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

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Abstract

Do high-profile crimes deter future offending or signal weak enforcement? We study the effects of the highly publicized rape and murder of a seven-year-old girl in Kasur, Pakistan, in 2018 on child sexual abuse. Using district–month data from 2015–2024 and a synthetic difference-in-differences design, we compare Kasur to a constructed counterfactual from other districts. We find a large, persistent increase in reported child abuse, about ten additional cases per month, concentrated in opportunistic offenses and weakly supervised settings. The increase emerges most clearly following subsequent institutional responses and coincides with judicial congestion, consistent with inverse deterrence driven by institutional strain rather than transient reporting effects.

Keywords: Child sexual abuse, Crime deterrence, Crime reporting, State capacity
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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 impact this event 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). Given the heinous nature of the crime, the authorities acted swiftly: the perpetrator was arrested on the 23rd of January 2018 and accused of several other similar crimes,[3] sentenced to death on 17th February 2018 (via an anti-terrorism court),[4] and executed by hanging on the 17th of October 2018.[5]

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.[6] Public anger intensified after the family located CCTV footage showing Zainab being led away by an unidentified man.

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

[3] See more on the arrest here: https://time.com/5115502/zainab-amin-murder-arrest/

[4] See more on the conviction here: https://www.voanews.com/a/pakistan-court-hands-down-four-death-sentences-to-child-killer/4258888.html

[5] More on the execution here: https://time.com/5426780/pakistan-executes-zainab-ansari-killer/

[6] 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.

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.[7]

Consistent with theories of blame avoidance (Weaver, 1986), and isomorphic mimicry (Andrews, Pritchett, and Woolcock, 2017), the post-Zainab response in Kasur reflected a common reform pattern in which acute public outrage generated visible accountability actions and symbolic institutional gestures. Importantly, however, it failed to deliver any institutional changes to the policing structure, outside of a symbolic firing of the District Police Officer (DPO) of Kasur, following violent protests, on January 11th, 2018.[8] However, another high profile incident involving the rape and murder of three boys occurred in the nearby city of Pattoki and their bodies recovered in the city of Chunian (both in the Kasur district) occurred on September 17th 2019.[9] The aftermath of this event brought about swift changes in the Kasur police structure, with explicit intervention by the then Prime Minister, Imran Khan.[10] Specifically, the Prime Minister directed the Inspector General of Police (IGP) to take action against the chain of command of Police in the Kasur district, which then led to the suspensions of Kasur District Police Officer (again), but also the Superintendent of Police Investigation, the Deputy Superintendent of Police, and the Station House Officer (basically the entire chain of command).[11] While the measures taken in this instance were more severe than the ones taken in the aftermath of the Zainab incident, there is limited evidence of any lasting institutional changes as a result of these cases.

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). 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 (and also the Chunian murders) 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).

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[7] 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/.

[8] More on this event here: https://www.dawn.com/news/1382209

[9] See more on this event here: https://tribune.com.pk/story/2059229/1-kasur-rocked-protests-new-cases-sexual-abuse

[10] See the Prime Minister's statement here: https://www.dawn.com/news/1506009

[11] More details here: https://www.dawn.com/news/1506009

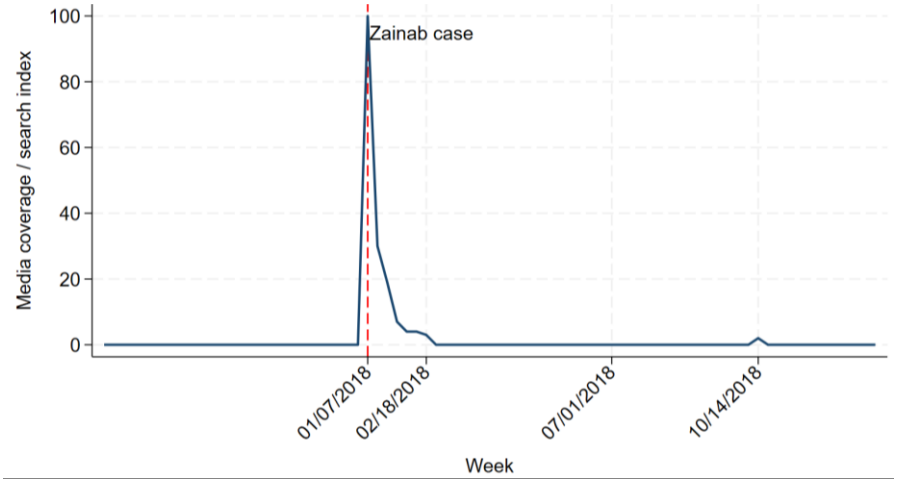


Figure 1: Media coverage spike following the Zainab rape case

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 long term 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, sharply increasing in 2020, and persisting for several years beyond the immediate aftermath, far longer than any other reported in the literature.[14] Because the observed increase does not occur immediately after the initial incident, we examine whether later institutional responses, most notably the perpetrator's execution and a subsequent policing overhaul, coincide with sharper changes in reporting. A series of robustness checks confirms that these patterns are not driven by pre-trends, donor composition, or long-run drift.

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 evidence of what we term *inverse deterrence*: heightened crime visibility following a salient event

[14] 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.

