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The Silenced Women

Can Public Activism Stimulate Reporting of Violence against Women?

Abhilasha Sahay

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Abstract

Although violence against women is pervasive and can have severe adverse implications, it is considerably underreported. This paper examines whether public activism against such violence can stimulate disclosure of socially sensitive crimes such as rape and sexual assault. The analysis uses a quasi-experimental setting arising from an *infamous* gang rape incident that took place on a moving bus in Delhi in 2012. The incident sparked widespread protests demarcating a nationwide '*social shock*'. Exploiting regional variation in exposure to the shock, the analysis finds an increase of 27 percent in reported violence against women after the shock but no change in gender-neutral crimes such as murder, robbery and riots. Additional evidence—generated from self-compiled high frequency crime data—suggests that the increase can be attributed to a rise in reporting rather than an increase in occurrence.

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The Silenced Women: Can Public Activism Stimulate Reporting of Violence against Women?

Abhilasha Sahay*

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1 Introduction

Owing to several structural and societal barriers, a survivor's willingness to report cases of violence against women (VAW hereafter) could be undermined. These barriers include social stigma and shame (García-Moreno et al., 2005), distrust of institutions (Belknap, 2010), fear of retaliation by the perpetrator (Kishor and Johnson, 2005), lack of awareness and access to referral services (Casey et al., 2011; Hossain et al., 2010), financial barriers (Wolf et al., 2003), and in certain cultural settings, high tolerance towards VAW (Fugate et al., 2005). According to a recent global study, only 7% of women who have ever experienced violence have reported to a formal source such as the police, health systems or social services and 37% to an informal source such as a family member or a friend (Palermo et al., 2014).[1] Such under-reporting can be detrimental; it could weaken deterrence and perpetuate incidence. Under-reporting also limits our understanding of the actual magnitude of VAW; thereby, rendering an insufficient knowledge base to devise effective mitigation strategies.

This paper investigates whether public activism against VAW can overcome some of the above-mentioned barriers and boost reporting. I investigate this question in a quasi-experimental setting arising out of a brutal gang-rape incident that took place in Delhi on a moving bus in December 2012 (incident hereafter). The incident received widespread media attention and ignited intense public outrage. Protests and demonstrations of an unprecedented magnitude broke out across the country, marking the onset of a large social movement, referred to as *"India's Arab Spring"* (Barn, 2013; CNN, 2013). The surge in public activism also paved the way for several legislative and policing reforms, demarcating a transformative *social shock*.

I estimate the effect of this social shock on reported VAW using a difference in difference (DiD) strategy. I use official crime data published by the National Crimes Records Bureau (NCRB), which records crime incidents for all 640 districts[2] in India over a period of 18 years (2001-2018) for six key types of VAW, namely rape, kidnapping of women and girls, sexual assault, sexual insult, cruelty by husband or his relatives and dowry deaths.[3] I identify the effect of the shock by exploiting regional variation in exposure to the incident, where exposure is conceptualized as *socio-economic proximity* or people's *connectedness* to the incident. To measure exposure, I construct a composite index using an array of district-specific baseline indicators.[4] This index encapsulates three key elements of exposure: (i) coverage of media (which measures access to information about the incident and associated

[1] Sample includes 24 countries across four regions: Central Asia and Eastern Europe, Latin America and Caribbean, India and East Asia and Africa.

[2] District is a second-level administrative unit (sub-state level), akin to counties in the United States.

[3] Sexual insult entails verbal remarks or gestures intended to insult the modesty of a woman. Cruelty by husband or his relatives is an act of causing grave injury or danger to life of the woman, perpetrated by an intimate partner or his family members. Cruelty by husband or his relatives is a criminal offense described under Section 498(A) of the Indian Penal Code. Alongside, the Parliament of India enacted Protection of Women from Domestic Violence Act in 2005, which is a civil law meant primarily for protection orders (and not meant to penalize criminally).

[4] The exposure index is synonymously referred to as socio-economic index in subsequent sections.

protests), (ii) demographic factors (which measures similarities/connectedness with the victim and her family), and (iii) coverage of public transport (which measures connectedness with circumstances and place of the incident). I provide more details on the construction of the exposure index in Section 4.2.

I find that districts that were 1 standard deviation (SD) more exposed to the shock witnessed a sharp increase in reported VAW - an increase of 0.18SD. Specifically, I find a significant increase in reported rape, kidnapping of women and girls, sexual assault and cruelty by husband or his relatives (in the range of 0.12SD-0.24SD). Notably, I do not find any corresponding change in reported gender-neutral crimes (crimes that are not necessarily targeted towards women) such as murder, robbery and riots as well as other related outcomes such as female deaths and female suicides; thereby, suggesting that the estimated effect cannot be entirely attributed to other changes in the crime climate. The key findings of this paper are robust to an array of sensitivity checks including choice of empirical specification, alternative constructions of the exposure index, alternative treatment assignments and restricted sample tests. I also show that exposure to the shock was not correlated with the initial level of reported VAW nor its trend prior to the shock; thereby, lending credibility to the identification strategy.

Considering that the 2012 rape-incident was followed by several legislative and policing reforms to mitigate violence (detailed in Section 2.2), the *increase* in reported VAW is somewhat surprising. I hypothesize that the estimated effect could be attributed to a rise in *reporting* of cases rather than an increase in occurrence. To test this, I conduct auxiliary analyses on new, incident-level micro-data that I compiled using information from official crime reports - published by the department of Delhi Police - through a web-scraping algorithm I developed.[5] This dataset includes rich contextual information on more than 300,000 crime incidents that took place in Delhi during years 2011-2015.[6] Specifically, it records information on two important dates: (i) date of crime occurrence and (ii) date of crime reporting. Using these dates, I construct a measure of lag in reporting, i.e. the number of days elapsed between occurrence and reporting of a crime. This measure is used as a proxy of latent reporting-bias in disclosure of cases, i.e. cases that are reported with a longer lag are considered to have a higher reporting bias.[7]

After the shock, I find a significant decrease in the proportion of cases reported with a lag (15% decrease) and a measurable decline in number of days of lag (35% decrease). These estimates indicate a reduction in reporting-lag, both at the extensive margin and at the intensive margin. These findings provide, to my knowledge, the first evidence on changes in

[5]These crime reports are referred to as first information reports (FIRs). An FIR is the first document issued by the police when a complaint is registered. These reports are uploaded by the Delhi Police on its official website.

[6]Notably, the FIR dataset is only available for Delhi, not for all of India.

[7]If a case is reported at least 3 days after it occurred, it is considered to be reported with a lag. The 72-hour cutoff was decided based on consultations with officials from the Delhi Police. I find that the key findings are robust to changing the cutoff (results available on request).

reporting of VAW, via measuring reporting-lag.[8] Notably, the rise in public activism against VAW could have emboldened women to disclose their own experiences of violence - similar to what followed after the global *MeToo* movement. Nonetheless, I explore alternative interpretations of these findings in Section 6.

This paper makes two key contributions. First, it speaks to the growing body of work on reporting of VAW. Past scholarship has identified a few key interventions that can encourage reporting, such as increase in women's political participation (Iyer et al., 2012), greater female representation in police and judiciary (Amaral et al., 2018; Miller and Segal, 2019; Kavanaugh et al., 2019), and introduction of no-drop policies[9] (Aizer and Dal Bo, 2009). Adding to this evidence base, the findings from this study demonstrate that public activism against VAW can also increase disclosure of cases.[10]

In a related stream of work, some studies have examined the effect of community-based interventions, 'edutainment', and media campaigns on core attitudes towards VAW (Abramsky et al., 2016; Jensen and Oster, 2007; Green et al., 2020).[11] However, none of these studies evaluates the effect on *explicit* reporting behavior.[12] Notably, social or collective disapproval of VAW is distinct from being willing to report one's *own* experience of violence. Therefore, this paper systematically examines the effect on *formal disclosure* of VAW.

