City of Shame: Crime Signaling and Inverse Deterrence in a Weak State

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Abstract

Do high-profile criminal incidents deter future crime or inadvertently increase it by signaling weak enforcement? This paper studies the effects of the highly publicized rape and murder of seven-year-old Zainab Ansari in January 2018 on child sexual abuse patterns in Kasur, Pakistan. Using a district–month panel from 2015–2024 constructed from verified newspaper reports and applying the Synthetic Difference-in-Differences estimator, we compare Kasur's post-incident trajectory to a synthetic counterfactual drawn from other districts in Punjab. We find a large and persistent increase in reported child abuse in Kasur, equivalent to roughly ten additional cases per month, that does not appear in neighboring or comparable districts. The increase is concentrated in opportunistic offenses involving strangers and acquaintances, single-episode abuse, and locations with weak supervision, while supervised environments show no comparable rise. We further show that judicial congestion is positively associated with reported abuse in Kasur but not elsewhere, suggesting that institutional strain weakened deterrence in the post-incident period—a pattern consistent with inverse deterrence, in which heightened visibility does not translate into effective punishment. While we cannot fully disentangle reporting from incidence, the persistence, localization, severity, and institutional patterns indicate durable behavioral and institutional changes rather than a temporary media-driven reporting spike. The findings highlight a mechanism of inverse deterrence, whereby salient crimes can reshape criminal behavior when public attention rises faster than enforcement capacity.

Keywords: Child sexual abuse, Crime deterrence, Crime reporting, State capacity
JEL Classification Codes: K42, O17, C23, D74

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I. Introduction

Do high-profile criminal incidents deter future crime, or can they instead increase it by signaling weak enforcement? Standard economic models of crime predict that salient punishment raises the perceived probability of conviction and suppresses offending (Becker, 1968). When crimes receive widespread public attention, arrests, prosecutions, or heightened policing may strengthen deterrence by increasing the expected costs of criminal activity. Yet in settings characterized by limited state capacity, the same publicity may reveal institutional fragility rather than strength. If public attention rises without a commensurate expansion in enforcement or judicial capacity, deterrence may weaken rather than strengthen, potentially increasing subsequent criminal activity, an effect that we term *inverse deterrence*. Whether salient crimes deter or amplify crime therefore remains an open empirical question.

While there is theoretical support for both channels, the empirical evidence is mixed. For instance, Draca, Machin, and Witt (2011) find that London's heightened police deployments after terrorist attacks significantly reduced street crime. Prescott and Rockoff (2011) similarly show that enhanced police monitoring through sex-offender registration led to fewer reported sex offenses. At the same time, Mathur et al. (2023) find that in the aftermath of a high-profile rape and murder of a 23-year-old woman in Delhi, India, crime reporting increased in the immediate aftermath. Empirically, therefore, whether salient crimes deter or amplify subsequent criminal activity and crime reporting, and under what institutional conditions, remains unresolved.

Of all possible criminal activities, child sexual abuse is perceived to be among the most serious (Blumenthal, 2006; Sebba, 1984). In the aftermath of a particularly egregious crime against a child, one that caught nation-wide attention and led to multiple protests, we ask what impacts this had on similar crimes. We consider the impact of the 2018 rape and murder of seven-year-old Zainab Ansari, who was abducted outside her home in Kasur, Pakistan, on her way to Quran recitation classes on the 4th of January 2018. Her body was found near Lahore, Pakistan on 9th January 2018. The autopsy report noted that she had been "extensively raped and tortured before being strangled to death."[2] Furthermore, the perpetrator was identified as a serial killer, with another seven rapes and murders attributed to him (Alam, Raza, & Raza, 2024). Kasur had already been associated with serious child sexual abuse scandals, most notably the 2015 child pornography ring, creating a context in which Zainab's murder was perceived not as an isolated tragedy but as evidence of continued institutional failure.[3] Public anger intensified after the family located CCTV footage showing Zainab being led away by an unidentified man. The footage spread rapidly across television and social media, transforming the case into a national crisis (Chughtai, 2018). Mass protests erupted across Kasur, with demonstrators attacking police stations and blocking major roads; two civilians were killed when police opened fire on crowds.[4]

The scale of public attention is captured in Google search trends, which show an extraordinary spike in search interest for "Zainab Kasur" during the week following the discovery of her body. This spike, shown in Figure 1 illustrates the intensity of media coverage and the depth of societal shock in the immediate aftermath. The suspect was apprehended and the case was tried in an anti-terrorism court. His execution later that year was widely understood as the state's attempt to respond forcefully to public outrage (Alam, Raza, & Raza, 2024).

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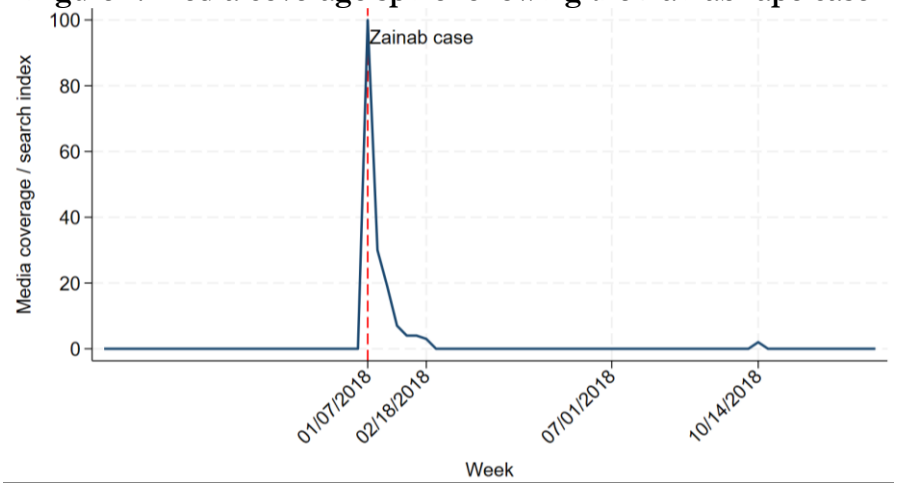
[2] More on the case here: https://en.wikipedia.org/wiki/Murder_of_Zainab_Ansari

[3] See *Al Jazeera* (11 March 2021), https://www.aljazeera.com/opinions/2021/3/11/when-will-there-be-justice-for-pakistans-victims-of-child-abuse.

[4] Laignee Barron, "Riots Turn Deadly After the Rape and Murder of a 7-Year-Old Girl in Pakistan," *TIME*, January 10, 2018, https://time.com/5098229/pakistan-murder-rape-riots-zainab/.

However, commentators noted that the case reflected deeper systemic failings, including weak child-protection systems and repeated institutional neglect in Kasur (Al Jazeera, 2021). The public outcry surrounding Zainab's case also catalyzed policy change. In 2020, Pakistan's Parliament passed the Zainab Alert, Response and Recovery Agency (ZARRA) Act, establishing the country's first national alert system for missing children—an institutional reform directly linked to the public mobilization after Zainab's death (The Guardian, 2020).

Figure 1: Media coverage spike following the Zainab rape case



For Kasur, the incident marks a critical break in time. The surge in media attention, civic mobilization, and policing responses created a distinct post-2018 environment, one characterized by heightened vigilance, changes in reporting behavior, and widespread outrage. This rupture provides a quasi-experimental setting to examine how patterns of child-abuse reporting shifted in Kasur in the aftermath of the Zainab incident.

We use Synthetic Difference-in-Differences (Arkhangelsky et al., 2021) to identify the effects of the Zainab incident on child sexual abuse reporting in Kasur. We use data from three main sources: child abuse reporting data from Sahil, demographic data from the Pakistan Bureau of Statistics, and policing and judicial capacity data from the Bureau of Statistics, Government of the Punjab and the Law and Justice Commission of Pakistan. Our study focuses on the Punjab province of Pakistan specifically, the most populous province in Pakistan (with a population of just over 127 million), and the second most populous province in the world (following the state of Uttar Pradesh in India). We find that in the aftermath of the Zainab incident, sexual abuse crime reporting increased in Kasur, with no similar increases observed in other districts in Punjab. Furthermore, we observe sustained increases in Kasur, persisting for several years beyond the immediate aftermath, far longer than any other reported in the literature.[5] To test the robustness of our findings, we conduct a series of restrictions to our donor district pool, accounting for spatial spillovers, law enforcement capacity, urbanization, and child employment levels. Our core results remain robust to these donor pool adjustments.

We further document heterogeneity in case increases that are broadly consistent with opportunistic child sexual abuse (higher single episodes, more likely to occur in known spaces, and more likely to involve child laborers or students), rather than systematic patterns of abuse. In addition, we offer evidence that the observed rise in reported child sexual abuse cases is attributable to a feedback loop between institutional weaknesses, and rising caseloads. Specifically, we show that the positive relationship between crime reporting and judicial congestion is higher in Kasur, relative to other districts in Punjab. We interpret this pattern as

[5] This observed increase is also consistent with contemporary media reports: see for example on child abuse in Kasur in 2025: https://images.dawn.com/news/1193908.

evidence of what we term *inverse deterrence*: heightened crime visibility following a salient event coincided with strained enforcement and judicial capacity, weakening effective deterrence and increasing opportunistic offending rather than suppressing it. Intuitively, this pattern implies that judicial congestion and reported child abuse move together in Kasur but not elsewhere, consistent with a setting in which limited institutional capacity weakened deterrence following the Zainab incident. Finally, the evidence suggests that the post-incident increases reflect a combination of heightened reporting and increased opportunistic abuse, underscoring the central role of state capacity in shaping crime responses to salient shocks.