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). 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). We show that this sustained increase follows the aftermath of a policing overhaul that occurred nearly two years after the incident. 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).[15] Judicial congestion, delays, or weak enforcement can therefore reduce deterrence by lowering the effective likelihood of punishment. This interpretation aligns with detailed institutional evidence on policing and criminal justice in Pakistan. Cheema et al. (2024) document extremely low levels of citizen trust in the police, heavy reliance on direct eyewitness testimony, and procedural barriers that discourage effective investigation and prosecution of crimes. In such settings, heightened visibility of crime need not translate into greater deterrence if enforcement capacity and judicial follow-through remain weak.

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.[16]

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.

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

[16] 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.

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 (as is likely in our case, with reforms being largely performative), 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.

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 (and post-2019) trajectory to synthetic counterfactuals 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.[17] 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.[18] 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.

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[17] 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.

[18] 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.

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.

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.[19]

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.[20] In addition, we provide alternative treatment dates using the execution of the perpetrator (October 2018) and a documented police chain of command

[19] 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.

[20] 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.

overhaul following another high profile incident (September 2019). 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.[21] Together, 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).[22] 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 Method (SCM) approaches, providing a

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

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

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. In our main specification, 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 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 the synthetic control method its data-driven weighting of controls, and from difference-in-differences, 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 for the main specification) 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 difference-in-differences 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 synthetic controls and the fixed-effects framework of difference-in-differences, 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[23]. 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, 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

[23] 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.

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 34 donor districts weighted to match Kasur's pre-treatment outcomes. The grey dotted lines mark October 2018 (execution of the perpetrator) and September 2019 (police overhaul in Kasur). Prior to January 2018, the two series track each other closely, indicating strong pre-treatment fit and supporting the credibility of the synthetic control as a counterfactual. After 2018, the series begin to diverge, with the gap becoming more pronounced in the subsequent years. From roughly 2021 onward, reported child-abuse crimes in Kasur rise substantially above the synthetic control and remain persistently elevated through the end of the sample. This sustained divergence suggests that the post-2018 increase in reported child-abuse incidents was concentrated in Kasur rather than reflecting province-wide trends.

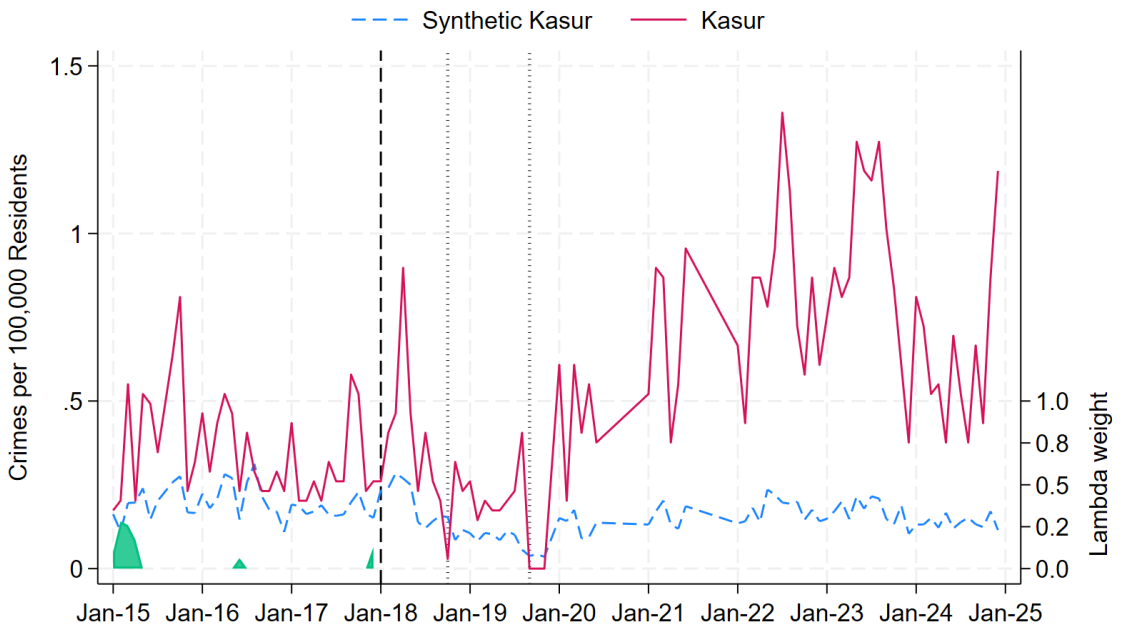


Figure 2: SDID: Treatment effect on child abuse crimes

Note: The blue dashed line represents the synthetic control, while the red line represents Kasur. The synthetic control is constructed from 34 donor districts weighted to match Kasur's pre-treatment outcomes. The vertical dashed black line marks January 2018, the month of the Zainab incident. Green shaded areas indicate time weights (λ). Grey dotted vertical lines indicate October 2018 (execution of the perpetrator) and September 2019 (police overhaul in Kasur).