This study most closely relates to a nascent body of work, which studies the effect of a movement that was similar to the revolution that took place in India, i.e. the global *MeToo* movement.[13] Levy and Mattsson (2019) document evidence from OECD countries, which suggests that the *MeToo* movement improved reporting of sexual crimes. In another study, Cheng and Hsiaw (2020) develop a theoretical framework to model the shift from a low reporting to a high reporting equilibrium owing to heightened public awareness on sexual

[8]One exception includes Levy and Mattson (2020). This study examines the effect of the *MeToo* movement on reported VAW and uses reporting-lag as a measure to examine heterogeneity in the effect of the movement.

[9]No-drop policies compel the prosecutor to continue with the prosecution even if the victim wishes to withdraw or drop the charges

[10]The results in this paper in no way suggest that the occurrence of a horrific crime incident is a necessary condition for rise in public activism or that a similar incident would need to take place to stimulate disclosure. Such social movements could originate from other exogenous factors such as proliferation of media, increase in youth population, etc.

[11]Jensen and Oster (2007), Bhushan and Singh (2014) and Arias (2019) find that increased access to media such as cable television and radio can reduce social acceptance of VAW. Similarly, (Abramsky et al., 2016) and Green et al. (2020) provide evidence, which suggests that community based interventions aimed at preventing violence can improve attitudes towards VAW

[12]Another related string of studies have examined the effect of street protests and political revolutions, such as the Arab Spring, on an array of outcomes: labor force participation (El-Mallakh et al., 2018; Selwaness and Roushdy, 2019; Heshmati et al., 2017), income mobility (Majbouri, 2017), intra-household decision-making (Bargain et al., 2019) and household social expenditure (Giesing and Musić, 2019). However, none of these studies investigates the effect on VAW - neither its incidence nor reporting.

[13]There is one important difference between the *MeToo* movement and the Indian social movement. While, the motivation for the *MeToo* movement was to share one's experience and overcome stigma associated with disclosing violence, the intended goal of the Indian movement was to condemn a specific crime incident. Notably, the movement in India preceded the global movement by almost 5 years.

misconduct. My research contributes to this scholarship by providing empirical evidence in the context of a low and middle income country (LMIC), where the socio-cultural dynamics of VAW is fairly distinct and where the issue of under-reporting is arguably more severe.

Particularly in the Indian context, a few descriptive studies have explored how the 2012-rape incident influenced the overall discourse on gender-based violence (Phillips et al., 2015; Nigam, 2012; Lapsia, 2015; Shah, 2019). Further, two recent studies are especially relevant to this paper: McDougal et al. (2018), which provides descriptive evidence on increase in reporting of rapes after the incident, using a set of spatial mapping techniques and graphical trend analyses,[14] and Bhatnagar et al. (2019), which finds an increase in reported crimes against women after the incident, using a synthetic controls approach.[15] While both these studies yield results consistent with my findings, there are a few important differences in the empirical approach and evidence on mechanisms. I discuss these details in subsequent sections.

Second, this study attempts to make a more specific *empirical* contribution. An ongoing challenge in any research on VAW and other such socially sensitive topics is to decipher how to disentangle the effect of an event or a policy on incidence versus its effect on reporting. Consequently, the evidence base on the *reporting mechanism* is largely suggestive. Past studies have adopted two key strategies to distinguish between incidence and reporting: (i) examine the effect on placebo or gender-neutral crimes such as murder and robbery, and (ii) investigate changes in outcomes relating to police activity and law-enforcement such as arrest rate and conviction rate (Aizer and Dal Bo, 2009; Bhatnagar et al., 2019; Amaral et al., 2018). In this paper, I propose a new and arguably more direct approach to generate evidence on reporting.[16] This approach is based on estimating changes in reporting-lag - a measure that encapsulates the number of days elapsed between the day a crime occurs and the day it gets reported. This approach enables us to measure the extent of reporting-bias, both at the extensive margin and the intensive margin; thereby, yielding meaningful insights on crime disclosure. While more research is needed to test the validity of this approach across different settings and data structures, its application in this paper provides an important proof of concept and helps in extending the empirical discussion on this topic.

The rest of this paper is divided into 6 sections. The next section provides a brief background of the incident and its immediate aftermath. Section 3 illustrates the conceptual framework. Section 4 describes the data and empirical strategy. Section 5 reports results and section 6 discusses the mechanisms of impact. Finally, section 7 concludes.

[14] McDougal et al. (2018) assesses trends in formal rape reporting and finds a strong correlation between reporting and proximity to Delhi.

[15] In applying the synthetic control design, the authors implicitly assume that the effect of the 2012-incident was confined to Delhi and therefore, use other Indian states to construct a synthetic Delhi. I discuss the validity of this assumption in Section 5.3.

[16] Besides, I also explore the robustness of my results to the two strategies used in past scholarship.

2 Context

2.1 Violence against Women in India

Studying this topic in the Indian context can advance our understanding of prevalence and reporting of VAW in important ways. India ranks lowest among other LMICs with respect to formal reporting; only 0.97% of women who have ever experienced any form of VAW have reported to a formal source (Palermo et al., 2014).[17] Further, only 0.56% reported to the police, 0.1% reported to a medical professional and 0.38% reported to a local NGO or a social worker. As per a victimization survey conducted in Delhi and Mumbai, only 1 in 13 and 1 in 9 cases of sexual harassment are reported (CHRI, 2015).

As discussed at the outset of this paper, a survivor may face several barriers in reporting VAW. Some of these barriers are more pressing in the Indian context: rigid social systems of caste, religion and traditional family structures can contribute towards the proliferation of violence, both within the private sphere as well as public spaces (Mitra, 2000; Ahmed-Ghosh, 2004; Dalal and Lindqvist, 2012; Sharma and Gupta, 2004).

2.2 Incident and Its Aftermath

On the evening of December 16, 2012, a 23-year-old physiotherapy student was brutally gang-raped and thrown out of a moving bus. The victim suffered extensive injuries and died of them on December 29, 2012. The incident spurred intense public outrage; a wave of widespread protests took over the entire country, demanding justice for the victim and more broadly, to seek a structural change in how VAW is perceived and dealt with in the country. Several of these protests were carried out in public offices. The protests united people from across social classes and political ideologies, making this movement one of the largest and strongest since India's independence. Appendix C describes the sequence of events that followed the rape incident.

The incident was widely covered in the national and international media. Most media reports included information about the incident, the victim's health condition and the protests (Phillips et al., 2015). Several reports also broadcasted personal testimonials from the victim and her family, highlighting her socio-economic and educational background, her dreams and aspirations, creating a feeling of *connectedness* among people. The circumstances under which the incident took place, i.e. on a moving bus in the capital city, also induced empathy, disbelief and anger among people (both men and women), especially among those who use public transport and claim public spaces in daily life. Overall, the incident resonated with the masses and galvanized them into a landmark social movement.

[17] This study evaluates bounds on underestimation of reporting, conditional on having experienced VAW, using data from the Demographic Health Survey for 24 countries for the period 2004 -11. For India, it analyses data for a sample of 27,175 women in the year 2005-06.