Our results contribute to important policy and scientific debates on the impact of high-profile events on crime deterrence. Unlike previous studies in this area, we focus on an environment with weak state capacity (Pakistan). Furthermore, we study a particularly heinous form of criminal activity, widely perceived to carry the highest level of sentences (child sexual abuse). Furthermore, while similar work conflates media distortions with reporting behavior and true incidence, we offer several pieces of evidence to support the interpretation that the increases observed are meaningful, and not just media driven. First, the dynamic pattern shows only a small rise in reporting in the year immediately following the incident, but large and sustained increases from the second year onward, persisting for at least four years, inconsistent with a one-time salience shock (DellaVigna and Gentzkow, 2010). Secondly, because our outcome concerns highly severe offences, which exhibit relatively inelastic reporting behavior and are less responsive to short-run media fluctuations (Baumer and Lauritson, 2010), variations are more plausibly related to shifts in reporting norms or true incidence (Iyengar, 2009). Finally, for the final year where both data sources are available (2024), newspaper reports align closely with official police records, reinforcing the validity of our proxy (Table 8). These facts together suggest that the observed increases represent durable underlying changes in either crime incidence or reporting, rather than temporary distortions in media attention.

II. Conceptual Framework

Economic models of criminal behavior, beginning with Becker (1968), provide a framework for understanding how changes in deterrence, opportunities, and institutional capacity shape the incidence of crime. In this framework, potential offenders weigh the gains from crime against the expected costs, which depend on the probability and severity of punishment. An individual commits an offense when its expected utility exceeds that of pursuing lawful activities. For intuition, we draw on Becker's expected-utility framework, in which the perceived payoff to offending depends on the probability of punishment:

$$E[U] = P \cdot U(Y - f) + (1 - P) \cdot U(Y)$$

Where P denotes the subjective probability of being apprehended and convicted, f is the sanction, and Y captures the monetary and psychic benefits of the offense. Crimes, including sexual violence, may generate psychic income, such as gratification, coercive power, or thrill. Accordingly, Becker's expected-utility framework applies broadly to both violent and non-violent offenses.

According to this framework, any decline in P raises the expected utility of crime, increasing the supply of offenses. In settings where public attention to crime increases without a commensurate expansion in enforcement or judicial capacity, this mechanism can reverse: deterrence may weaken rather than strengthen, giving rise to what we term inverse deterrence. Empirical reviews show that the probability of punishment is among the strongest deterrents for

both property and violent crime (Ehrlich 1973; Eide 1994; Levitt 1998).[6] Judicial congestion, delays, or weak enforcement can therefore reduce deterrence by lowering the effective likelihood of punishment.

In Kasur, judicial administrative data indicate a marked increase in the backlog of criminal cases. A growing backlog lowers the perceived probability of timely conviction, thereby diminishing deterrence. We emphasize that judicial congestion should not be interpreted as an exogenous shock in our setting. Because judicial data are only available for the later post-incident period (2022–2024), backlog is best viewed as part of a broader feedback process linking institutional capacity and crime rather than as a causal driver of the initial increase.

Within the rational-choice framework, rising congestion is consistent with an *inverse deterrence* mechanism, in which heightened crime visibility coincides with a decline in the perceived probability of timely punishment: slower courts weaken deterrence and raise the expected return to opportunistic offending (Pellegrina, 2008; Chappe and Thomas, 2006).

A second component of the theoretical framework concerns situational opportunities. Market-based theories of crime emphasize that offending is shaped not only by individual motivation but also by the availability of attractive targets and low-guardianship environments. In this view, crime emerges from the interaction between offenders seeking vulnerable targets and victims attempting to reduce their exposure (Ehrlich 1981, 1996; Cook 1986). This opportunity-based perspective, closely aligned with routine activity theory, predicts higher victimization where supervision is weak, targets are easily accessible, and the likelihood of detection is low.[7]

These mechanisms map closely onto the victim-level patterns observed in Kasur. Following the Zainab incident, child abuse reports increasingly involved boys, students, and child laborers, groups characterized by high exposure outside the home and limited supervision. We find that offenses shifted toward streets, abandoned spaces, fields, and other low-guardianship environments. Perpetrators were disproportionately strangers rather than family members or authority figures, consistent with opportunistic targeting rather than intra-household abuse. These patterns indicate an expansion of situational opportunities for predatory, single-incident abuse.

A unifying interpretation is provided by beliefs updating and contagion (Towers et al., 2015; Sah, 1991; Glaeser, Sacerdote & Scheinkman 1996; Banerjee, 1992). Salient violent events transmit information to both offenders and victims: about enforcement strength, victim vulnerability, community attention, and the perceived consequences of offending. Signals shape beliefs for both offenders and victims: offenders update expectations about punishment risk, while victims and families update reporting behavior and vigilance. When institutional responses are weak (such as Kasur's rising judicial backlog) the signal may convey heightened visibility but not increased enforcement capacity. Such mixed signals can simultaneously increase reporting and embolden opportunistic offenders.

A related mechanism arises from the salience shock associated with the Zainab incident. Highly publicized violent incidents have been shown to reshape behavior through belief updating, social interactions, and changes in perceived enforcement (Towers et al., 2015). If a salient event raises public scrutiny without strengthening deterrence, offenders may interpret the shock as increasing attention but not the probability of conviction, while victims may be more willing to report. The coexistence of rising crime and judicial congestion in Kasur is consistent with this dynamic.

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[6] See also Danziger & Wheeler (1975); Forst (1976); Holtmann & Yap (1978).

[7] Cohen and Felson's (1979) routine activity theory argues that criminal events emerge from the convergence of three elements: an offender ready to act, a vulnerable target, and the absence of a capable guardian to deter the offense.

Together, these mechanisms of rational-choice deterrence, opportunity-based targeting, and crime-signaling dynamics describe a process of inverse deterrence, generating clear predictions for how a high-profile violent event might reshape crime patterns. A reduction in the effective probability of punishment, combined with abundant opportunities for low-risk targeting in public or weakly supervised settings, should increase the incidence of opportunistic child abuse through a combination of increased offending and increased detection in low-guardianship settings. These effects are expected to concentrate among highly exposed demographic groups and in locations offering minimal guardianship. Our empirical analysis evaluates these predictions by comparing Kasur's post-2018 trajectory to a synthetic counterfactual constructed from comparable Punjab districts.

III. Data

We use three data sources in total: child abuse incidents from the NGO Sahil (which compiles these data for Pakistan), demographic data from the 2017 Population and Housing Census (obtained from the Pakistan Bureau of Statistics), and policing and judicial capacity data from the 2017 Statistical Pocketbook of Punjab (obtained from the Bureau of Statistics, Government of the Punjab), and the Judicial Statistics of Pakistan 2022–2024 (obtained from the Law and Justice Commission of Pakistan). After merging the incident-level data with census, policing, and judicial information, we obtain a strongly balanced district–month panel covering 35 districts of Punjab from 2015 to 2024.[8] Each row in our dataset represents a district–month pair containing verified abuse cases and the corresponding baseline and institutional covariates.

Child abuse data

We construct a district–month panel dataset spanning January 2015 to December 2024 using reported child abuse cases. The dataset integrates verified incident-level records of child sexual abuse with demographic, institutional, and policing indicators. The primary source of crime data is based on a decade of the *Cruel Numbers* reports, a series of annual reports produced by Sahil, a child-protection NGO headquartered in Islamabad.[9] The data contains a comprehensive list of individual, verified incidents of child sexual abuse across Pakistan. Each observation represents a single reported case and includes detailed information on the date of occurrence, district and sub-district (*tehsil*), province, and whether the incident took place in a rural or urban setting. Victim-level characteristics record the gender, age, and status of the child (student, domestic laborer, street child, or person with a disability) providing insight into the context of vulnerability. Sahil itself scans newspaper articles across all national and regional newspapers in Pakistan and contacts the victims' families to offer free legal counsel and advice. Each observation includes information from the article itself, from the First Information Report (FIR) filed with the police (if any), and from interviewing the family of the victim directly. The NGO therefore has direct incentives to include as many cases as possible, and reports having nationwide coverage. Furthermore, it is the only organization to compile such data in Pakistan. Data varies by region, but is the most comprehensive for the Punjab province, the focus of this study.

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[8] Two districts—Wazirabad, and Kot Addu—were excluded because Sahil's incident-level datasets do not consistently report cases for these areas over the full 2015–2024 period. Wazirabad and Kot Addu were only designated as separate districts in 2022 and therefore appear with near-zero or missing monthly observations in earlier years. Gujrat also contains numerous months with no recorded cases, making it incompatible with the balanced panel required for synthetic-control estimation.

[9] Sahil's *Cruel Numbers* annual reports are publicly available at https://sahil.org/cruel-numbers/. Each report summarizes provincial and categorical trends in reported cases of child sexual abuse collected through national and regional newspaper monitoring and subsequently verified through police and court follow-up. The incident-level dataset used in this study was obtained directly from Sahil and corresponds to the underlying records used in compiling these reports.

In addition to victim information, the dataset contains extensive perpetrator-level detail, including the number of perpetrators and abettors, their approximate ages, gender, and their relationship to the victim (i.e. acquaintance, neighbor, teacher, driver, or relative). Contextual variables further describe the place of abuse, such as the victim's or perpetrator's home, an educational institution, a workplace, or another public area, and record the duration of abuse, distinguishing between single incidents and repeated abuse extending over days, months, or years. Together, these variables enable a detailed characterization of both the social environment and the interpersonal dynamics surrounding each reported case.