To complement the average treatment estimates, Figure 3 presents event-study SDID estimates of the dynamic impact of the Zainab incident on reported child-abuse crimes in Kasur. Each blue dot represents the monthly treatment effect relative to the synthetic control, while the shaded areas denote placebo-based 95 percent confidence intervals. The pre-treatment estimates fluctuate around zero, suggesting parallel trends prior to January 2018. Following the incident, the point estimates gradually turn positive and remain persistently elevated relative to the synthetic control. Although month-by-month confidence intervals are wide, the divergence becomes more pronounced approximately three to four years after the event. The delayed yet sustained increase in reported child-abuse incidents indicates that the post-2018 surge in Kasur was not a short-lived shock or province-wide fluctuation. Rather, the gradual and persistent nature of the divergence—considered alongside the broader evidence presented in the paper—is more consistent with an inverse deterrence mechanism than with a temporary salience-driven reporting spike.

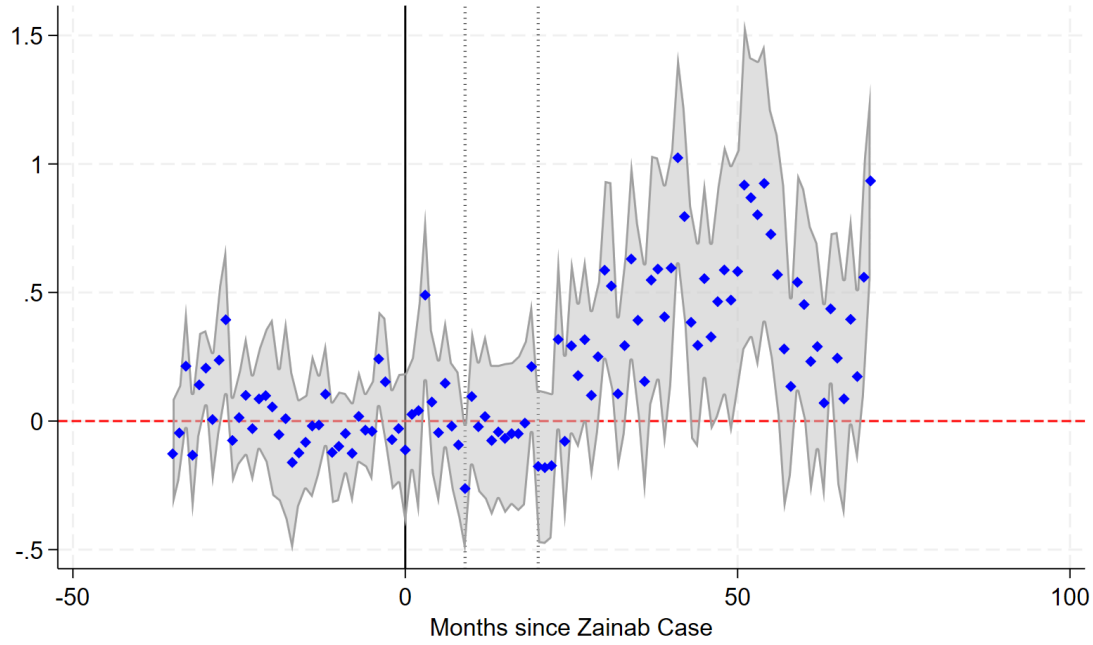


Figure 3: Event study SDID: Treatment effect on child abuse reports

Note: Dynamic treatment effects are estimated using the event-study extension of the Synthetic Difference-in-Differences (SDID) estimator. Blue dots represent monthly treatment effects for Kasur relative to a synthetic control constructed from 34 donor districts weighted to match pre-treatment outcomes. The vertical black line at event time 0 corresponds to January 2018, the month of the Zainab incident. Grey shaded regions denote 95% confidence intervals based on placebo inference with 500 replications. Grey dotted vertical lines indicate October 2018 (execution of the perpetrator) and September 2019 (police reorganization in Kasur).

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.

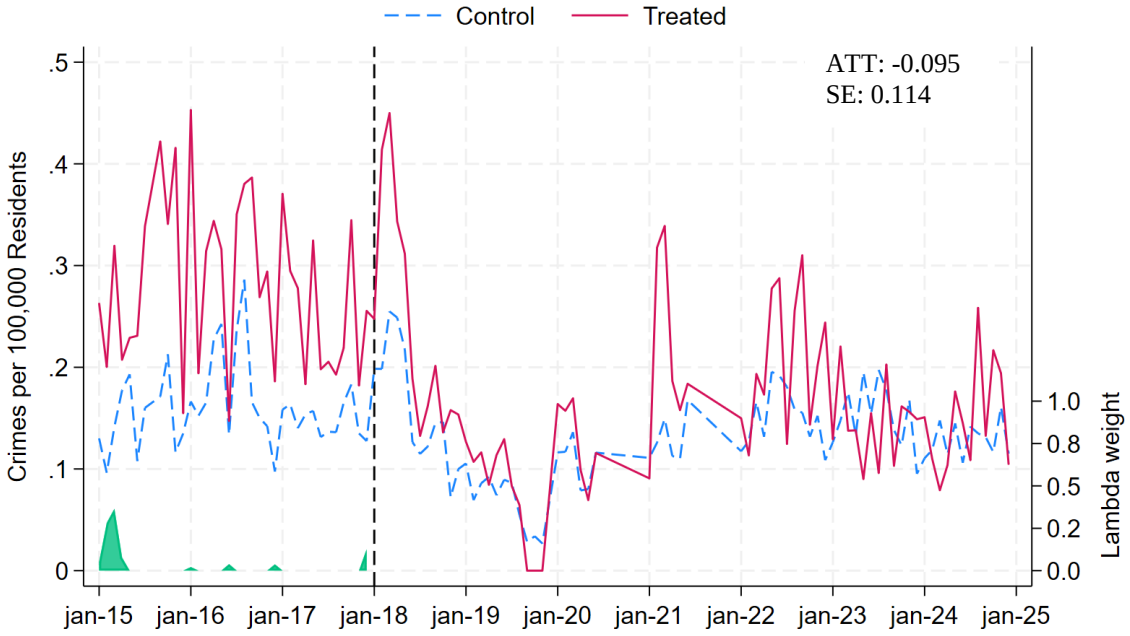


Figure 4: SDID spillover test: Grouping neighboring districts (Lahore, Sheikhupura, and Okara)

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.