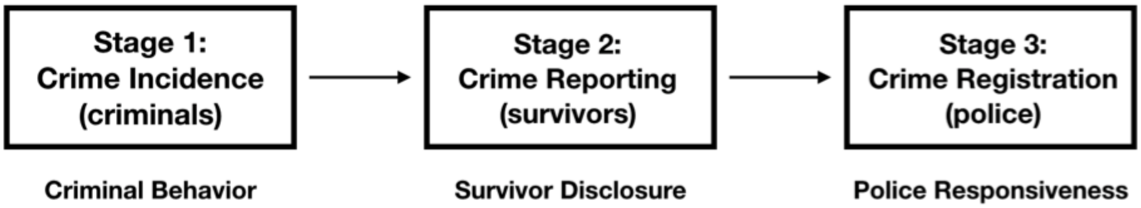
The movement also paved the way for several legislative and policing reforms. A committee, spearheaded by the former Chief Justice of India, was established to recommend amendments to the Criminal Law to facilitate quicker trial and impose stricter punishment for perpetrators of VAW. The committee sought public opinion and recommendations from a large cross-section of the society including women 's groups, intellectuals and jurists. The committee submitted its report on January 23, 2013. Based on these recommendations, the Criminal Law (Amendment) Act 2013 was passed on March 21, 2013 and came into effect on April 3, 2013. The report recommended stricter punishment for rape (rigorous imprisonment for seven years to life), broadening the definition of rape to any non-consensual penetrative sexual act (earlier restricted to penovaginal penetration), recognizing other acts of VAW like stalking, and voyeurism, broadening the scope to recognize sexual assault against men, transgender and transsexual persons, installing special procedures to protect persons with disabilities from sexual violence, updating guidelines on how to perform medical examination of a rape survivor, and removing the security blanket that protected civil servants and police officers from charges of VAW (Bhalla, 2013). Notably, registration of rape complaints was mandated; any officer, who fails to register a case of rape reported to him, or attempts to abort its investigation, would be held liable. Recommendations were also made to increase police vigilance, especially in public spaces: increase in night patrolling, installation of GPS devices in public buses, proper verification of public-bus staff, appointment of lady police officers, and introduction of home guards in night buses. A corpus fund equivalent to USD 0.14 billion was introduced to fund projects aimed at bolstering women 's safety.

3 Potential Effects of Public Activism on VAW

To examine the plausible channels of impact, I adopt a framework previously utilized by Donohue III and Levitt (2001) and Iyer et al. (2012). The framework illustrates three stages of crime: crime incidence, crime reporting and crime registration/investigation. Stakeholders at each stage face decisions. At stage 1, a (potential) criminal decides whether to commit a crime or not (*criminal behavior*). At stage 2, when a crime occurs, the survivor decides whether to report the crime to the police (*survivor disclosure*). Finally, at stage 3, it is on the police to register the crime and commence investigation (*police responsiveness*). The social shock could have affected each of these stages in both direct and indirect ways.

Stage 1 (*Criminal Behavior Channel*): This channel entails two competing effects:

- Deterrence channel: The increase in public outrage against the accused rapists (of the 2012 rape incident) may deter other (potential) criminals from committing such crimes.
- Retaliation channel: At the same time, such widespread condemnation of the accused could also create a feeling of retaliation. Some of the demonstrations included call-outs such as, “Beasts should be castrated”, “Hang them to death” and “Nothing less



Source: Adapted from Iyer et al. (2012)

than capital punishment". Such incitements can harbor vengeance among criminals, pushing them to commit more crimes against women.

Stage 2 (*Survivor Disclosure Channel*): The upsurge in public activism could have increased survivors' willingness to report crimes. Knowing that the society is more aware and sensitized towards VAW, survivors may feel encouraged to report their experiences. Further, such social movements make the knowledge of exposure to VAW public; previously this knowledge may have been confined to a survivor's private sphere. In light of this new common knowledge, survivors may feel more supported to reveal their own accounts of VAW. The survivor disclosure channel can further be divided into two sub-channels:

- Retrospective survivor disclosure: The increase in activism could initiate reporting of cases that had taken place several months or years before the shock, similar to the response garnered by the global *MeToo* movement.
- Contemporaneous survivor disclosure: At the same time, the rise in activism could also increase current-day reporting, i.e. cases that occurred after the shock are now being reported and may be in the absence of shock these cases may have not been reported or may have been reported with considerable lag.

Stage 3 (*Police Responsiveness Channel*): The rise in public activism could also increase police accountability to mitigate VAW towards the citizenry and the government (i.e. politicians). This could happen via strengthening vigilance, increasing case-registration and thoroughly investigating cases of VAW to bring the criminal to justice.

Further, each of these channels could interact with one another, yielding indirect effects.

Stage 1: Increase in police responsiveness can be a strong deterrent for criminals to reduce or discontinue criminal activities. Greater willingness to report among survivors can also send a strong signal to the perpetrator that the crime would not go unreported and that he would be brought to justice; thereby, enhancing the deterrence channel.

Stage 2: A survivor's willingness to report crimes may increase if she knows that the police would promptly respond to her complaints and facilitate justice.

Stage 3: An increase in survivor disclosure (and demand for case-registration and investigation) could increase police responsiveness. If there is an increase in criminal retaliation, the police would need to be more vigilant to prevent future crimes.

4 Data and Empirical Strategy

4.1 Crime Data

4.1.1 District-level Crime Data

I use official crime data published by the National Crime Records Bureau of India (NCRB). These data are structured at the district-year level (633 districts over 18 years). These data are aggregated from individual cases reported at the police station, which are first compiled by the District Crime Records Bureau (DCRB) in each district, then validated by the State Crime Records Bureau in each state and then finally consolidated by the NCRB Statistics department at the end of every calendar year. NCRB releases the state-level and district-level crime data annually under its "Crimes in India" publication. It includes data on all major crime categories defined under the Indian Penal Code.

My analysis includes crime data for all districts in India for the period 2001-2018. I use data on six categories of VAW namely, rape, kidnapping of women and girls, sexual assault, insult to modesty of women (or sexual insult), cruelty of husband and his relatives and dowry deaths. These categories together make up 95% of the total reported cases of VAW at baseline.[18] To conduct placebo checks, I use data on seven gender-neutral crimes. These include property crimes such as robbery, burglary, dacoity and riots, bodily offences such as murder, and economic offences such as breach of trust and counterfeiting.[19] Please refer to Appendix B for precise definition of each crime category.[20,21] The key outcome variable is rate of crime, which is calculated as number of crimes per 100,000 female population for VAW crimes and number of crimes per 100,000 total population for gender-neutral crimes.

[18] Source: Crimes in India (2012), National Crime Records Bureau

[19] Admittedly, some of these gender neutral crimes could be classified as gender-based crimes; for instance, murder of women could take place due to gendered reasons. However, I cannot observe disaggregated district-level crime data, neither by gender nor reason for crime. Thereby, I closely follow the crime classification followed in Iyer et al (2012) and Amaral et al (2018) to make the distinction between gender-neutral crimes and violence against women. Both these studies classify murder as a gender neutral crime.

[20] Under the Indian Penal Code (IPC) each crime is associated with a unique section number and all police stations report crimes based on the corresponding IPC section. For instance, rape is reported under Section 376 of the IPC.

[21] One limitation of the NCRB data is that it abides by the 'Principle Offence Rule' for classification of crime, i.e. if a case is registered under multiple offences, then only the most heinous crime (maximum punishment) will be considered as a counting unit. For example, murder with rape is accounted as murder. Consequently, the actual count of each crime head, especially low-intensity crimes, may be under-estimated. Nonetheless, this does not seem to threaten the empirical strategy since NCRB has been following the same counting rule throughout the sample period.

Population data were obtained from the Census.[22]

One technical challenge in compiling the crime data is that the NCRB records cases at the police-district level, which is (weakly) one unit below the census district. As of 2011, there were 692 police districts in India and 640 census districts. A police district could either be completely within a census district or could span multiple census districts. In the first case, the police district could be uniquely mapped to the parent census district. In the second case, I use a rule of thumb where I map the police district to the census district under which the majority of its land-area lies. This is done through comparing police district maps and census district maps. In most cases, this comparison clearly delineates the land-share of the police district among parent census districts.[23]

I adhere to district boundaries as defined in Census 2011. To account for districts that were created after 2011, a similar mapping procedure was used. In case a new district is created from within a census district, the new district would be mapped to its erstwhile parent district. Alternatively, in case a new district is created from parts of multiple districts, then the new district is mapped to the parent district from which it gets the majority of its land-share. Finally, after conducting this mapping, the resulting dataset records crime data for 633 unique census districts over a period of 18 years.[24,25] Each census district is assigned a unique three-digit district code. This code is used as the unique identifier to merge datasets.