The dataset also records law-enforcement responses, including the name of the police station where the complaint was filed and a case-status variable indicating whether the incident was registered with the police, unregistered, or refused registration. In nearly all verified cases, the report was formally registered, as Sahil's inclusion criteria require police confirmation or multiple independent media verifications before a case is recorded. Consequently, the dataset reflects actual, substantiated incidents of child sexual abuse rather than unverified reports. Each case is further cross-referenced with up to three independent newspaper sources, accompanied by verification fields confirming consistency across outlets before inclusion in Sahil's official database.

For this study, Sahil provided the underlying incident-level datasets for all years 2015–2024. We harmonized variable names across years, standardized district identifiers, and aggregated the verified cases to the district–month level, summing all incidents per district and month. The dependent variable, crime rate measures the number of reported child-abuse incidents per 100 000 population, using 2017 census population as the denominator to ensure that changes over time reflect variation in reporting rather than demographic growth.[10] Kasur, where the Zainab incident occurred in January 2018, serves as the treated district, while the remaining 34 districts of Punjab constitute the donor pool for constructing a synthetic counterfactual. The pre-treatment period spans January 2015–December 2017, and the post-treatment period begins January 2018, coinciding with the surge of national media attention and public outrage following the case.[11] While the data cannot capture abuse that goes entirely unreported, the richness of the incident-level records—covering timing, location, perpetrator relationship, and case status—allows us to examine whether post-incident changes are consistent with shifts in reporting behavior, changes in the composition of cases, or institutional responses.

Demographic data

To account for heterogeneity in socioeconomic structure across districts, we compile several cross-sectional covariates measured in 2017 from the *Population and Housing Census 2017* (Pakistan Bureau of Statistics, PBS). These include population density, literacy rate, and the share of the population living in urban areas, which proxies for exposure to media, awareness, administrative reach and settlement density. We also construct a child-employment rate, defined as the number of children aged 10–14 engaged in work, including paid family workers, divided by the total population of children aged 10–14, using census-based child population counts.[12] Together,

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[10] Population counts are taken from the *Population and Housing Census 2017*, Pakistan Bureau of Statistics (PBS). District-level population data are available only for 2017 and 2023; hence, we fix the denominator at 2017 population throughout to ensure consistency and to avoid introducing measurement error from interpolation. This approach also follows standard practice in panel analyses when yearly population estimates are unavailable.

[11] Data for August 2015 are missing due to the discovery of a large child-abuse ring in Kasur that month, involving over 280 children and 400 video recordings. See *Al Jazeera* (11 Aug 2015), https://www.aljazeera.com/news/2015/8/11/pakistan-stumbles-upon-its-biggest-child-abuse-case. For 2020 and 2021, only January–June observations are available from Sahil's *Cruel Numbers* dataset due to pandemic related complications.

[12] This indicator approximates exposure to labor environments and socioeconomic vulnerability.

these baseline characteristics capture key socioeconomic variation relevant for pre-treatment comparability across districts.

Policing and judicial capacity data

To gauge differences in institutional strength, we incorporate measures of policing density and judicial performance. Data on police-station counts for 2017 come from the *Statistical Pocket Book of Punjab,* Bureau of Statistics, Government of the Punjab). We compute policing density as the number of police stations per 100 000 residents (2017) to proxy for law-enforcement presence and accessibility.

To measure district-level judicial performance, we draw on the *Judicial Statistics of Pakistan 2022–2024*, compiled annually by the Law and Justice Commission of Pakistan (LJCP).[13] These reports provide a comprehensive account of criminal case-flow in each district's sessions courts. For every district, the dataset reports (i) Pendency, the stock of criminal cases pending at the start of the year; (ii) Institution, the number of new criminal cases filed during the year; (iii) Received, the number of cases transferred in from other courts; (iv) Disposal, the number of cases concluded: whether through conviction, acquittal, withdrawal, or compromise; (v) Transfer, the number of cases forwarded to other courts; and (vi) Balance, the number of cases still pending at year-end. Together, these variables summarize the full annual lifecycle of criminal litigation within each district. Using this structure, we construct a judicial-backlog indicator that captures congestion and procedural delay: the ratio of end-of-year pending cases (Balance) to the total cases handled during the year (Pendency + Institution + Received), multiplied by 100. This backlog measure provides a standardized proxy for judicial congestion across districts in the post-incident period, allowing us to assess whether Kasur experienced unusually severe institutional strain relative to other districts and to examine how crime reporting and judicial congestion co-moved following the Zainab incident.

IV. Methodology

Our empirical strategy relies on the Synthetic Difference-in-Differences (SDID) estimator (Arkhangelsky et al., 2021) which is particularly well suited to settings with a single treated unit and long pre- and post-periods. The method combines the key features of the classical Difference-in-Differences (DID) and Synthetic Control (SC) approaches, providing a transparent weighting framework that improves identification when the standard parallel-trends assumption may not exactly hold.

We estimate the impact of the January 2018 Zainab incident on monthly child abuse reporting in the Kasur district (where the incident took place), using other districts in Punjab as potential controls. Treatment is defined as January 2018 onward, coinciding with the sudden and well-defined public shock following the Zainab incident. Let i and t denote districts and months, respectively. The baseline specification is:

$$Y_{it} = \alpha + \tau D_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes reported child abuse reports per 100,000 population in district i and month t; D_{it} equals 1 for Kasur in all months after the event and 0 otherwise; λ_t and μ_i represent month and district fixed effects capturing, respectively, province-wide shocks such as province-wide shocks including COVID and time-invariant district characteristics such as geography and culture; and ε_{it} is the idiosyncratic error term. The coefficient τ measures the average treatment

[13] Law and Justice Commission of Pakistan (2022–2024). *Judicial Statistics of Pakistan.* Islamabad: LJCP. https://ljcp.gov.pk

effect of the Zainab incident on crime reporting in Kasur relative to its synthetic counterfactual. Equation (1) serves as a benchmark; our preferred estimates use SDID:

The SDID estimator is obtained by minimizing a weighted least-squares objective function:

$$\left(\hat{\tau}^{sdid}, \hat{\alpha}, \hat{\mu}, \hat{\lambda}\right) = argmin_{\tau,\alpha,\mu,\lambda} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \alpha - \mu_i - \lambda_t - \tau D_{it})^2 \, \omega_i^{\text{sdid}} \, \lambda_t^{\text{sdid}} \right\} \quad (2)$$

where the unit weights ω_i^{sdid} align the treated unit's pre-treatment trajectory with a weighted combination of control units, and the time weights λ_t^{sdid} re-weight time periods to improve comparability between pre- and post-treatment outcomes. In doing so, SDID inherits from SCM its data-driven weighting of controls and from DID its additive fixed-effects structure suitable for large panels. Together, the unit weights ensure that the synthetic control reflects Kasur's pre-treatment child abuse trends, while time weights account for temporal shifts, providing a more precise estimate of the treatment effect. We use the placebo-based approach to estimate standard errors, given that our analysis involves only a single treated unit. Kasur (post January 2018) is the treated case, and placebo inference is most appropriate when the number of control units exceeds the number of treated units. In contrast, bootstrap or jackknife methods rely on having multiple treated units to yield valid statistical inference (Arkhangelsky et al., 2021).

For the SDID estimator to recover a causal interpretation, three conditions are required: Firstly, treatment in Kasur does not directly affect outcomes in control districts. Although the Zainab case received widespread media attention, we assess potential spatial spillovers by conducting SDID analyses on Kasur's bordering districts—Lahore, Sheikhupura, and Okara—jointly assigning them placebo treatment in January 2018. We find no statistically significant post-2018 increase for this neighboring group, suggesting limited spatial spillovers from the Zainab incident. Secondly, in the absence of treatment, Kasur's outcomes would have followed the same trajectory as a weighted combination of control districts chosen by the SDID algorithm. This generalizes the DID parallel-trends assumption by allowing differential pre-treatment levels but matching trends through optimal weights. Finally, district fixed effects capture persistent differences across districts, and month fixed effects absorb shocks common to all districts, ensuring that residual variation is plausibly exogenous after weighting.

Overall, SDID combines the advantages of both methods: the data-driven re-weighting of SCM and the fixed-effects framework of DID, yielding estimates that are more robust when pre-treatment trajectories differ and when the number of treated units is small (Arkhangelsky et al. 2021).

V. Main Results

This section presents our empirical results. We begin by examining the impact of the Zainab incident in Kasur on child abuse reporting within the district. We then perform a series of robustness checks to assess the validity of our main findings. Identification comes from comparing Kasur's post-January-2018 trajectory to a synthetic counterfactual constructed to closely match its pre-treatment trends, allowing us to isolate deviations specific to the Zainab incident. We interpret these deviations through the lens of inverse deterrence, in which heightened crime salience coincides with weakened effective deterrence in settings with limited institutional capacity.

Table 1 presents summary statistics on monthly child-abuse reports in Kasur over the period 2015–2024, comparing outcomes before and after the January 2018 Zainab incident. The data reveal a marked rise in reported incidents following the case: the average number of total monthly crimes increased from 12.14 to 21.09. The largest increases occurred in abduction (from

3.74 to 9.78 cases per month) and missing cases (from 0.34 to 1.01). Reports of rape and sodomy also rose modestly, while crimes mentioning the words "gang," "child marriage," and "murder" declined slightly. Attempted crimes nearly doubled following the Zainab case. These patterns indicate a substantial post-2018 increase in reported child-abuse incidents in Kasur, motivating the causal analysis that follows.