To further assess whether the Kasur estimates reflect mechanical features of the SDID design or broader province-wide shocks, we conduct placebo-in-space SDID analyses by iteratively assigning treatment to each of the 33 control districts in Punjab other than Kasur. Figure 5 presents the distribution of placebo ATT estimates, excluding Kasur. Each bar represents the estimated SDID effect when a control district is falsely designated as treated, while the vertical dashed line marks the ATT for Kasur. The vast majority of placebo districts yield estimates centered around zero, and Kasur lies in the extreme right tail of the distribution. The corresponding synthetic-control path plots for each placebo district are shown in Appendix Figure A1 and confirm that most districts exhibit no sustained post-2018 divergence from their synthetic controls. Together, these results indicate that the Kasur effect is unusually large relative to the distribution generated under random reassignment and is unlikely to reflect generic province-wide shocks or mechanical features of the estimator.

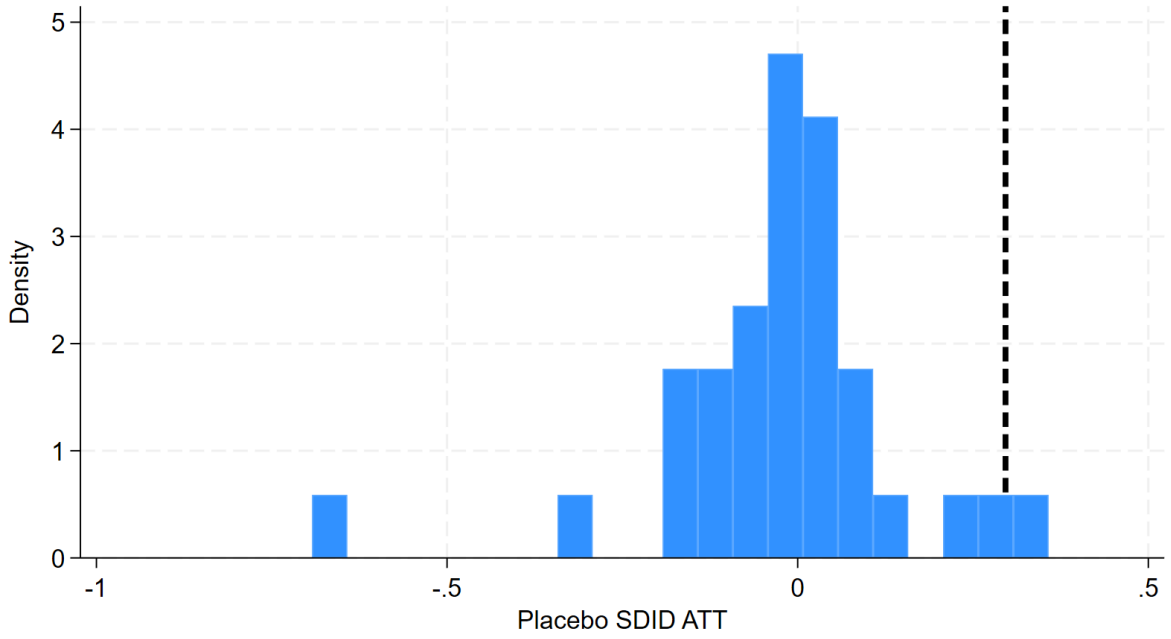


Figure 5: Distribution of Placebo-in-Space SDID Estimates

Note: The histogram displays SDID ATT estimates obtained by reassigning treatment to each of the 33 control districts (excluding Kasur). The vertical dashed line indicates the ATT for Kasur.

Robustness tests

To address concerns that the estimated effects reflect gradual long-run drift rather than a discrete shock, we re-estimate the SDID model assigning January 2016 as a fake treatment date while maintaining the identical seven-year post-treatment horizon and donor pool used in the baseline specification. As shown in Table 3, the estimated ATT under the placebo treatment is 0.066 and statistically insignificant, in sharp contrast to the sizable and significant effect obtained when January 2018 (the Zainab case) is used as the treatment date. Because both specifications use the same estimator, donor pool, and post-treatment horizon, the only difference is the timing of treatment. The absence of an effect under the placebo timing confirms that the divergence observed in Kasur is triggered by the January 2018 shock rather than reflecting slow-moving trends.

