, etc.). Interactions split groups by pre-sanction charity presence. Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4: Sanctions and Group Relationships

	Allies		Associates		Supporters		Rivals		Competitors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post-Sanction	0.242***	0.213***	0.220**	0.196*	0.105***	0.105***	0.028	0.023	0.061**	0.102**
	(0.049)	(0.055)	(0.107)	(0.110)	(0.023)	(0.022)	(0.040)	(0.045)	(0.028)	(0.045)
Observations	26754	349	26754	349	26754	349	26754	349	26754	349
Terror Group FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MDV	0.037	0.172	0.035	0.235	0.016	0.037	0.012	0.026	0.025	0.029
Control Group	All	Not yet	All	Not yet	All	Not yet	All	Not yet	All	Not yet

Notes: This table uses data from the Militant Group Alliances and Rivalries (MGAR) Database; see Blair et al. (2022). The dependent variables are the inverse hyperbolic sine transformation of the number of allies, associates, supporters, rivals, and competitors per group according to the MGAR dataset. Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5: Sanctions and Charities Involvement per Individual

Panel A: Sanctioned Individuals

	Active at district				asinh(# Charities)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Sanction	0.079***	0.229***	0.107***	0.176***	0.059***	0.208***	0.084***	0.158***
	(0.010)	(0.028)	(0.011)	(0.015)	(0.012)	(0.030)	(0.012)	(0.017)
Observations	137277	24234	137264	18919	137277	24234	137264	18919
Person X District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓			✓	✓		
District X Year FE			✓	✓			✓	✓
MDV	0.347	0.320	0.346	0.377	0.361	0.349	0.360	0.412
Control Group	All	Not yet	All	Not yet	All	Not yet	All	Not yet

Panel B: Unsanctioned Individuals Affected by Sanctions in Their Network

	Active at the district				asinh(# Charities)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sanctioned Network	0.085***	0.241***	0.114***	0.188***	0.064***	0.221***	0.091***	0.171***
	(0.011)	(0.029)	(0.011)	(0.016)	(0.013)	(0.032)	(0.013)	(0.018)
Observations	134337	21294	134337	16399	134337	21294	134337	16399
Person X District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓			✓	✓		
District X Year FE			✓	✓			✓	✓
MDV	0.345	0.308	0.345	0.365	0.358	0.335	0.358	0.398
Control Group	All	Not yet	All	Not yet	All	Not yet	All	Not yet

Notes: Person-level outcomes include *Active at District* (any charity participation by individual i in district d, year t) and asinh(# Charities) (IHS of the number of distinct charities individual i participates in). Panel A restricts to sanctioned individuals; Panel B restricts to unsanctioned individuals indirectly exposed via personnel ties (*Sanctioned Network*). All models include individual (or individual×district) fixed effects and common time effects; some specifications add district×year fixed effects. Standard errors clustered at the individual level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: Sanctions and Terror Casualties

	Any Casualty				Num. of Casualties			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Sanction	0.082***	0.112***	0.168***	0.131***	7.871***	9.957***	9.081***	8.157**
	(0.018)	(0.021)	(0.019)	(0.035)	(2.006)	(2.422)	(1.823)	(3.383)
Observations	13981	13393	3784	2956	13981	13393	3784	2956
Terror Group X District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year X District FE		✓		✓		✓		✓
MDV	0.071	0.069	0.049	0.018	2.777	2.781	2.716	0.998
Control Group	All	All	Not yet	Not yet	All	All	Not yet	Not yet

Notes: Outcomes are *Number of Casualties* (killed + injured) and *Any Casualty* (indicator). *Post-Sanction* is defined at the group level; fixed effects follow the main terror specifications (e.g., group×district and time effects). Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Sanctions and Terror – Capital Intensity

	Capital Intensive Attacks			Non-Capital Intensive Attacks		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Sanction X No Charity	0.057	0.176		0.023	0.016	
	(0.128)	(0.120)		(0.044)	(0.018)	
Post-Sanction X Charity Presence	0.644***	0.531**	0.422**	0.214***	0.215**	0.184***
	(0.170)	(0.243)	(0.184)	(0.053)	(0.098)	(0.054)
Observations	13393	2956	5332	13393	2956	5332
Terror Group X District FE	✓	✓	✓	✓	✓	✓
Year X District FE	✓	✓	✓	✓	✓	✓
Sanction Year X Year FE			✓			✓
MDV	0.213	0.045	0.292	0.054	0.014	0.093
Control Group	All	Not yet	Sanctioned w/o Charities	All	Not yet	Sanctioned w/o Charities

Notes: Outcomes are split by attack type: *Capital-Intensive* (bombings and armed assaults) versus *Non-Capital-Intensive* (all other attack types). Interactions compare groups with versus without a pre-existing charity arm. Fixed effects follow the main terror specifications. Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: Sanctions, Charities, and Terror – Group Size Matched Sample

	Prob. of Attack		Num. of Attacks	
	(1)	(2)	(3)	(4)
Post-Sanction X No Charities	-0.006		0.079	
	(0.025)		(0.162)	
Post-Sanction X Had Charities	0.153^{***}	0.128^{***}	0.859^{***}	0.606^{***}
	(0.026)	(0.030)	(0.220)	(0.231)
Observations	13393	5332	13393	5332
Terror Group X District FE	✓	✓	✓	✓
Year X District FE	✓	✓	✓	✓
Sanction Year X Year FE		✓		✓
MDV	0.085	0.105	0.267	0.385
Control Group	All	Sanctioned w/o Charities	All	Sanctioned w/o Charities

Notes: Sample matched on pre-sanction group size (e.g., number of districts of activity). Outcomes are *Number of Attacks* and *Probability of Attack*. Interactions compare groups with versus without a charity arm. Standard errors clustered at the group level are shown in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.