Table 1: Summary statistics of monthly reported child abuse crimes in Kasur

Dependent Variables	Pre Zainab	Post Zainab
Total crimes (monthly avg)	**12.14**	**21.09**
Attempted	1.29	2.49
Abduction	3.74	9.78
Sodomy	3.94	4.76
Rape	5.14	5.72
Child marriage	0.09	0.01
Gang	1.51	1.29
Missing	0.34	1.01
Murder	0.43	0.31

Note: Table reports the average monthly number of reported cases in Kasur before and after the January 2018 Zainab incident. Pre-2018 period covers January 2015–December 2017 (excluding August 2015, which had an anomalously high number of reports coinciding with the discovery of a child abuse criminal ring). Post-2018 covers January 2018–December 2024. All values represent mean monthly counts by crime category. Each crime-type dummy is coded from its corresponding text field. If the string contains "rape," "sodomy," "abduction," etc., the corresponding dummy equals 1. Multiple tags (e.g., rape; abduction) trigger multiple flags.

To assess the impact of the high-profile rape and murder of Zainab Ansari in January 2018 in Punjab, Pakistan (and the nationwide protests which followed) we use a Synthetic Difference-in-Differences (SDID) estimator to compare changes in child abuse reporting to a weighted counterfactual drawn from districts in Punjab. This method constructs a synthetic control group that replicates the Kasur district's pre-treatment crime trends using a weighted combination of districts selected from a donor pool of the 34 remaining districts in the Punjab province. Table 2 reports the estimated treatment effects of the Zainab case on child-abuse reporting, measured as monthly crimes per 100,000 population. Panel A shows that the SDID estimate indicates a statistically significant increase of about 0.296 reported child-abuse cases per 100,000 population following the Zainab case: equivalent to approximately 10 additional reported cases per month[14]. This sustained increase is consistent with inverse deterrence: despite heightened visibility and public scrutiny, reported abuse rises rather than falls in the post-incident period. The weights of the donor pool are presented in the Appendix Table A1. While conventional DID yields precise estimates, SDID is better suited to our setting because it explicitly accounts for the fact that only one district was treated and evaluates significance using placebo-based inference.

To compare the SDID estimates with traditional approaches, we also report Difference-in-Differences (DID) and Synthetic Control Method (SCM) results in Panel B of Table 2. Both methods yield positive treatment effects, indicating an increase in reported child-abuse crimes in Kasur following the Zainab incident. The DID estimate (0.272) is statistically significant at the 1 percent level, suggesting a robust increase in monthly reported cases relative to control districts. The SCM estimate (0.25) is similar in magnitude but less precisely estimated. Compared with these benchmarks, SDID produces a slightly larger effect and remains significant, reflecting its improved ability to match pre-treatment trajectories. These differences highlight the advantages of the SDID framework: while DID assumes strict parallel trends and SCM lacks time-weighting,

[14] The outcome variable is measured as monthly reported cases per 100,000 population. Using Kasur's 2017 population of 3,454,881, an increase of 0.296 cases per 100,000 population implies approximately 10.2 additional reported cases per month.

SDID simultaneously balances unit and time dimensions, yielding more credible causal estimates of the Zainab incident's impact on child-abuse reporting in Kasur.

Table 2: Estimated average treatment effects on child abuse reporting

Methods	Crime rate (per 100,000)	N
Panel A:		
SDID	0.296* (0.160)	3710
Panel B:		
DID	0.272*** (0.026)	3710
SCM	0.248* (0.120)	3710
Panel C:		
DID with controls	0.300*** (0.029)	3710
SCM with controls	0.397** (0.124)	3710

Notes: The sample is a district–month panel for Punjab, Pakistan, covering January 2015 to December 2024. The sample size consists of 35 districts x 106 months. The treated unit is Kasur, and the post-treatment period begins in January 2018 (coinciding with the rape and murder of Zainab Ansari on January 4th-9th, 2018). The donor pool comprises of the remaining 34 districts in Punjab. Panel A reports Synthetic Difference-in-Differences (SDID) estimates. Panel B reports Difference-in-Differences (DID) and Synthetic Control Method (SCM) estimates. SCM uses the average monthly crime rates in 2015, 2016, and 2017 as predictors to construct a synthetic Kasur. DID includes district and month fixed effects. Panel C extends SCM by adding baseline district characteristics: population density, literacy rate, urban share, child employment rate, and police per capita, along with average monthly crime rates in 2015–2017 as pre-treatment covariates. In this panel, DID includes district and year fixed effects, with interactions between year and the same baseline covariates. In all specifications, standard errors are clustered at the district level. SDID standard errors are computed using the placebo/permutation inference method with 500 repetitions. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Unlike the standard DID and SCM literature (e.g., Borjas 2017; Peri and Yasenov 2019; Billy and Packard 2022), we do not rely on additional covariates to construct synthetic controls, as the SDID estimator inherently balances pre-treatment outcomes without requiring explicit predictors. By matching both unit and time weights, SDID minimizes researcher discretion and bases the control weights solely on observed outcome trajectories. The DID estimate reported in Panel B was obtained using all non-Kasur districts in Punjab as the control group, without including covariates in the model. For the SCM estimate, synthetic control was selected based on outcomes.

To compare SDID with more refined versions of DID and SCM, we re-estimate these models including baseline district characteristics as control variables (Panel C). When these covariates are incorporated, both DID and SCM continue to show positive and statistically significant effects on child-abuse reporting, consistent in magnitude with our main SDID results. DID with controls yields an estimated increase of 0.30 crimes per 100,000 population, while SCM with controls produces a slightly larger effect of 0.397 crimes per 100,000. These findings indicate that the estimated treatment effect of the Zainab incident is robust to the inclusion of baseline district characteristics and confirm that SDID's data-driven weighting achieves a comparable and credible causal estimate without relying on researcher-specified covariates.

To further examine the dynamics behind the estimated effects, Figure 2 plots the SDID-estimated monthly child-abuse crime rates for Kasur and its synthetic control over the 2015–2024 period. The red line represents Kasur, while the blue dashed line depicts the synthetic control constructed from the 34 other districts that closely match Kasur's pre-treatment trends. Before January 2018, the two series move closely together, indicating a good pre-treatment fit and supporting the validity of the synthetic control as a counterfactual for Kasur. Following the Zainab incident, however, the trends diverge sharply: child-abuse reports in Kasur increase substantially and remain persistently higher than in the synthetic control throughout the post-2018 period. This sustained divergence indicates that the surge in reported child-abuse crimes after the Zainab incident was largely concentrated in Kasur, with no comparable increase observed across other districts in Punjab.

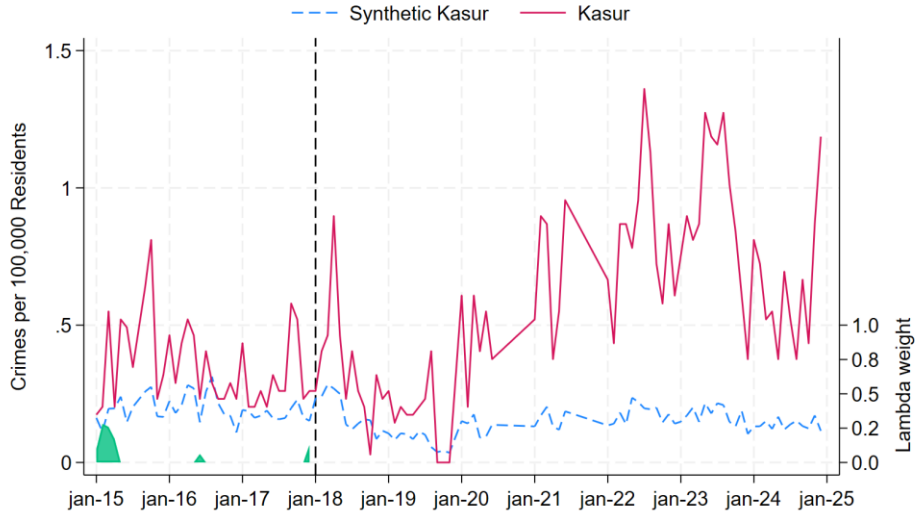


Figure 2: SDID: Treatment effect on child abuse crimes

Note: The blue dashed line represents the synthetic control group, while the red line represents Kasur. The synthetic control is constructed from 34 districts based on pre-treatment outcomes. The vertical dashed black line at Jan 2018 marks the start of the month when the high-profile Zainab rape case occurred. Shaded areas indicate time weights (λ).

To complement average treatment effects, Figure 3 presents the event-study SDID estimates of the dynamic impact of the Zainab incident on reported child-abuse crimes in Kasur. The figure plots monthly treatment effects relative to synthetic control, allowing us to trace how estimated effects evolved before and after January 2018. Each blue dot represents the point estimate of the treatment coefficient for a given month, with the shaded areas denoting 95 percent confidence intervals. The estimates show that Kasur and its synthetic control followed parallel trends prior to the Zainab incident, supporting the credibility of the identification strategy. Beginning immediately after January 2018, the treatment effect turns positive and remains consistently above zero for most of the post-treatment period, indicating a persistent rise in reported child-abuse incidents. The magnitude of the effect peaks around three to four years after the event, suggesting that heightened reporting sustained well beyond the immediate aftermath. Overall, the dynamic pattern reinforces the conclusion that the surge in child-abuse crime reporting was concentrated in Kasur and persisted over time, rather than reflecting short-term volatility or province-wide fluctuations. The persistence of the effect—emerging gradually and remaining elevated for several years—is consistent with inverse deterrence rather than a temporary salience-driven reporting spike.