Table 3: SDID Estimates Using True and Placebo Treatment Dates

	Jan 2018 (True)	**Jan 2016 (Placebo)**
ATT	0.296*	0.0661
	(0.160)	(0.0866)

Notes: Each column reports the Synthetic Difference-in-Differences (SDID) estimate of the average treatment effect on the treated (ATT). Column (1) uses January 2018 (Zainab case) as the treatment date. Column (2) assigns a placebo treatment date of January 2016. Both specifications use the identical donor pool and 84-month post-treatment horizon. Standard errors are obtained via placebo-based inference. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 examines the sensitivity of the SDID estimates to the exclusion of heavily weighted donor districts. The baseline specification yields an average treatment effect (ATT) of 0.296, statistically significant at conventional levels. Excluding Hafizabad—the largest-weight donor district—produces an identical estimate of 0.296, indicating that the baseline result is not driven by this single district. Removing the two highest-weight donors (Hafizabad and Rawalpindi) slightly increases the estimated ATT to 0.327, while excluding the top three donors (Hafizabad,

Rawalpindi, and Sheikhupura) yields an ATT of 0.279. Although precision declines when excluding three donors, the estimated effect remains positive and economically similar in magnitude. Overall, the results suggest that the main findings are not driven by any single comparison district and are robust to alternative donor pool compositions.

Table 4: Donor Sensitivity of SDID Estimates

Specification	ATT
Baseline SDID	0.296* (0.160)
Drop Hafizabad	0.296* (0.151)
Drop Top 2 (Hafizabad, Rawalpindi)	0.327* (0.171)
Drop Top 3 (Hafizabad, Rawalpindi, Sheikhupura)	0.279 (0.175)

Note: The table reports average treatment effect (ATT) estimates from the Synthetic Difference-in-Differences (SDID) model under alternative donor pool exclusions. Each specification sequentially removes the highest-weight donor districts from the synthetic control. Standard errors are reported in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01. All models use placebo-based inference with 500 replications.

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 5.

Table 5: 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

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.

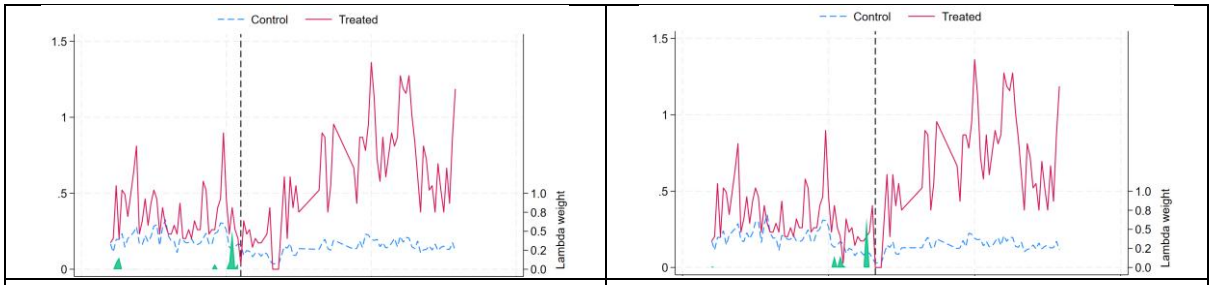
Finally, we assess whether differences in socioeconomic exposure of children could explain the observed reporting surge. The child-employment rate (defined as the share of children aged 10–14 engaged in work, including paid family workers relative to the population of children aged 10–14) captures the 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. Timing and Institutional Response

We next examine the timing and institutional mechanisms underlying the estimated effects by exploiting variation in the intensity and sequencing of policing interventions following the initial

shock. Note that Figures 2 and 3 show a sharp increase in reported cases 18-24 months after the initial shock.[24] Since the validity of the synthetic control may similarly weaken as we go further into the future, we might be concerned that the effects are spurious. Furthermore, we also note two additional points in the aftermath of the Zainab incident, the execution of the perpetrator 10 months after the incident (October 2018) and policing overhauls following the rape and murder of three boys, 20 months after the incident (September 2019). While it is clear that the Zainab incident constituted a large external shock, it is also clear that relatively larger changes occurred at significant points of time after the initial incident. For this reason, we replicate our main analysis using these two dates as alternative interventions.

Figure 6 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. Figure 6(a) uses the execution of the perpetrator of the Zainab murder as the intervention date (October 2018), signaling the logical end of the incident. Figure 6(b) uses the policing overhaul (replacement of the entire management chain of the Kasur police) in September of 2019, following rape and murders of three young boys in Kasur. Before the intervention dates, as before, the series move closely together, indicating a good pre-treatment fit and supporting the validity of the synthetic control as a counterfactual for Kasur. As above, the trends differ sharply after the intervention dates, as observed in Figure 2. Reassigning treatment to each control district at these intervention dates in turn yields null effects in the vast majority of cases, with only a small number of placebo districts exhibiting statistically significant increases. Kasur remains an outlier in magnitude and persistence[25]. These alternative intervention dates should not be interpreted as replacing the original shock, but rather as capturing distinct moments of institutional response that plausibly mediate the persistence and visibility of reporting effects.



(a) Intervention: Execution of perpetrator

(b) Intervention: Policing overhaul

Figure 6: SDID: Treatment effect on child abuse crimes (alternate interventions)

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 (a) Oct 2018 marks the execution of the perpetrator of the Zainab murder, and (b) overhaul of the policing management following rape and murders of three young boys. Shaded areas indicate time weights (λ).

[24] We are grateful to Nathaniel Hendren for pointing this out.