4.1.2 Incident-Level Crime Data

I compile new, incident-level micro-data using first information reports (FIR), accessed from the Delhi Police website.[26,27] FIR is a report that documents first-hand information on a crime

[22] I use district population figures from census years 2001 and 2011 and interpolate population for the periods 2002-2010 and 2012-2018.

[23] An alternative mapping strategy may be to assign parent district based on where the majority of the population of the police district resides. However, I do not have data on population of police district. Census, which is the key source of population data, records population only at the census district level.

[24] There are four island districts in India that are away from the primary landmass; these have been excluded from the sample to avoid any outliers. Further, NCRB does not record crime data for two small districts in the Puducherry union territory, i.e. Yanam and Mahe. Additionally, it was found during interactions with NCRB officials that the crime data for the district of Mumbai-suburban (a distinct census district) is recorded under district of Mumbai; I follow the same recording strategy. Thus, my analysis includes 633 of the 640 districts in India.

[25] Unfortunately, I cannot use the same procedure to map districts that were formed between 2001 and 2011. Consider a district was formed in 2007. NCRB would report crime statistics for this district under its new district name 2008 onwards. For the period between 2001-07, its crime statistics would be reported as part of its parent district and there may be no *exact* way to prorate the crime figures for the newly formed district. Thus, for each pre-shock year, the crime panel may include varying number of districts, depending on current year's district boundaries. Nonetheless, given that these changes took place in the pre-shock period, the re-organization of boundaries does not affect composition of the treatment group, which is based on data in 2011.

[26] Link of Delhi Police Website

[27] All FIRs used to assemble this dataset were available in the public domain.

incident, as provided by the complainant when he or she first registers the case at a police station. Police investigation commences only once an FIR is registered. In compliance with a Writ Petition issued by the Delhi High Court in 2010, the department of Delhi Police uploads FIRs registered under its jurisdiction on its official website. I compiled information from these reports, using a web-scraping algorithm I developed in Python. The algorithm was designed to perform two key tasks: (i) extract FIR report corresponding to a given district, police station, year and FIR number and (ii) extract relevant data points from each report, such as type of crime, incident date, report date, name of police-station and police-district.[28] Each FIR includes sections from the Indian Penal Code (IPC) under which the accused is booked. Using these IPC codes, I am able to identify and compile the data for specific categories of VAW and gender-neutral crimes. Overall, the compiled dataset includes information on 315,219 cases from 176 police stations across 9 districts in Delhi over the period February 2011 to June 2015.[29]

4.2 Data and Construction of the Exposure Index

The exposure index forms the main variable of treatment intensity. It is made of ten baseline district-specific indicators. Table A.1 describes these indicators and Table 1 provides summary statistics of each indicator. Data on all 10 indicators comes from Census 2011. As mentioned previously, the exposure index is made of three key components.

The first component measures *transmission of information*, i.e. sources through which people received information about the incident, victim, case trajectory and outbreak of protests. It is measured using district-specific coverage of media sources such as newspapers, television, radio, phone and Internet.

Data on coverage of television, radio, phone and Internet are obtained from Census modules, which record data on household-level asset ownership. Household specific data are aggregated to get district-level measures. Data on coverage of daily newspapers supply are obtained from the District Census Handbook (DCHB), published by Census of India. This handbook records information on availability of amenities at the village level. It only includes data for the rural population (which makes up 66% of the population in India). In order to construct district-specific aggregates including both urban and rural areas, I impute the data assuming that urban areas within a district have full coverage of basic amenities like newspaper supply. Thus, I construct population-weighted aggregates of overall coverage using:

$$NewspaperCoverage_d = (ruralsupply_d \times pcruralpop_d) + (1 \times pcurbanpop_d)$$

The second component measures *socio-economic connectedness* with the victim and her family. It is measured using demographic indicators such as female literacy, religion,

[28]The primary packages used for these two tasks are selenium and beautiful soup, respectively.

[29]Data before 2011 are not available. FIR reports for the period after June 2015 are not available in a compatible digital format.

proportion of urban population and proportion of young population. Data on all demographic indicators come from Primary Census Abstracts (PCA), published by Census of India. I discuss the motivation for including each indicator below:

1. Female literacy: The victim was a young physiotherapy student. She belonged to a middle-class family and aspired to be a doctor. She was emblematic of an *aspirational India* and her struggle resonated with several women. Drawing from the notion of driving "*empowerment through empathy*",[30] it is likely that districts with high female literacy felt more connected to the victim and were more exposed to the shock.

2. Young population: Here, there could be two pathways of exposure. First, most survivors and perpetrators of VAW belong to a young demographic; as per the NCRB report in 2012, 51% of survivors and 50% of perpetrators are in the age group 18-30 years old.[31] Second, youth are more active in protests and in organizing for social change (Acemoglu et al., 2018). Thus, districts where the age-structure is weighted towards the youth are likely to be more exposed to the shock.

3. Religion: The victim belonged to a Hindu family. Similarity in religious backgrounds can form strong social connectedness; thereby, districts with higher percentage of Hindu population may relate more with the victim and her family.

4. Urban population: The incident occurred in the heart of the capital city and everyone involved in the incident was an urban resident. Thus, it is likely that districts with higher urban population would relate more with this incident, than districts that are largely rural.

The third component measures *connectedness with circumstances of the incident.* Given that the incident took place on a public-bus, districts where public transport is predominant and where people frequently claim public places are likely to be more connected with the shock, compared to regions where people largely rely on private transport. Data on coverage of public-buses are drawn from DCHB and is calculated using a method similar to that of newspaper coverage.

All 10 indicators are aggregated to form the composite exposure index. In the preferred construction, the index is calculated by taking a simple unweighted average of the normalized indicators as shown in Equation 1.[32] Results are robust to tweaking weights and to alternative aggregation methods such as principal components analysis and a ranking method. In another robustness check, I drop one indicator each time and reconstruct the exposure index. I find my results to be stable across all these alternative constructions (results provided in Section 5.3). Notably, the correlation among the 10 indicators is

[30] This phrase has commonly been used to describe the global *MeToo* movement.

[31] Crimes in India, National Crime Records Bureau (2012).

[32] Each indicator is normalized to ensure unit comparability

moderate,[33] suggesting that each indicator adds distinct information to the index. The index takes values between 0 and 1 such that a district with a larger index value is more exposed. Figures 1 - 3 depict the spatial dispersion in treatment intensity across districts in India.[34]

$$Index_d = \frac{1}{10}\sum_{j=1}^{10} Indicator_j \tag{1}$$

I compare this conceptualization of shock-exposure to measures of treatment intensity used in past studies. The growing body of work that examines the effect of the Arab Spring protests uses different measures of protest intensity such as number of protesters (Acemoglu et al., 2018), number of martyrs (El-Mallakh et al., 2018) and number of fatalities, injuries and arrests (Bargain et al., 2019). I do not use such measures in this study for three key reasons. First, unlike the Arab Spring, most protests in India were peaceful.[35] Second, while the details of protests during the Arab Spring have been documented well (see Egyptian Revolution Database, Survey of Young People in Egypt, Project Wiki Thawra) there is no systematic documentation or database available in the Indian context. Third, the shock in India was not only confined to street protests; it also entailed intense media coverage, digital activism, community mobilization and civic engagement. In this light, I try to adopt a more comprehensive measure of treatment intensity, encompassing three distinct pathways of exposure, as discussed previously.