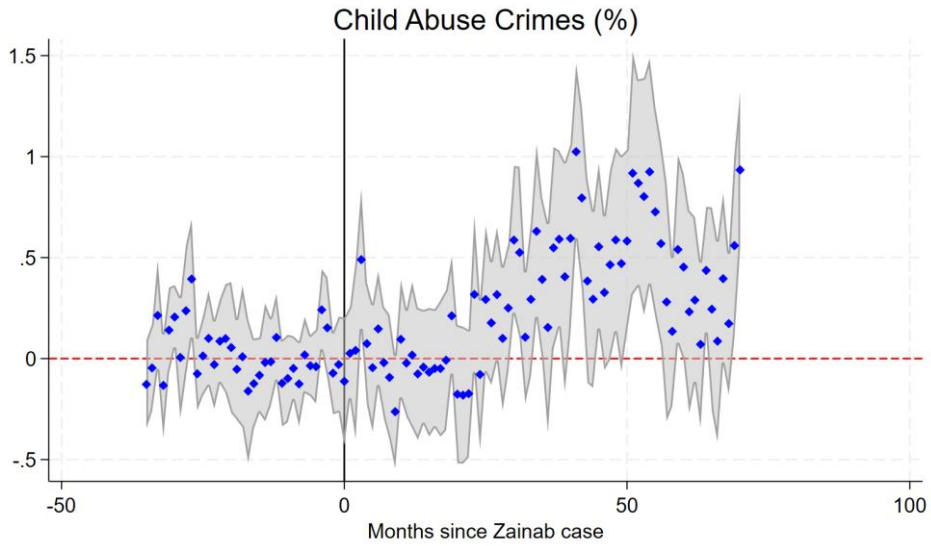


Figure 3: Event study SDID: Treatment effect on child abuse reports

Note: Dynamic treatment effects are estimated using the event study extension of the Synthetic Difference-in-Differences (SDID) method. The blue dots represent the estimated treatment effect of the Zainab incident in Kasur relative to synthetic control, constructed from 34 districts matched on pre-treatment outcomes. The vertical black line at event time 0 corresponds to Jan 2018, the month of the incident. Shaded regions represent 95% confidence intervals based on placebo-based inference.

We conducted a similar analysis for Kasur's bordering districts—Lahore, Sheikhupura, and Okara—to test for potential spillover effects of the Zainab incident. The donor weights for this group are reported in Appendix Table A2. The SDID plot and ATT, presented in Figure 4, show that the estimated treatment effect for the neighboring districts is small and statistically insignificant (ATT = –0.095, $p = 0.41$). As shown in Figure 4, reported child-abuse crimes in the neighboring districts follow similar pre- and post-2018 trajectories to their synthetic controls, with no discernible upward shift after January 2018. This contrasts sharply with Kasur's positive and statistically significant estimate (ATT = 0.296, $p < 0.10$), shown earlier in Table 2. The absence of a measurable effect among adjacent districts indicates that the surge in reporting was highly localized, reinforcing the conclusion that the Zainab case triggered a distinct behavioral response in Kasur rather than a province-wide or regional change in reporting practices. To further assess whether the Kasur estimates reflect mechanical features of the SDID design or broader province-wide shocks, we conduct placebo SDID analyses for each district in Punjab other than Kasur, iteratively assigning treatment to districts not exposed to the Zainab incident. As shown in Appendix Figure A1, most districts exhibit no sustained post-2018 divergence from their synthetic controls.

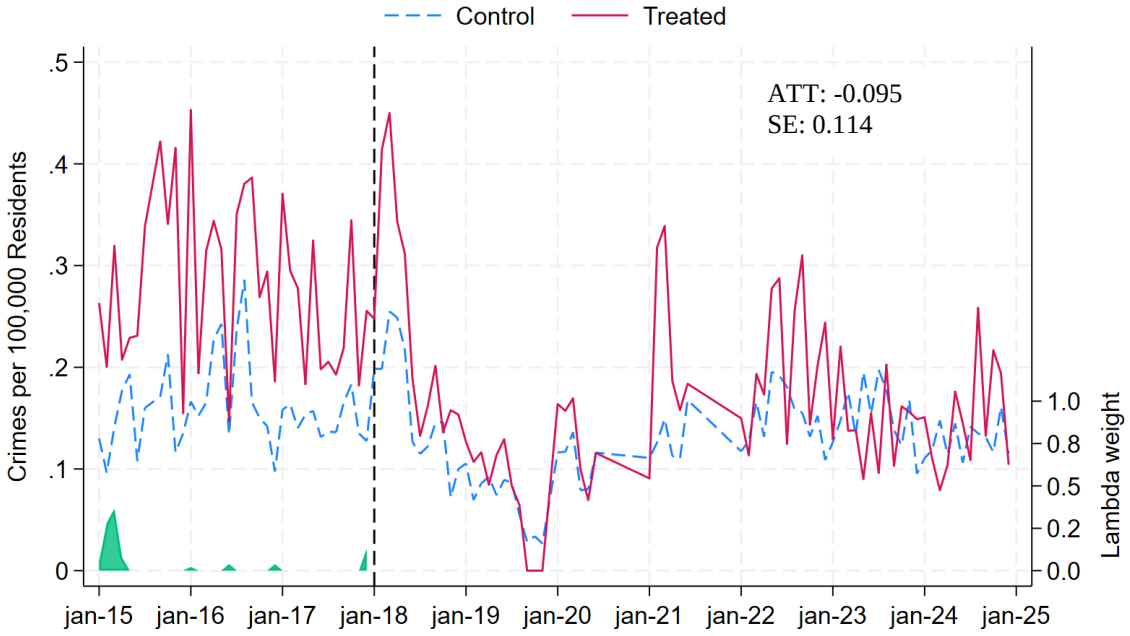


Figure 4: SDID spillover test: Grouping neighboring districts (Lahore, Sheikhupura, and Okara)

Note: The figure plots Synthetic Difference-in-Differences (SDID) estimates for Lahore, Sheikhupura, and Okara treated jointly as Kasur's border districts. The red line shows the treated average, and the blue dashed line shows the synthetic control. The vertical dashed line marks January 2018, the onset of the Zainab incident.

Robustness tests

The SDID estimator relies on the Stable Unit Treatment Value Assumption (SUTVA), which requires that treatment in one unit does not affect outcomes in others (i.e., no spillover effects across districts). To assess the validity of this assumption and the robustness of our main findings, we implement a series of donor-pool restrictions summarized in Table 3.

Table 3: Robustness Checks on Estimated Treatment Effects on Child Abuse Rates

Robustness Checks	**Child Abuse Rate (per 100,000)**	**N**
Panel A: Spillover Exclude Adjacent Districts	0.262 (0.181)	3286
Panel B: Policing Capacity Exclude Districts> ±1 SD of Kasur's policing capacity	0.317** (0.147)	2544
Panel C: Urbanization Exclude Districts> ±1 SD of Kasur's urbanization rate	0.326** (0.149)	3180
Panel D: Child Employment Exclude Districts> ±1 SD of Kasur's child employment rate	0.288** (0.136)	2332

Robustness Checks	Child Abuse Rate (per 100,000)	N

Note: The sample size represents number of districts x 106 months. SDID standard errors are computed using the placebo/permutation inference method with 500 repetitions. For Panel A, the ATT is marginally significant at the 10% level. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

To address potential spatial spillovers, we exclude Kasur's neighboring districts—Lahore, Sheikhupura, and Okara—from the donor pool and re-estimate the SDID model. Given their geographic proximity, these districts could plausibly be indirectly affected by heightened media coverage and policing responses following the Zainab incident, which would violate the SUTVA assumption and contaminate the counterfactual. After implementing this geographic restriction, the estimated treatment effect remains positive and similar in magnitude to the baseline as shown in Panel A (ATT = 0.262 versus 0.296), though it is no longer statistically significant. This stability in magnitude, despite reduced precision, indicates that the main estimates are not driven by spatial spillovers from neighboring districts.

Next, we examine whether the results are sensitive to differences in law-enforcement capacity across districts. In 2017, Kasur had 0.58 police stations per 100,000 population—below the provincial average of 0.67, indicating relatively weak policing density. To ensure that the estimated effect is not confounded by policing capacity, we restrict the donor pool to districts with police-station density within ± 1 SD of Kasur's policing capacity, yielding a subset of 23 districts in Kasur's donor pool. This restriction preserves institutional comparability while maintaining sufficient donor variation. Re-estimating the SDID model on this police-matched donor pool produces an average treatment effect of 0.317 as shown in Panel B, even larger and more precisely estimated than the baseline ATT of 0.296. The stronger and more significant effect among institutionally similar districts confirms that Kasur's post-2018 reporting surge was not driven by greater policing resources; rather, it reflects a behavioral response to the Zainab incident that occurred despite limited law-enforcement capacity.