[25] Placebo-in-space tests reassign treatment to each control district in turn, yielding 33 placebo estimates. For the January 2018 intervention date, only Faisalabad and Sialkot yield statistically significant positive effects. For October 2018, only Faisalabad and Rawalpindi do so. For September 2019, only Faisalabad and Toba Tek Singh produce significant positive estimates. In all other districts, effects are statistically indistinguishable from zero.

One potential concern is that estimated effects become larger further into the post-treatment period, raising the possibility that long-run divergence—rather than the intervention itself—drives the results. Because the credibility of the synthetic control may weaken as we move further from the pre-intervention period, we re-estimate the SDID model while restricting the post-treatment window to the first 24 and 36 months following each intervention date. If the baseline effects were driven purely by long-run extrapolation, we would expect them to attenuate sharply under these restrictions.

Table 6 shows that this is not the case for the September 2019 policing overhaul. Even within the first 24 and 36 months, we observe economically large and statistically significant increases in reported child-abuse crime rates following this intervention. In contrast, the January 2018 murder and October 2018 execution dates yield no meaningful short-run effects. This pattern suggests that the sustained divergence observed in the full sample is not an artifact of long-run drift, but rather reflects a response that became salient following visible institutional intervention.

Table 6: SDID Estimates by Treatment Date and Post-Treatment Horizon

Treatment date	Full sample	First 24 months	First 36 months
Jan 2018 (Murder)	0.296* (0.160)	-0.00996 (0.0994)	0.01003 (0.103)
Oct 2018 (Execution)	0.282** (0.130)	0.0144 (0.0757)	0.105 (0.080)
Sep 2019 (Police overhaul)	0.446*** (0.116)	0.234*** (0.0590)	0.396*** (0.0836)

Note: Each entry reports the SDID estimate of the average treatment effect on the treated (ATT). Column (1) uses the full post-treatment period through 2024. Columns (2) and (3) restrict the post-treatment window to the first 24 and 36 months following each intervention date, respectively. Standard errors (in parentheses) are obtained via placebo-based inference. The donor pool consists of 34 control districts and is identical across specifications. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

What is immediately clear from the table is that we observe consistent positive effects on reporting in the immediate aftermath of the police management overhaul following the rape and murder of three boys in September 2019. While still lacking deeper structural reforms found in developed country contexts (Draca, Machin, and Witt, 2011), it is interesting to note that the main effects arise in the aftermath of a follow up (and relatively more severe) action taken by the Pakistani government in response to repeated events. The concentration of effects around the September 2019 policing overhaul suggests that large initial shocks may be insufficient to generate sustained reporting absent visible institutional response. In this sense, the Zainab case appears to have initiated a process, while later reforms activated it.

VII. Behavioral Mechanisms: Opportunity and Guardianship

We next examine whether the composition of the post-Zainab increase is consistent with inverse deterrence. If heightened salience operates in a setting of constrained enforcement capacity, the rise in reported abuse should be concentrated in opportunistic contexts characterized by mobility and weak guardianship rather than uniformly across all forms of abuse.

Crime Type and Mobility

Panel A of Table 7 shows that the clearest and most precisely estimated post-2018 increase occurs in abduction-related incidents, along with a smaller rise in missing-child reports. In contrast, rape, sodomy, gang-related offenses, murder, and child marriage exhibit no statistically significant change. The concentration of effects in abduction and disappearance cases suggests heightened vulnerability in mobile, transitional spaces rather than sustained or organized abuse. These patterns align with inverse deterrence: increased visibility and reporting pressure disproportionately affect offenses involving movement and limited oversight.

Location and Guardianship

Location-based heterogeneity reinforces this interpretation. As shown in Panel B of Table 7, incidents occurring in private homes and in streets or public spaces show significant post-2018 increases, while schools, workplaces, and religious institutions exhibit declines or no meaningful change. The divergence between informal environments (homes, streets, abandoned plots) and regulated institutional settings suggests substitution across environments rather than uniform escalation. Following the Zainab incident and subsequent police intervention, institutional spaces appear to have tightened supervision, while exposure shifted toward everyday settings characterized by weaker guardianship.

Duration and Opportunism

Duration patterns provide further support. As shown in Panel C of Table 7, single-episode incidents increase significantly, whereas medium-term abuse declines and long-term abuse remains unchanged. Heightened scrutiny may have curtailed prolonged abuse but left opportunistic, one-off incidents more feasible. The post-2018 rise is therefore concentrated in incidents consistent with mobility and exposure rather than sustained predation.

Table 7: 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.

Perpetrator Relationship

Perpetrator-level heterogeneity, as shown in Table 8, points in the same direction. Incidents involving strangers and acquaintances rise sharply, while cases involving institutional actors (teachers, employers, religious leaders, and other formally supervised roles) show no meaningful change. The increase is concentrated in interactions characterized by anonymity or informal proximity rather than structured oversight.

Overall, these compositional patterns indicate that the post-Zainab increase was not broad-based but concentrated in contexts defined by mobility, limited supervision, and opportunity.

Conditional on the reporting activation following the September 2019 policing overhaul, the evidence suggests that heightened salience reshaped where and how abuse occurred rather than uniformly increasing all categories of crime. Detailed victim-level heterogeneity results are reported in Appendix Table A3.

Table 8: 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.