Relatedly, few recent studies have used networks on online social media platforms to measure social connectedness. For instance, Bailey et al. (2018) analyzes patterns of social connectedness between counties in the United States using friendship links on Facebook. It may be argued that a similar concept can be used to measure connectedness (direct or indirect) with the victim or her family. However, in light of India's low social media user base (in Q4 2012, only 6% of the Indian population was active on Facebook compared to 54% in United States), using traditional media channels such as newspaper, television and radio is more suited.

Notably, there are several factors that could influence exposure to such a shock; in the constructed index I include indicators that are most relevant to the local context and for which reliable, district-level data were available.

[33] The pairwise correlation is less than 0.5 for most indicators.

[34] The treatment intensity map been divided into three parts - northwest, east and south - based on guidelines provided to the World Bank Map Clearance team by the World Bank Legal department.

[35] Most protests were candle-light vigils. In very few instances the protests got violent and required police intervention. One such instance also led to the demise of a police constable in Delhi – the only fatality associated with these protests.

4.3 Empirical Strategy

Considering that the incident triggered a *nation-wide* shock and did not exclusively impact a subset of locations or cohorts, I cannot identify pure treatment and control groups. Consequently, I use a treatment intensity approach where treatment is assigned as a continuum between 0 and 1, based on exposure to the shock. I estimate the following DiD equation:

$$y_{dst} = \beta(Exposure_d \times Post_t) + \alpha_d + \tau_t + \gamma_{st} + \epsilon_{dst} \tag{2}$$

where y_{dst} is the main outcome variable and measures rate of VAW, i.e. number of cases per 100,000 female population in district d from state s in year t. α_d and τ_t are district and year fixed effects, respectively. γ_{st} represents state by year fixed effects. ϵ_{dst} is the idiosyncratic error term that is clustered at district level. $Exposure_d$ is the main variable of treatment intensity, which varies at the district level and takes values between 0 and 1. Post takes value 1 if year is between 2013-18, and 0 otherwise.[36] Each observation is recorded at district-year level. I use standardized coefficients so as to effectively compare coefficient estimates across models.[37]

District fixed effects account for unobserved characteristics at the local region level, including gender norms, perception of women's safety and capacity of local police and administration. Inclusion of year fixed effects absorb any time-varying unobserved characteristics that may affect crime, such as economic shocks, weather changes.[38] Including state by year fixed effects accounts for any state-specific changes in law and policing over time. In India, issues of policing and public order are subjects on which the state governments have the power to legislate (as long as the decision taken is not repugnant to any law made by the central government).[39] Thus, including state by year fixed effects accounts for any such changes that may take place across states during the sample period.

In alternative specifications, I include district-year linear trends (M2) and control for physical proximity to the district where the incident took place, i.e. Southwest Delhi (M3). District specific time trends are included to control for pre-existing trends of reported VAW, which may vary across districts. In M3, I incorporate an alternative measure of treatment intensity, which encapsulates physical proximity to the district where the incident took

[36] The incident took place on 16$^{\text{th}}$ December 2012. Thus, in terms of full years the post-period includes years 2013-2018.

[37] Standardized coefficients are derived from a regression analysis where both the dependent and independent variables have a variance of 1.

[38] The effect of climate changes on crime is especially salient for agrarian regions.

[39] As per the Constitution of India, matters of legislation are divided into 3 lists; union list, state list and concurrent list. Central government has exclusive power to legislate on issues in the union list. These include matters of defence, foreign affairs, citizenship, etc. State governments can independently take decisions on subjects in the state list such as public order, police, public health, agriculture, etc. State governments can also take decisions on matters relating to criminal law, criminal procedure and preventive detention. Subjects in the concurrent list can be decided on both by the central and state government. These include matters related to contracts, trade unions, etc.

place or the focal district. Geographical proximity to the focal district could be another pathway of exposure to the shock: regions that are closer to the place of the crime may identify more with the incident and its circumstances, feel more connected to the victim and participate more in street protests and public debates. Findings from McDougal et al. (2018) validate this notion; it finds a strong positive association between increase in reported rape and proximity to Delhi.[40] Thus, in the M3 model I check whether the estimated effect - stemming from variation in socio-economic exposure to the shock - persists on controlling for physical proximity to the focal district.[41]

5 Results

5.1 Main Estimation

Table 2 presents the main DiD estimates. Column 1 shows results for the preferred specification (M1), which rules out any bias stemming from unobserved heterogeneity specific to local region (i.e. district fixed effects), time (i.e. year fixed effects) and changes in policing/law (i.e. state by year fixed effects). This estimate suggests that districts that were 1 standard deviation (SD) more exposed (s.d. = 0.14) witnessed 0.18SD increase in reported VAW after the shock (p value = 0.000).

This result is robust to including district-year time trends (M2) and controlling for physical proximity to focal district (M3).[42] Admittedly, the estimate size reduces to 0.14SD and 0.13SD in M2 and M3, respectively, but reassuringly, the associated p values are stable (0.000 and 0.001, respectively).

Table 3 presents the effect on individual categories of VAW. I find a significant increase in rape, kidnapping of women and girls, sexual assault and cruelty by husband or his relatives, post-shock. The effect ranges between 0.12SD and 0.24SD, with p values ranging between 0.000 and 0.001. Interestingly, I find a significant decrease in sexual insult and dowry death; although the effect is quite small for dowry deaths (0.07SD) and the effect for sexual insult has low significance (p = 0.06). I defer the discussion on results for these two categories to Section 6.1.

[40] This study provides suggestive evidence on the effect of the 2012-rape incident on rape reporting. It finds that 0.2 fewer rapes are reported to police (per 100,000 women) for each 100 kilometers from Delhi.

[41] Physical proximity is measured as time taken to travel by road between district d and the focal district. This data on driving time were obtained from Google Maps API: I first obtained the latitude and longitude coordinates of the centroid of each district and then evaluated three key metrics, namely (i) crow-fly distance to focal district, (ii) driving distance to focal district, and (iii) time taken to commute by road to the focal district. In the preferred specification, I use *time taken* to travel instead of distance since the former takes into account both the locational distance between two districts as well as the quality of roads, accessibility and ease of commute. Nonetheless, the results are robust to using distance measures - results available on request.

[42] The cross-district correlation between the exposure index and physical proximity is very low, i.e. 0.0052

5.2 Identification Checks

5.2.1 Satisfaction of Parallel Trends

The applicability of difference-in-difference strategy hinges on satisfaction of the parallel trends assumption. Before presenting results from the formal identification check, it is instructive to highlight three key aspects of the empirical framework. First, the rape incident was an unanticipated and exogenous shock, which could not have factored into reporting decisions beforehand. Second, the differences in exposure to the shock are determined by baseline socio-economic indicators, which are slow moving and do not change drastically over time. I also check whether districts that were more exposed also had higher (or lower) reported VAW pre-shock. The data does not exhibit any such association; the cross-district correlation between the exposure index and pre-shock level of reported VAW is quite low, i.e. 0.16.[43] Third, there is no anomaly in trend of police supply during the sample period. Figure A.2 shows stable trends at the national level across three police-supply measures: population per policemen, police-population ratio and police-area ratio.

To test the parallel trends assumption more formally, I follow Autor (2003) and run the following event-study specification:

$$y_{dst} = \alpha_d + \tau_t + \gamma_{st} + \sum_{\tau=1}^{m} \mu_{-\tau}(Exp_d \times T_{t-\tau}) + \sum_{\tau=1}^{q} \mu_{+\tau}(Exp_d \times T_{t+\tau}) + \epsilon_{dst} \tag{3}$$

where y_{dst} is the is the rate of reported VAW per 100,000 female population in district d from state s in year t. As in equation 2, α_d, τ_t and γ_{st} represent district FE, year FE and state by year FE, respectively. ϵ_{dst} is the idiosyncratic error term that is clustered at district level. The fourth and fifth terms represent interaction of treatment intensity with year-dummies before (m periods) and after the incident (q periods).