We also examine whether Kasur's level of urbanization could explain the observed effect. In 2017, Kasur's urban share was 25.8 percent, slightly below the provincial average of 28.2 percent, placing it among moderately urban districts. To ensure that the comparison is not biased by differences in city size, media access, or reporting infrastructure, we exclude five highly urbanized metropolitan districts from the donor pool: Lahore, Faisalabad, Rawalpindi, Gujranwala, and Multan. The resulting sample of structurally comparable districts yields an estimated ATT of 0.326 (as shown in Panel C) even higher and more precise than the baseline. This indicates that Kasur's reporting surge cannot be attributed to greater urbanization or media presence, reinforcing the interpretation of a behavioral response following the Zainab incident.

Finally, we assess whether differences in socioeconomic exposure of children could explain the observed reporting surge. The child-employment rate (defined as the share of children aged 10–14 engaged in work, including paid family workers relative to the population of children aged 10–14) captures the extent to which children are economically active and potentially exposed to abuse outside the home. In 2017, Kasur's child-employment rate was 4.6 percent, slightly below the provincial mean of 5.3 percent, indicating moderate exposure by regional standards. Restricting the donor pool to districts within ±1 SD of Kasur's rate yields an ATT of 0.288 as shown in Panel D, comparable in magnitude and significance to the baseline estimate. This robustness check confirms that Kasur's post-2018 increase in child-abuse reports is not driven by differences in baseline socioeconomic vulnerability or exposure.

VI. Exploratory Results

To further understand how the post-Zainab increase in reporting is distributed across different types of incidents, we conduct a set of heterogeneity analyses along three dimensions: victim characteristics (gender, age, and activity), incident characteristics (crime type, place of abuse and period of abuse), and perpetrator characteristics (number of abusers and abuser's relationship to the victim). These heterogeneity patterns allow us to assess whether the post-incident increase aligns with the predictions of inverse deterrence, which emphasize opportunistic offending in low-guardianship settings rather than uniform increases across all crimes.

Victim Characteristics

We first examine whether the post-Zainab increase in reporting varies across key victim characteristics. According to Panel A of Table 4, boys experience a statistically significant rise in victimization after 2018, while the estimate for girls (though larger in magnitude) is imprecisely estimated. A plausible interpretation is that, following the intense public scrutiny surrounding the Zainab case, crimes against girls may have been subject to increased supervision or reporting whereas abuse against boys (often more stigmatized and historically underreported) may have continued with a lower perceived risk of detection.

Table 4: Heterogeneous Effects of the Zainab incident on Child Abuse using SDID: Victim Characteristics

Victim Characteristics	Child Abuse Rate (per 100,000)	N
Panel A: Gender		
Male	0.107** (0.047)	3710
Female	0.160 (0.116)	3710
Panel B: Age		
0-5	0.023*** (0.007)	3536
6-10	0.042** (0.019)	3710
11-15	0.111** (0.051)	3710
16-18	0.084*** (0.022)	3604
Panel C: Status		
Child laborer	0.011*** (0.002)	2322
Domestic laborer	0.005 (0.006)	2080
Disabled	0.009 (0.007)	1512

Student	0.043*** (0.014)	3675

Note: Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Age patterns show a similar logic in Panel B. All age groups exhibit positive post-2018 effects, but the increases are considerably larger for children aged 11–15 and 16–18, with 11–15 showing the largest effect. The smallest increases appear for the 0–5 group, followed by the 6–10 group. Younger children likely became the focus of heightened parental protection in the aftermath of the case, while older children (who move more independently) remained more exposed, making any rise in underlying crime more detectable among them.

Finally, heterogeneity by children's status shows that students experience the clearest post-Zainab increase, followed by child laborers, whereas effects for disabled and domestic-labor children are minimal as shown in Panel C. Because students and child laborers spend substantial time in public or semi-public spaces, routine mobility may have kept them vulnerable even as general vigilance in Kasur rose. In contrast, children who spend most of their time indoors face fewer exposure opportunities, yielding weaker detectable changes in these groups.

Incident Characteristics

We next examine heterogeneity across incident characteristics to identify which types of offenses contributed to the post-Zainab changes. According to Panel A of Table 5, the clearest and most precisely estimated increase appears for abduction-related incidents, which show a sizable and statistically significant rise after 2018. We also find a smaller but statistically significant increase in missing-child reports, suggesting heightened vulnerability (or increased detection) of cases involving children who disappear from public or transitional spaces. For all other categories, including rape, sodomy, gang-related offenses, attempted crimes, child marriage, and murder, the estimates are small and statistically insignificant. Some categories show positive point estimates, but none are precise enough to indicate a systematic post-2018 change. The concentration of effects in abduction and missing-child cases aligns closely with crimes that involve mobility and weak guardianship rather than prolonged or organized abuse. This concentration is consistent with inverse deterrence, under which heightened salience and limited enforcement capacity disproportionately affect opportunistic, mobile offenses rather than sustained or institutionalized abuse.

Table 5: Heterogeneous Effects of the Zainab Case on Child Abuse using SDID: Crime Characteristics

Crime Characteristics	**Child Abuse Rate (per 100,000)**	**N**
Panel A: Abuse Type		
Abduction	0.127** (0.061)	3710
Rape	0.043 (0.059)	3710
Sodomy	-0.001 (0.030)	3710
Murder	-0.013 (0.011)	3168
Gang	0.022 (0.025)	3710

Missing	0.009* (0.005)	3360
Child Marriage	-0.004 (0.004)	2277
Attempt	0.017 (0.028)	3710
Panel B: Location of Abuse		
Victim's home	0.109*** (0.040)	3710
Abuser's home	0.059** (0.029)	3710
Abandoned building/empty plot	0.011*** (0.004)	2052
Open field/jungle	-0.029 (0.025)	3640
Religious institution	-0.013* (0.007)	2268
Educational institution	-0.012*** (0.003)	2204
Workplace/hospitals/hotels	-0.006*** (0.002)	1725
Street/public space	0.064*** (0.023)	3570
Panel C: Period of Abuse		
Single episode	0.271* (0.139)	3710
Short term	0.008 (0.006)	1885
Medium term	-0.009*** (0.003)	1848
Long term	0.006 (0.024)	1378

Note: Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

We also examine heterogeneity by the location where abuse occurred. According to Panel B, several locations show clear post-Zainab increases. Incidents occurring in the victim's home show the largest rise after 2018. A significant increase is also observed for abuse committed in

the abuser's home. Similarly, street and public spaces (streets, shops, markets, roads, parks, bus stops, vehicles, canals, gardens, graveyards) show a strong and significant rise. These patterns point to heightened risks in private homes and unregulated public spaces where children may continue routine movement or informal play. In this setting, private homes (particularly in extended-family or informal living arrangements) may also represent environments with limited effective guardianship. Smaller but still significant increases are found for abandoned or isolated structures (havelis, abandoned buildings, empty plots).

In contrast, several locations exhibit declines or no meaningful change. School or educational settings show a highly significant decline after 2018, likely reflecting heightened supervision and institutional caution following the Zainab incident. Religious institutions, including mosques, madrassas, shrines, and worship spaces, also show a marginally significant decline. Workplaces and formal establishments exhibit a small but statistically significant decline, suggesting that more regulated or monitored environments became relatively safer or more closely scrutinized. Importantly, the decline in schools, workplaces and religious institutions suggests substitution across environments rather than a uniform rise in abuse. Finally, open fields or rural open areas (fields, jungles, bushes) show no significant change. Overall, place-based heterogeneity indicates that the post-Zainab rise in reporting was concentrated in private and informal settings with limited oversight, while institutional or supervised environments became relatively safer after the incident.

Finally, we examine heterogeneity by the duration of abuse as shown in Panel C. A single episode includes incidents reported as occurring once, or between 2-3 days and shows a positive and statistically significant post-Zainab increase. Short-term abuse, defined as cases lasting roughly a week or two weeks, displays a small positive but insignificant effect. In contrast, medium-term abuse (episodes lasting around two months) shows a statistically significant decline after 2018. Finally, long-term abuse, which includes extended patterns described as six months or more, shows a small and insignificant increase. These patterns suggest that heightened vigilance, media attention, and community mobilization after the Zainab incident may have curtailed prolonged abuse by increasing the likelihood of detection, while one-off or opportunistic incidents remained more feasible, contributing to the observed post-Zainab rise.

Taken together, these patterns indicate that the post-Zainab rise in reporting in Kasur was not broad-based but reflects the operation of inverse deterrence, concentrated in incidents shaped by child mobility, limited supervision, and opportunity (abductions, missing-child episodes, and one-time events occurring in homes, streets, and informal spaces). In contrast, supervised or regulated environments, including schools, workplaces, and religious institutions, became relatively safer, reflecting heightened monitoring after 2018. Overall, the heterogeneity suggests that the Zainab incident reshaped the geography and timing of abuse, amplifying risks in everyday settings with weak guardianship rather than increasing all forms of child abuse uniformly.

Perpetrator Characteristics

We further examine heterogeneity by the perpetrator's relationship to the victim. According to Panel A of Table 6, the largest and most precisely estimated post-Zainab increase appears in cases where the abuser is a stranger, showing a substantial significant rise after 2018. A similarly sizable and significant increase is observed when the perpetrator is an acquaintance or neighbor. Both patterns indicate that risks in anonymous and everyday-proximity environments intensified in Kasur after the incident.