VIII. Institutional Mechanisms: Judicial Capacity, Salience, and Inverse Deterrence

A central mechanism in our framework is that heightened crime salience, when combined with limited enforcement capacity, may weaken deterrence rather than strengthen it. If heightened salience increased reporting pressure and media scrutiny without a commensurate expansion in judicial capacity, Kasur's courts may experience congestion. In such an environment, institutional strain may coexist with rising reported crime. Examining the relationship between judicial congestion and reported child abuse therefore provides indirect evidence on whether heightened salience operated alongside constrained enforcement capacity in the later post-shock period.

The judicial statistics are available only for 2022–2024, following both the January 2018 Zainab incident and the subsequent police reorganization. Accordingly, this analysis does not test the immediate institutional response to the shock. Instead, it examines whether Kasur exhibits a distinct relationship between judicial congestion and reported child abuse in the later post-shock

period. We relate district-level child-abuse reporting to annual criminal case-flow statistics from the *Judicial Statistics of Pakistan*. Because judicial backlog may both influence and respond to crime reporting, we interpret the following estimates as descriptive correlations rather than causal effects. Our goal is to assess whether Kasur differs systematically from other districts in how reported abuse covaries with institutional congestion.

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 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 year-fixed effects and the interaction term β_2 identifies whether Kasur's relationship with judicial congestion differs from that of other districts in Punjab.

Table 9: 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 9 reveal two clear 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 may reduce incentives to report or slow case processing.

Second and more importantly, Kasur exhibits a markedly different relationship. The interaction term is large, positive, and highly significant, indicating that when judicial congestion rises in Kasur, reported child abuse increases sharply.

This divergence suggests that in the post-Zainab period, institutional strain in Kasur coincided with increased crime visibility rather than suppression. One plausible interpretation is that public scrutiny and heightened awareness increased the likelihood that incidents surfaced, even when judicial capacity was strained. In such a setting, congestion may reflect not improved deterrence, but a system simultaneously overwhelmed and exposed.

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 9 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.

These findings indicate that Kasur exhibits a systematically different relationship between judicial congestion and reported abuse than other districts in the post-Zainab period. While these results are descriptive, they are consistent with a setting in which heightened salience, increased reporting pressure, and constrained enforcement capacity operate simultaneously. Rather than suppressing crime visibility, institutional strain in Kasur appears to coincide with rising reported abuse, consistent with the inverse-deterrence framework developed in this study.

IX. 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 (particularly in the aftermath of policing overhaul in September 2019), and remain elevated for the time horizon we have. 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 10). 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 10: 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.

X. 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. More broadly, the results underscore that in low-capacity settings, the deterrent effects of salience depend critically on the state's ability to convert attention into credible enforcement.

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.

Table A3: 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: This table reports SDID estimates of the effect of the January 2018 Zainab incident on child-abuse rates (per 100,000 population), disaggregated by victim characteristics. Each coefficient represents the average treatment effect for the specified subgroup. Standard errors are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Figures