To satisfy the parallel trends assumption, all coefficients associated with lead dummies (i.e. period before the incident) should be insignificant. Insignificance of leads dummies demonstrates that the estimated effect cannot be attributed to any pre-existing differences in reported VAW between more and less exposed districts. Coefficients associated with lag dummies (i.e. periods after the incident) shows the effect of the policy over time. Figure 4 plots the μ coefficients over time and clearly depicts that the parallel trends assumption is satisfied.[44] The lead dummies vary between 0.004SD-0.07SD (p values range between 0.02 and 0.9), and the lag dummies vary between 0.1SD to 0.21SD (p values range between 0.000 and 0.018).

Similarly, Figure A.1 plots the event study graphs for individual categories of VAW. These

[43]Correlation between each individual indicator of the exposure index and pre-shock reported VAW is also quite low, i.e. in the range 0.04-0.2

[44]Consistent with how the primary β estimates are modeled, the μ coefficients are also standardized. As expected by design, the trends with unstandardized coefficients is also the same and satisfies the parallel trends assumption.

graphs demonstrate that the parallel trends assumption is satisfied for almost all crime categories, except cruelty by husband and his relatives, where I find some evidence on pre-trends in years 2001-08. However, in time periods just preceding the shock, i.e. years 2009-2011, the parallel trends assumption is satisfied.

5.2.2 Placebo Checks

Varying the Timing of the Incident

This placebo test examines whether the effect is stemming from any pre-existing trends. I limit the sample to pre-shock years and assign a placebo treatment or "fake" shock in pre-incident years. I replicate the primary analysis (Equation 2) with the only difference that now the $Post$ dummy variable represents a "fake" shock in pre-incident periods (2006-2011). Figure 5 shows that none of the placebo estimates are significantly different from zero, indicating that the effect is not driven by any systematic difference in trend of reported VAW between more and less exposed districts, pre-shock.

Effect on Gender Neutral Crimes

In this test, I replicate the primary DiD analysis to investigate the effect of the shock on gender-neutral crimes. Estimates from Table 4 show that the 2012-incident had no significant effect on gender-neutral crimes, indicating the primary effect cannot be attributed to *other* changes in the crime climate. These results are also depicted in a graphical form in Figure A.3, using an event study specification similar to Equation 3.

As an additional check, I conduct a triple difference analysis by exploiting an additional source of variation, i.e. difference based on crime type. The data includes 13 different crime types, of which 6 are VAW and 7 are gender-neutral crimes. In this triple difference design, the gender neutral crimes represent an additional control or placebo group. I estimate the following equation:

$$y_{dsct} = \beta(Exposure_d \times Post_t) + \rho(Exposure_d \times Post_t \times VAW_c) + \alpha_{dc} + \tau_{tc} + \gamma_{stc} + \epsilon_{dsct} \quad (4)$$

where y_{dsct} is crime rate in district d from state s in year t for crime type c. VAW_c is a dummy, which takes value 1 if the crime type is VAW. ρ is the main coefficient of interest, which indicates whether crime rate for VAW category was significantly different than gender-neutral category in more exposed regions post-shock. α_{dc} is district by crime type fixed effects; τ_{tc} is year by crime type fixed effects; γ_{stc} is state by year by crime type fixed effects and ϵ_{dsct} is the idiosyncratic error term that is clustered at the level of district by crime type. All other variables follow the same definition as Equation 2. Each observation is recorded at district-year-crime type level.

Column 3 of Table 5 shows β and ρ estimates from the above estimating equation. The results indicate a significant increase in reported crime rate for VAW (compared to gender neutral crimes) in more exposed regions (compared to less exposed regions) post shock (compared to pre-shock).

5.3 Robustness Checks

5.3.1 Alternative Sample Restrictions

Drop Major Cities

I examine whether the estimated effect is driven by a few big cities that are likely to have higher level of awareness on VAW and other gender issues. To test this, I exclude 10 major city districts from the sample, namely Ahmedabad, Bangalore, Chennai, Hyderabad, Jaipur, Kolkata, Mumbai, New Delhi, Pune and Surat.[45,46] I find that the primary results remain robust (see panel A of Table A.2), indicating that the effects are not localized to few select locations.

Drop State Capitals

Similarly, it can be argued that the estimated effect is mainly stemming from the effect in capital cities. A capital city is the political or administrative center of a State and may have better education, labor market opportunities, stronger institutions and in general, greater awareness on VAW and gender issues. In this test, I drop all state capital districts from the sample and replicate the primary analysis.[47] Estimates from panel B of Table A.2 indicate that the results are robust.

Drop Delhi

Finally, another hypothesis could be that the since the incident took place in Delhi, the primary finding is largely driven by the effect in Delhi. This hypothesis also relates to a key identifying assumption made in Bhatnagar et al. (2019), which utilizes a synthetic control strategy to estimate the effect of the 2012-incident. The study by Bhatnagar and colleagues considers Delhi as the treatment state and constructs a "synthetic" Delhi using other states in India. In doing so, it assumes that the effect of the shock was *only* confined to Delhi and therefore, other states can be used as suitable control units. If this assumption were to hold,

[45] A similar check is performed in Sekhri and Storeygard (2014)

[46] In most cases, cities are administrative headquarters of districts. For instance, Ahmedabad city is the administrative headquarter of Ahmedabad district. Since the dataset does not include crime data for specific cities, I drop the corresponding *district* for each major city to conduct this restricted sample test.

[47] Similar to the case of major cities, most capital cities are the administrative headquarter of its namesake district. To conduct this restricted sample test, I drop districts where the capital city is located. I drop 32 districts from the sample (two neighboring states Punjab and Harayana share their capital).

we should expect the estimated effect to fade or weaken on dropping Delhi from the sample. On the contrary, I find that the primary estimates are fairly stable to this alternative sample, as shown in panel C in Table A.2; thereby, demonstrating that the effect of the shock was also felt across other states in India.

5.3.2 Alternative Construction of the Exposure Index

I check if the main results are sensitive to how the exposure index is constructed. To examine this, I conduct three tests.

First, I sequentially drop one indicator each time from the composite index and re-construct the index using the remaining nine indicators. Coefficients depicted in Table A.3 show that the results are robust across all three models (M1-M3).

Second, I re-construct the exposure index using a principal component analysis (PCA) technique and replicate the primary analysis.[48] Estimates from the top panel in Table A.4 shows that the primary results are robust to this construction, across all three models.

Third, I re-construct the index using a ranking method. Under this method, all 633 districts are ranked based on its performance against each of the 10 indicators (1 being the lowest and 633 being the highest).[49] The composite index is then constructed by taking sum of these ranks. Again, I find that the estimates derived using the rank based index are consistent with the primary results (see bottom panel in Table A.4).

Finally, I also provide results for a model that uses each of the 10 individual components of the exposure index as a distinct variable of treatment intensity. These results are presented and discussed in Appendix E.[50]

5.3.3 Alternative Treatment Assignment

Binary Treatment

DiD estimates in the primary analysis were obtained based on a continuous measure of treatment. I now report results based on binary treatment. I use the median value of the exposure index as a threshold to assign treatment; districts that have above-median exposure belong to the treatment group ($treat = 1$) and districts with below-median exposure form the control group ($treat = 0$). Estimates from column 2 of Table A.5 show a significant increase in reported VAW - a relative effect of 27% compared to the

[48]PCA is a standard tool used for dimensionality-reduction. It assigns optimal weights to components based on how it performs in explaining the composite variable. The underlying algorithm picks the most valuable parts of all the variables and drops the least valuable ones. Further, each of the components furnished by PCA are independent of each other.