We also find a smaller but statistically significant increase in cases involving family members or relatives, suggesting that abuse occurring within extended family networks or close domestic circles also became more visible in the post-incident period. By contrast, incidents involving religious or spiritual leaders and those committed by institutional or professional actors (teachers, employers, transport workers, police/security personnel, and health professionals)

show estimates close to zero. These settings may involve structured oversight, clearer adult supervision, or institutional accountability, limiting opportunities for abuse or making detection more immediate, which could dampen any detectable change after 2018. Overall, the perpetrator-level patterns indicate that the post-Zainab rise in Kasur was concentrated in interactions involving limited oversight rather than in institutional or formally supervised environments (strangers, neighbors, acquaintances, and family members). These patterns further support an inverse deterrence interpretation, in which weakened effective deterrence disproportionately affects anonymous and everyday-proximity interactions.

Table 6: Heterogeneous Effects of the Zainab Case on Child Abuse using SDID: Abuser Characteristics

Abuser Characteristics	Child Abuse Rate (per 100,000)	N
Panel A: Relationship to Victim		
Acquaintance/neighbor	0.160** (0.080)	3710
Family member/relative	0.009** (0.004)	3710
Stranger	0.140*** (0.036)	3604
Spiritual leader	0.002 (0.003)	2277
Teacher/employer/police/ driver/doctor	-0.000 (0.017)	3434
Panel B: Number of Abusers		
1	0.113 (0.079)	3710
2-3	0.030 (0.034)	3604
4 or more	0.011 (0.035)	3675

Note: Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

We also examine whether the post-Zainab patterns vary with the number of perpetrators involved in an incident. According to Panel B, cases involving a single abuser show the largest positive post-2018 estimate, but the effect is statistically insignificant. Incidents involving two to three perpetrators and those with four or more perpetrators also yield small and statistically insignificant effects. This implies that the post-Zainab rise was not driven by offenses involving multiple offenders but is better explained by earlier patterns related to perpetrator relationship and victim exposure.

These patterns show that the post-Zainab rise in Kasur was driven primarily by incidents involving perpetrators with limited formal oversight: strangers, neighbors, acquaintances, and to a lesser extent family members. The absence of meaningful changes in cases involving multiple

offenders further indicates that the increase reflected opportunistic, individualized incidents rather than coordinated or group-based abuse. Overall, the perpetrator-level evidence suggests that the post-2018 rise was concentrated in everyday interactions and informal social settings where vigilance and supervision were weakest.

VII. Mechanisms

To explore whether institutional strain is associated with Kasur's post-Zainab reporting patterns, we relate child-abuse reporting to district-level measures of judicial congestion. Judicial performance is measured using annual criminal case-flow statistics from the Judicial Statistics of Pakistan (2022–2024). Because these data are only available several years after the Zainab incident, and because judicial backlog may both influence and respond to crime reporting, we interpret the following results as descriptive correlations rather than causal estimates. Our goal is to assess whether Kasur differs systematically from other districts in how reported abuse covaries with institutional congestion in the post-Zainab period. Judicial performance measures for each district include the stock of pending cases, new filings, transferred-in cases, disposals, and transfers. From these components, we construct a standardized backlog rate for each district: the proportion of unresolved cases relative to the total caseload processed during the year.

$$Backlog\ rate_{it} = \frac{Balance_{it}}{Pendency_{it} + Institution_{it} + Received_{it}} * 100$$

Merging this measure with district-level yearly crime rates for the years 2022-2024 yields a balanced district–year panel for Punjab. We then estimate the association between judicial congestion and crime reporting using the following fixed-effects specification:

$$Crime\ Rate_{it} = \alpha + \beta_1 Backlog\ rate_{it} + \beta_2 (Kasur_i * Backlog\ rate_{it}) + \gamma_t + \mu_i + \varepsilon_{it}$$

Where μ_i captures time-invariant district characteristics (e.g., baseline crime propensity, institutional culture), γ_t indicate time-fixed effects and β_2 term identifies whether Kasur's relationship between judicial congestion and crime reporting differs from the rest of Punjab in the post-Zainab years.

Table 7: Judicial Capacity Measures and Child Abuse Reporting in Kasur

Judicial Capacity Measures	**Child Abuse Rate (per 100,000)**
Panel A: District Congestion	
Backlog rate	-0.083* (0.048)
Kasur*Backlog rate	1.524*** (0.166)
District FE	yes
Year FE	yes
N	105
Panel B: Provincial Burden	
Relative backlog	-0.072 (0.095)
Kasur*Relative backlog	1.161*** (0.095)

District FE	yes
Year FE	yes
N	105

Note: Each panel reports coefficients from a separate district fixed-effects regression with year fixed effects. Robust standard errors are clustered at the district level. The outcome variable is the yearly child-abuse report rate per 100,000 population. Panel A uses a district congestion measure (unresolved cases as a share of total caseload). Panel B uses a provincial burden measure (district's share of Punjab's total pending cases). The interaction terms capture how Kasur's relationship between judicial strain and reported child abuse differs from the rest of Punjab. *** p<0.01, ** p<0.05, * p<0.10.

The results reported in Table 7 reveal two striking patterns. As shown in Panel A, in the rest of Punjab, higher judicial backlog is associated with slightly lower reported crime, with a small, negative, and marginally significant coefficient. This is consistent with the idea that congested courts suppress reporting, slow case processing, and weaken incentives for victims to approach the justice system. Second and more importantly, Kasur behaves in the opposite way. The interaction term is large, positive, and highly significant, indicating that when judicial congestion rises in Kasur, reported child abuse increases sharply.

This divergence is meaningful. In other districts, backlog signals institutional slowdown and reduced reporting. In Kasur, however, backlog appears to correlate with more reported crime. One plausible explanation is that, in the aftermath of the Zainab incident, public pressure, media scrutiny, and community mobilization dramatically increased the likelihood that incidents surfaced, even when the judicial system was strained. In such an environment, judicial congestion may amplify crime visibility rather than suppress it, reflecting a system simultaneously overwhelmed and exposed, with limited deterrence and high social vigilance.

Taken together, these findings show that Kasur exhibits a systematically different relationship between judicial congestion and reported abuse than other districts in the post-Zainab period, consistent with inverse deterrence in a setting where institutional strain and heightened scrutiny coexist.

As a complementary test, we examine Kasur's position within the broader provincial judicial landscape. For each year, we compute the district's share of Punjab's total backlog:

$$Relative\ backlog\ rate_{it} = \frac{Balance_{it}}{\sum_j Balance_{jt}} * 100$$

which captures the percentage of all pending criminal cases in Punjab that are concentrated in a given district i. We then estimate a fixed-effects model of the form:

$$Crime\ Rate_{it} = \alpha + \beta_1 Relative\ backlog_{it} + \beta_2(Kasur_i * Relative\ backlog_{it}) + \gamma_t + \mu_i + \varepsilon_{it}$$

The results in Panel B of Table 7 again reveal a stark contrast. For the rest of Punjab, a district's share of the provincial backlog has no systematic relationship with reported child abuse. The coefficient is small, negative, and insignificant. Kasur, however, shows a dramatically different pattern. The interaction term is large, positive, and highly significant, indicating that when a rising share of Punjab's unresolved caseload is concentrated in Kasur, the district's reported child-abuse rate increases sharply.

This pattern suggests that Kasur's vulnerability is most acute precisely when it shoulders a disproportionate share of the province's judicial burden. In such years, institutional strain may further erode deterrence, delay justice, and intensify public reporting pressure—conditions that make abuse more likely to be both committed and documented.

VIII. Interpretation

A well-known challenge in using crime reporting data is that reported crime is jointly determined by underlying criminal activity and victims' willingness and ability to report (Levitt 1998; Iyengar 2009). Because our primary outcome is based on newspaper-reported cases, variation may in principle reflect changes in (i) true incidence, (ii) reporting behavior, or (iii) media selection. To clarify the mechanism, we draw on several pieces of evidence and triangulations that help interpret the estimated effect.

First, we examine the dynamic pattern of the treatment effect. If the increase in reports following the high-profile case were driven purely by short-lived salience or temporary media attention, then we would expect the effect to dissipate quickly. Instead, we find that reported crimes rise modestly in the first year but then increase substantially and persistently from the second year onward, remaining elevated for at least four years. This long-run and monotonic adjustment is difficult to reconcile with a transient reporting shock or a one-off change in media attention. Sustained effects of this magnitude are more consistent with structural changes in reporting norms, willingness to come forward, or shifts in institutional responsiveness.

Second, the nature of the crimes in our data (child sexual abuse) provides additional interpretive guidance. Unlike minor property crimes or low-severity offences, which exhibit high elasticity with respect to media coverage or reporting incentives, severe sexual violence, particularly against minors, is known to have reporting rates that are closely tied to true incidence and are less likely to exhibit large short-run swings driven solely by media attention. In other words, while under-reporting is generally severe, temporal variation in reporting for such crimes is typically attributed in the literature to meaningful changes in either victim empowerment, institutional trust, or actual incidence, not to short-run fluctuations in media coverage. This supports the view that the observed long-run rise likely reflects deeper changes rather than reporting noise alone.

Third, we validate the external accuracy of our outcome measure by comparing the final year of data (2024), when both newspaper reports and police administrative data are available (Table 8). The levels and spatial distribution of cases recorded in newspapers closely match those in official police statistics for that year, suggesting that (i) media-based reporting is a reasonable proxy for overall reporting of such crimes, and (ii) systematic biases in newspaper coverage (if present) do not appear to grow over time. This comparison provides reassurance that the upward trajectory seen in earlier years is unlikely to be driven solely by changes in media behavior.