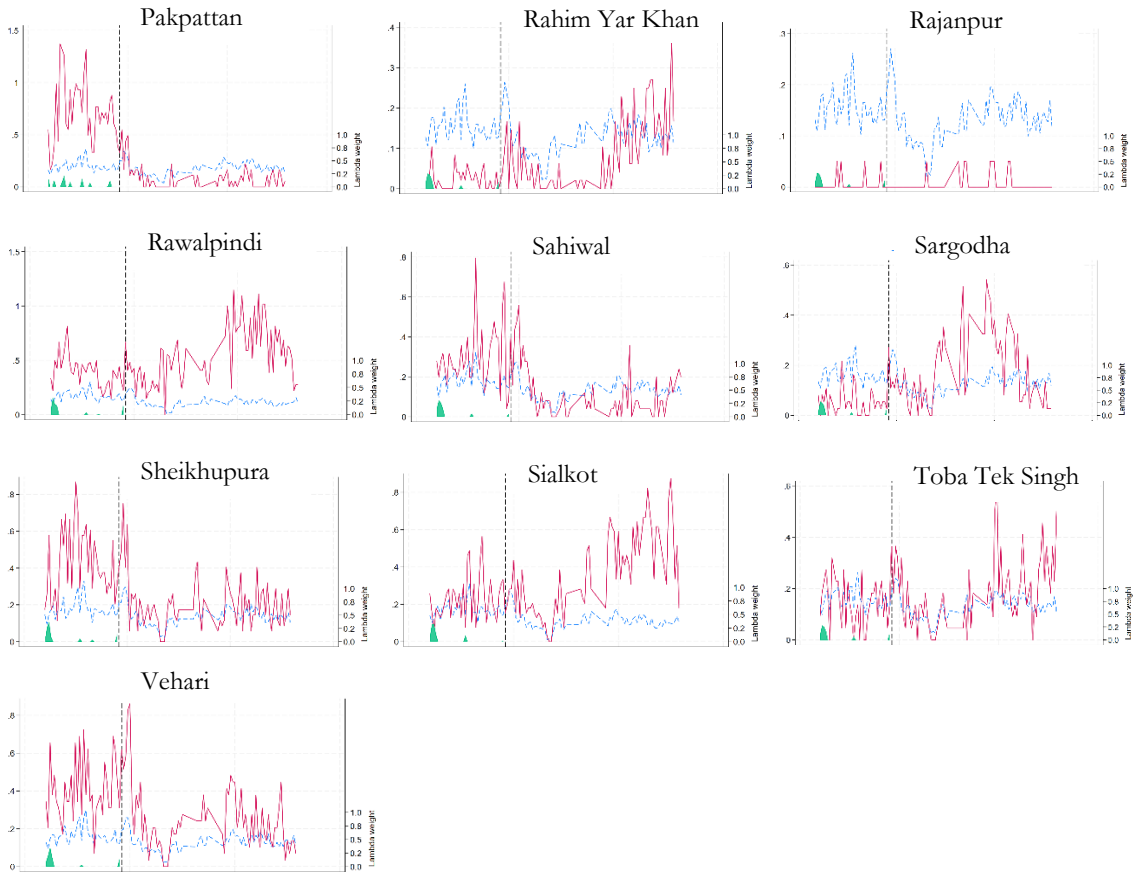


Figure A1: Placebo Synthetic Difference-in-Differences Estimates by District

Notes: These figures present placebo SDID plots obtained by iteratively assigning treatment to each district other than Kasur. Solid red lines indicate treated and dashed blue lines indicate control districts. 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).

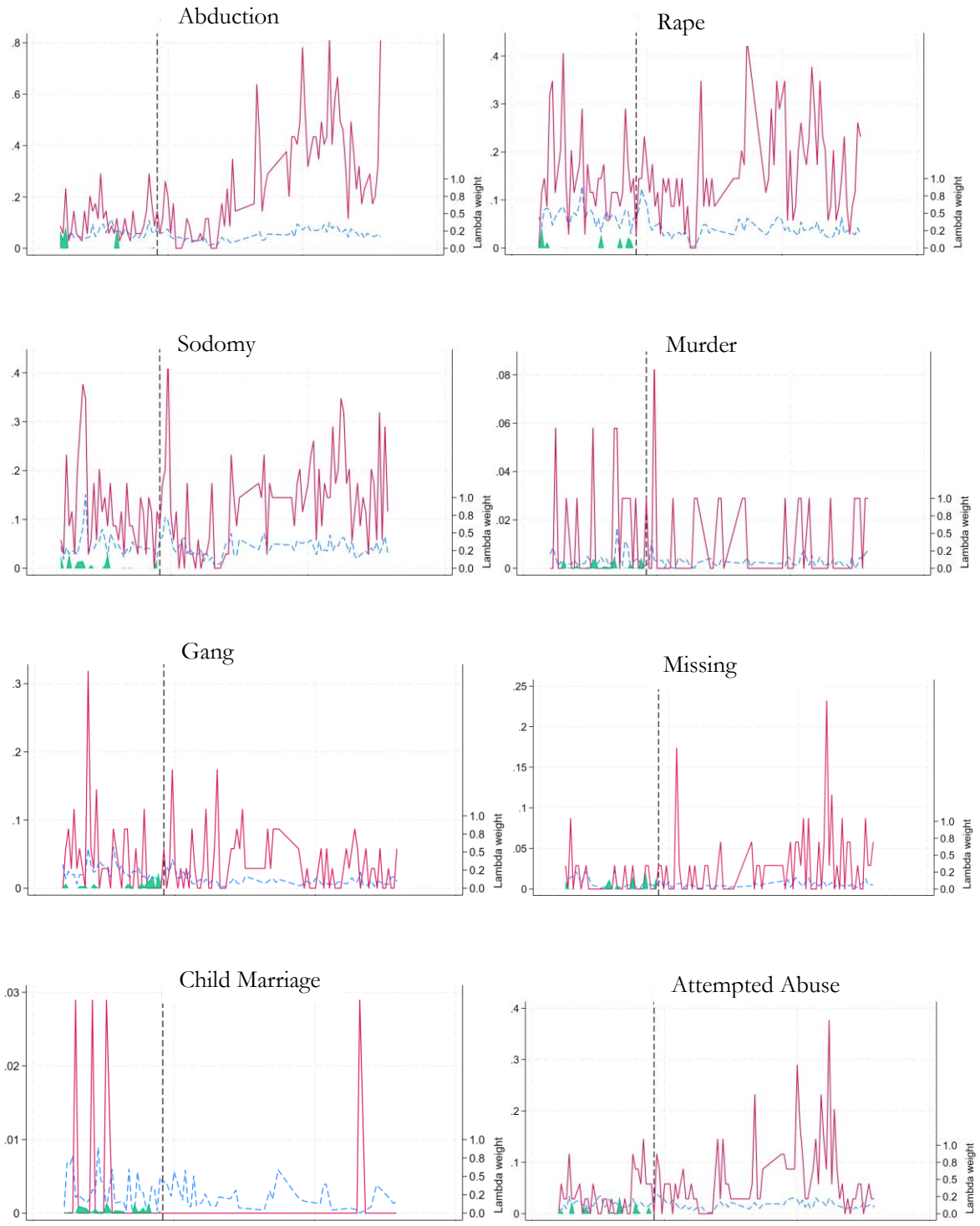


Figure A2: Synthetic Difference-in-Differences Estimates by Crime Category

Notes: These figures show SDID plots comparing Kasur (red line) to its synthetic control for each crime category, with the vertical line indicating January 2018. While most categories show no significant divergence, cases classified as abduction and missing cases exhibit significant post-Zainab increases.

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