[49]Same indicator performance score is given the same rank

[50]Similarly, I also examine the results using each of three key components - media, demography and transport - as a distinct variable of treatment intensity. Results available on request.

pre-shock control group mean of 30.61 per 100,000 female population. Comparable effects stemming from an increase in women's political participation, establishment of all-women justice centers and introduction of all-women police stations is 46% (Iyer et al., 2012), 40% (Kavanaugh et al., 2019) and 22% (Amaral et al., 2018), respectively.

Discrete Treatment

In column 3 of Table A.5, I present results for discrete treatment. I split the districts into four quintiles of increasing intensity: high intensity (top 160 districts), medium intensity (next 158 districts), low-intensity (next 156 districts) and the control group (remaining 161 districts). The results show that the high and medium exposure districts witnessed a considerable increase in reported VAW, i.e. 41% and 22%, respectively (compared to the pre-shock control group mean). Notably, the effect size rises monotonically with intensity of exposure. This also indicates that the exposure index carries some relevant information to adequately capture treatment intensity. However, the estimate for the low-exposure group is insignificant, suggesting that alternatively it could have been classified as part of the control group. The relative effect calculated as the mean impact over the three treated groups is around 21%.

6 Interpretation of Results

Based on the conceptual framework described in Section 3, I now examine the plausible mechanisms underlying the estimated increase in reported VAW.

6.1 Criminal Retaliation Channel

Can the estimated increase in reported VAW be attributed to an increase in occurrence?

To examine whether the shock led to an increase in *occurrence* of VAW, I conduct two tests - closely following Iyer et al. (2012) and Sekhri and Storeygard (2014). In the first test, I investigate whether the shock led to any change in female deaths and female suicides. In the second test, I examine whether the shock led to any change in VAW crimes that are likely to have a relatively lower reporting bias, such as sexual insults and dowry death.

Past scholarship argues that female deaths and female suicides may have a lower reporting bias, since these events necessarily amount to death and it is relatively difficult to hide the death of an adult (Sekhri and Storeygard, 2014; Dreze and Khera, 2000).[51] If the results in Table 2 were due to an increase in occurrence, then we should find some increase in these

[51]Female deaths include deaths from natural or unnatural causes, including gendered or non-gendered crimes. Disaggregated data on cause of death or motive of crime are not available.

outcomes as well. However, I find no significant change, neither in female deaths nor in female suicides - shown in Figures A.4 and A.5 - thereby, indicating that we cannot attribute the estimated effect solely to a rise in incidence.

Notably, data on female deaths and female suicides are only available at the state level (not district). Therefore, I exploit a variant of the primary empirical strategy. In this variant treatment intensity - originally assigned at the district-level - is aggregated at the state level (shown in Equation 5).

$$y_{st} = \gamma_s + \delta_t + \sum_{\tau=2}^{m} \mu_{-\tau}(AvgExp_s \times T_{t-\tau}) + \sum_{\tau=0}^{q} \mu_{+\tau}(AvgExp_s \times T_{t+\tau}) + \epsilon_{st} \quad (5)$$

Each observation is recorded at state by year level. y_{st} is the outcome variable for state s in year t; γ_s is state fixed effects and δ_t is year fixed effects. $AvgExp_s$ refers to treatment intensity aggregated at the state level; it takes values between 0 and 1. Post takes value 1 if year is between years 2013-17 and 0 otherwise. $\epsilon_{s,t}$ is the idiosyncratic error term that is clustered at the state level. There are 33 states in the sample. Figures A.4 and A.5 plot the μ parameters, over time, for female death rate and female suicides, respectively. I find no discernible change in either outcome.

In the second test, I examine the effect of the shock on VAW categories that have a *relatively* low reporting bias. Among the six key categories examined in this study, the reporting bias is seemingly lower for sexual insult and dowry deaths.[52] Sexual insult is arguably a *less severe* crime; it entails verbal remarks or gestures intended to outrage modesty of a woman. The stigma and shame associated with reporting verbal insults is likely to be lower, compared to bodily offenses such as rape and sexual assault, which explicitly violate the bodily integrity of a woman. Dowry deaths, like murder and suicide, are crimes that necessarily amount to death. Considering that it is difficult to hide a dead body and such events are also recorded by Department of Vital Statistics, dowry deaths are less likely to be under-reported, compared to rape and cruelty by husband and his relatives.[53]

To further corroborate that sexual insult and dowry deaths have relatively low reporting bias, I present a few descriptive statistics from the incident-level micro-data (discussed in Section 4.1.2). These statistics indicate that sexual insult and dowry deaths have a lower reporting-lag (proxy of reporting bias), compared to other categories such as rape and cruelty by husband/his relatives. The proportion of cases reported with a lag among total cases of dowry deaths and sexual insult is 15% and 22%, respectively, compared to 42% and 52% for rape and cruelty by husband/his relatives, respectively. Moreover, the average lag (i.e. number of days of lag) is 75 days and 17 days for dowry deaths and sexual insult, respectively, compared to 187 days and 947 days for rape and cruelty by husband/relatives.

If the criminal retaliation channel were to hold, i.e. more crimes against women were indeed

[52] These two categories cumulatively make up 10% of total reported VAW.

[53] As per an Indian law (first introduced in 1986), postmortem examinations are compulsory in cases in which a woman dies within seven years of marriage, reducing the likelihood of such cases being unreported or mis-reported.In most cases, these crimes are reported by family and friends of the bride.

taking place, we should find an increase in reported cases of sexual insult and dowry deaths. On the contrary, estimates from column (5) and (6) of Table 3 indicate a significant reduction exclusively for these two categories.[54] This indicates that between the two sub-channels - criminal retaliation and criminal deterrence - the latter is seemingly stronger. Moreover, these reductions are not observed for the remaining four categories of VAW (see columns (1)-(4) in Table 3), possibly due to a countervailing increase in reporting – discussed in the next sub-section.

6.2 Survivor Disclosure

Can the estimated increase in reported VAW be attributed to an increase in disclosure?

I attempt to answer this question by investigating the impact of the shock on *reporting-lag*. Considering that the primary data are aggregated at the district-level and we cannot observe information on individual cases, I use the daily, incident-level data (available only for Delhi) to conduct this analysis.

As mentioned before, these data provides rich contextual information on registered cases.[55] They records information on two important dates: (i) date of crime occurrence and (ii) date of crime reporting. Using these dates, I construct a measure of reporting lag. A case is considered reported with a lag if it was reported more than 72 hours after it occurred.[56]

It is instructive to note that in 43% of the FIR reports pertaining to VAW, the date of crime occurrence was missing; the corresponding number for gender-neutral crimes was only 20%.[57] Among the VAW cases where incident date was missing, 96% were cases relating to cruelty by husband or his relatives. Qualitative evidence from in-depth interviews with police officials suggests that in most cases of cruelty by husband/his relatives, the survivor is unable to recall the exact date when violence took place for the first time, especially since most cases are usually reported only after repeated and prolonged abuse. Consequently, several reports have missing incident dates. This renders a sub-sample - 74% of the full sample - that can be used for the reporting-lag analysis.[58]

[54] Female deaths include dowry deaths and female suicides, and several other categories that correspond to natural or unnatural causes of death. Therefore, it is unsurprising that we find a significant decrease in dowry death, but no change in suicide and female deaths.

[55] At the same time, these data should be used with some care and caution. In Appendix F, I provide a few caveats on using these data.

[56] The 72 hour cutoff was decided through consultations with officials from Delhi Police. The cutoff is considered to minimize inclusion error; some cases may not get registered immediately due to limited access to police station, absence of police official at help desk, or in some cases the aggrieved may wait to resolve matters internally before escalating it to the police (this is especially common in property disputes). The results remain stable to altering the 72-hour cutoff (results available on request).

[57] I use the same crime categories used in the primary analysis; VAW includes rape, sexual assault, sexual insult, cruelty by husband/his relatives, dowry deaths and kidnapping. Gender neutral crimes include murder, robbery, burglary, dacoity, counterfeiting, criminal breach of trust and riots.