Table 8: External Consistency of Sexual-Abuse Case Counts Across Independent Data Sources (2024)

Panel A: Punjab	
Data Source	**Number of Sexual Abuse Cases**
Sahil's *Cruel Numbers*	2516
Police RTI Totals (SSDO)	2506
Panel B: All Provinces	
Sahil's *Cruel Numbers*	3027
Police RTI Totals (SSDO)	2954

Notes: Counts from Sahil's *Cruel Numbers* are aggregated from incident-level cases independently verified through multiple newspaper sources for the year 2024. Police RTI totals refer to officially recorded sexual-abuse cases for the year 2024 reported by provincial police departments in response to Right to Information (RTI) requests, as

compiled and published by the Sustainable Social Development Organization (SSDO, 2025). The close correspondence in levels indicates that newspaper-verified incidents closely track official police records.

Taken together, three pieces of evidence: (i) the long-term persistence of the effect, (ii) the high-severity nature of the crimes studied, and (iii) the close alignment between newspaper data and police records in the final year, strengthen the interpretation that the documented increases reflect real behavioral and institutional adjustments, operating through increased victim reporting, increased underlying incidence, or both. While our data do not permit us to fully disentangle these components, the weight of evidence suggests that the high-profile case triggered more than a temporary surge in attention: it likely altered reporting norms, institutional practices, or actual safety conditions in a lasting way.

IX. Conclusions

This paper studies how a highly salient criminal event can reshape subsequent crime patterns in settings characterized by weak institutional capacity. Using district–month data from Punjab, Pakistan, and a Synthetic Difference-in-Differences design, we show that the rape and murder of seven-year-old Zainab Ansari in January 2018 was followed by a large, persistent increase in reported child sexual abuse in Kasur relative to a synthetic counterfactual. The rise is substantial in magnitude, localized to Kasur, and sustained for several years after the incident.

Beyond documenting an aggregate increase, we show that the post-2018 surge is concentrated in offenses consistent with opportunistic abuse: incidents involving strangers and acquaintances, single episodes rather than prolonged abuse, and locations characterized by weak guardianship such as streets, private homes, and informal spaces. In contrast, supervised and institutional environments (schools and religious institutions) experienced declines or no change. These patterns align with opportunity-based theories of crime and suggest that heightened salience and public scrutiny did not uniformly deter abuse, but instead reshaped where and how it occurred.

Finally, we provide evidence consistent with institutional capacity playing a central role in mediating these dynamics. In Kasur, increases in judicial congestion are strongly associated with higher reported abuse, a relationship not observed elsewhere in Punjab. While not causal, this divergence points to an inverse deterrence channel: when enforcement institutions are strained, heightened visibility may coexist with diminished deterrence, producing conditions under which both reporting and opportunistic offending rise.

Taken together, the findings highlight a central policy lesson. High-profile criminal cases can mobilize public attention and institutional reform, but without commensurate investments in enforcement capacity, they may fail to deter, and may even exacerbate, certain forms of crime. For environments with limited state capacity, effective responses to extreme crimes against children require not only visibility and outrage, but durable improvements in policing, judicial throughput, and child protection systems.

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Appendix Tables

Table A1: SDID Donor Weights for Child Abuse Incidents

Districts	Weights
Attock	0.0218
Bahawalnagar	0.0313
Bahawalpur	0.0294
Bhakkar	0.0133
Chakwal	0.0334
Chiniot	0.0256
Dera Gazi Khan	0.0256
Faisalabad	0.0330
Gujranwala	0.0274
Hafizabad	0.0619
Jhang	0.0080
Jhelum	0.0306
Khanewal	0.0262
Khushab	0.0469
Lahore	0.0187
Layyah	0.0330
Lodhran	0.0261
Mandi Bahauddin	0.0265
Mianwali	0.0240
Multan	0.0158
Muzaffargarh	0.0092
Nankana Sahib	0.0231
Narowal	0.0328
Okara	0.0353
Pakpattan	0.0416
Rahim Yar Khan	0.0221
Rajanpur	0.0255
Rawalpindi	0.0581
Sahiwal	0.0237
Sargodha	0.0240
Sheikhupura	0.0523
Sialkot	0.0149
Toba Tek Singh	0.0319
Vehari	0.0470

Notes: Sample includes district-level monthly data on child abuse reports for Punjab from 2015–2024, constructed from Sahil's *Cruel Numbers* reports. Donor weights represent the relative contribution of each district to the SDID estimation for the outcome crime rate, which measures child abuse reports per 100,000 population.

Table A2: SDID Donor Weights for Child Abuse Incidents for Kasur's Bordering Districts (Lahore, Sheikhupura, Okara)

Districts	Weights
Attock	0.0321
Bahawalnagar	0.0351
Bahawalpur	0.0336
Bhakkar	0.0286
Chakwal	0.0320
Chiniot	0.0266
Dera Gazi Khan	0.0340
Faisalabad	0.0307
Gujranwala	0.0324
Hafizabad	0.0314
Jhang	0.0335
Jhelum	0.0297
Khanewal	0.0336
Khushab	0.0343
Layyah	0.0339
Lodhran	0.0293
Mandi Bahauddin	0.0344
Mianwali	0.0320
Multan	0.0279
Muzaffargarh	0.0291
Nankana Sahib	0.0299
Narowal	0.0307
Pakpattan	0.0299
Rahim Yar Khan	0.0323
Rajanpur	0.0322
Rawalpindi	0.0379
Sahiwal	0.0340
Sargodha	0.0328
Sialkot	0.0337
Toba Tek Singh	0.0369
Vehari	0.0355

Note: Donor sample consists of 31 districts. Kasur is excluded from the sample because including it among potential controls would bias the synthetic counterfactual toward the post-treatment trajectory of Kasur itself, undermining identification. Sample includes district-level monthly data on child abuse reports for Punjab from 2015–2024, constructed from Sahil's *Cruel Numbers* reports. Donor weights represent the relative contribution of each district to the SDID estimation for the outcome crime rate, which measures child abuse reports per 100,000 population.

Appendix Figures



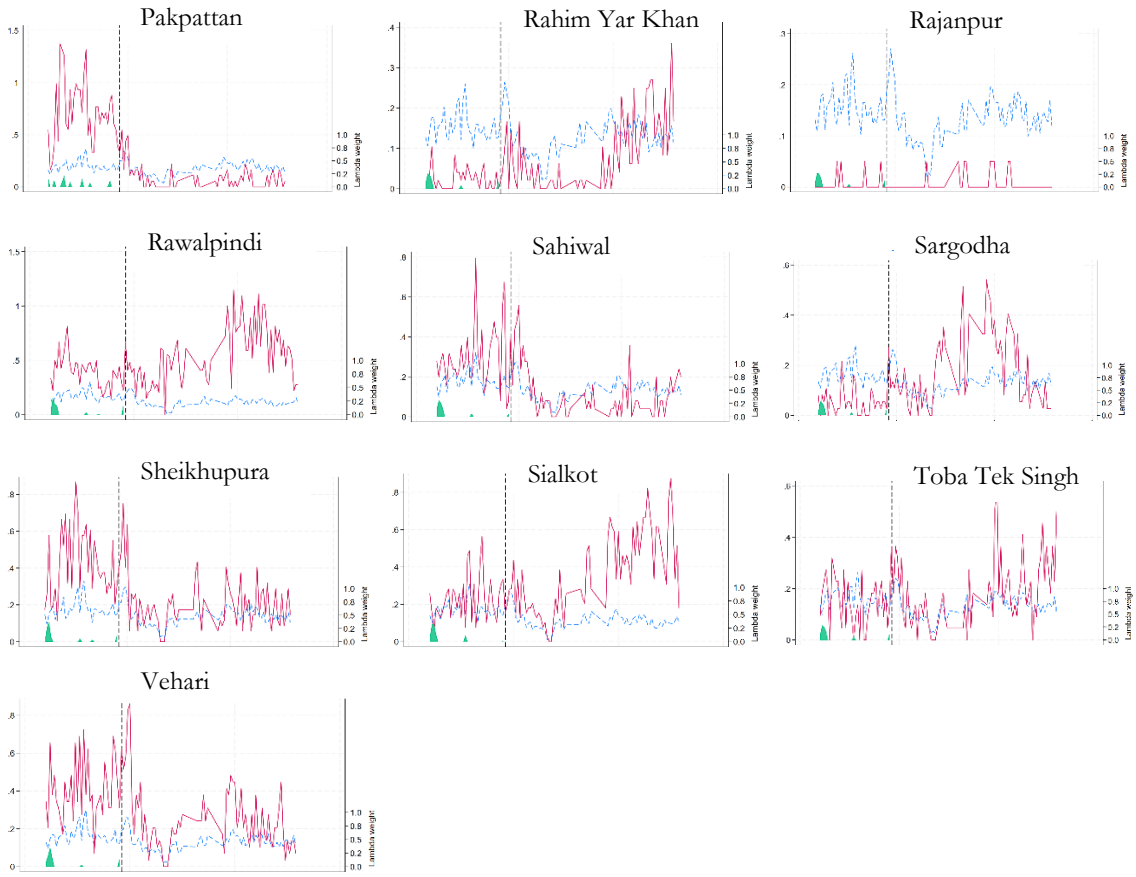


Figure A1: Placebo Synthetic Difference-in-Differences Estimates by District

Notes: These figures present placebo SDID plots obtained by iteratively assigning treatment to each district other than Kasur. Each panel shows the estimated pre- and post-treatment outcome trajectories and the implied post-treatment gap when a district is artificially treated. Most placebo plots show no sustained post-treatment divergence, while a small number display visible upward deviations (Faisalabad and Sialkot).