[58] It is possible that if a case is being reported after a very long delay, then either the complainant or the

Descriptive Evidence

In the resulting sub-sample, I find that 38% of VAW cases were reported with a lag, compared to 15% for gender-neutral crimes. Reporting lag is calculated as the number of days elapsed between occurrence and reporting of crime. I find that the average lag among cases of VAW is 370 days. The lag is highest among cases of cruelty by husband and his relatives, i.e. 947 days, on average. This is consistent with the past evidence, which suggests that survivors of intimate partner violence face substantial reporting barriers (García-Moreno et al., 2005; Kishor and Johnson, 2005). On the other hand, the average lag for gender neutral crimes is 121 days. The lag among gender neutral crimes also seems to be on the higher side; most of the lag is stemming from property crimes such as counterfeiting and breach of trust. Evidence from the field reveals that in cases of property disputes, complainants may first try to resolve the conflict among themselves and only on drawing a blank, they may contact the police.

The average lag among VAW cases increased slightly from 369 days (reported before the shock) to 371 days (reported after the shock). However, if I exclude the cases that were reported retrospectively, i.e. cases that had *occurred* before the shock but were reported after the surge in public activism, I find that the average lag falls to 29 days.[59] This reduction in lag-days indicates a decline in reporting-bias and provides suggestive evidence in support of *contemporaneous disclosure*.

Further, I find that the average lag among cases that were reported retrospectively is quite high, i.e. 1,737 days. Expectedly, these are cases that could have occurred several months/years before the shock and got reported only after the rise in public activism against VAW. This phenomenon is akin to the surge in disclosure of cases after the global *MeToo* movement and provides suggestive evidence in support of *retrospective disclosure*. These retrospectively reported cases make for 20% of VAW cases that were reported after the shock; the analogous proportion for gender-neutral crimes is 5%.

An important caveat in interpreting results from this lags analysis is that it could suffer from a right-censoring problem. For instance, consider an extreme case where a crime occurred in 2014, but it was reported with a lag as large as 1700 days. Such cases will not be observed in the FIR dataset as the report date lies outside time frame for which the data are available, i.e. till June 2015.

recording officer may strategically choose to not add information on the incident date in the FIR report. This may bias the results on reporting-lag and I cannot completely rule-out the possibility of such strategic behavior. Although, evidence from the field does not suggest any indication of such manipulation on behalf of the police. On the contrary, in instances where there may be missing fields in the FIR report, the recording officer is likely to follow-up with the complainant and complete the report. I provide more discussion on strategic recording of cases in Appendix F.

[59] Retrospectively reported cases include cases that were reported after December 16, 2012 (date of gang-rape incident) and had occurred before December 13, 2012.

Regression Framework

To estimate the effect of the shock on reporting-lag more formally, I utilize a DiD specification, exploiting variation by crime type and over time. I do not use the primary empirical strategy based on district-wise exposure, since I do not observe meaningful regional variation in exposure *within* Delhi. This is unsurprising because the gang-rape incident took place in Delhi. Being a local crime and *one of its kind* incident, all regions within Delhi were similarly exposed, yielding little variation that can be exploited to identify the effect.[60] Therefore, I utilize an alternative DiD strategy, which is based on variation by crime type (i.e. VAW vs. gender neutral crimes) and by time (before and after the shock).[61] The sample includes 13 crime categories, six VAW and seven gender-neutral crimes, observed over four years (2011-15). Each observation is recorded at the level of police station (176) $\times$ crime type (13) $\times$ month-year of crime report date (57).

I test two predictions: (i) proportion of cases reported with a lag, out of the total cases reported, falls significantly after the shock (i.e. effect on the extensive margin) (ii) average number of lag-days reduces significantly post-shock (i.e. effect on the intensive margin).

$$y_{ps,c,t} = \beta(post_t \times VAW_c) + \gamma_{ps} + \delta_t + \alpha_c + \epsilon_{ps,c,t} \tag{6}$$

$y_{ps,c,t}$ is the outcome variable recorded for police station ps for crime type c on month-year t. Outcome variables include (i) percentage of cases that were reported with a lag and (ii) average lag-days. Post is a dummy that takes value 1 if the case was reported after the shock (i.e. December 2012) and 0 otherwise. VAW takes value 1 if the crime category c is a type of VAW and 0 otherwise. Consistent with the primary analysis, types of VAW include rape, sexual assault, sexual insult, cruelty by husband or his relatives, dowry deaths and kidnapping of women and girls. Gender neutral crimes include murder, dacoity, burglary, robbery, riot, counterfeiting and criminal breach of trust. γ_{ps}, δ_t and α_c are police-station, month-year and crime type fixed effects, respectively. $\epsilon_{ps,c,t}$ is the idiosyncratic error term that is clustered at the level of crime type. Since there are only 13 crime types or clusters, standard asymptotic tests could over-reject the null. Therefore, I utilize wild cluster bootstrap procedure to estimate standard errors, clustered by crime type (Cameron et al., 2008). In order to cleanly identify changes in reporting-bias before and after the shock, I exclude cases that were reported retrospectively from this estimating sample. It is pertinent to exclude these cases in order to pin-down changes in reporting behavior among cases that *occurred* after the shock and thereby, furnish evidence on contemporaneous disclosure.

Estimate from column(1) of Table 6 shows a decrease in percentage of cases reported with a lag after the shock - a reduction of 15% (relative to pre-shock mean). Similarly, estimate from column (2) of Table 6 shows a decrease in the magnitude of lag - a reduction of around 35% (relative to pre-shock mean). These estimates demonstrate a measurable decline in

[60] Standard deviation of the exposure index within Delhi is 0.03, compared to 0.13 for the national sample. Mean exposure within Delhi is 0.77, which is almost at 99 percentile of the national sample exposure distribution (mean of national sample= 0.42)

[61] I show that the primary findings can be replicated using the alternative DiD strategy in Appendix D.

reporting-lag after the shock, both at the extensive as well as at the intensive margin.

Notably, these results indicate that the effect of the shock was not only confined to adjusting a backlog in reporting (through retrospective disclosure), but more importantly, it may have also engendered changes in subsequent reporting behavior (i.e. contemporaneous disclosure). This interpretation is also consistent with the trends shown in Figure 4, which depicts that the primary effect was not just a one-time spike in 2013, instead it continued to hold in subsequent years.

Finally, I present results on relevant identification and consistency checks in Appendix D. I test if: (i) the alternative DiD strategy (based on variation by crime type and time) satisfies identification checks, (ii) the primary findings (shown in Table 2) can be replicated using the alternative strategy, and (iii) the primary findings generated at all-India level can also be generated if the sample is restricted to only Delhi. First, the event study graph in Figure D.1 demonstrates satisfaction of parallel trends. Second, similar to the primary results, estimates from column (1) of Table D.1 show a significant increase in reported crime among cases of VAW (compared to gender neutral crimes) post-shock (compared to pre-shock). Notably, results from the triple difference analysis (shown in Table 5) also lend credibility to the alternative DiD strategy. Third, the estimate from column (2) of Table D.1 indicates an increase in reported VAW, even when the sample is restricted to only Delhi.

6.3 Police Responsiveness

Can the estimated increase in reported VAW be attributed to an increase in registration or recording of cases?

To test the validity of this channel, I investigate the effect of the shock on arrest rate, charge-sheet rate, conviction rate and case pendency (each outcome is explained in subsequent discussion). These outcomes have commonly been used to measure police and judiciary responsiveness (Iyer et al., 2012; Amaral et al., 2018).

Since the data on these variables are not available at the district level, I use the alternative DiD strategy, which is based on variation by crime type and time (similar to the strategy used to examine survivor disclosure). Data on these variables are available for years 2007-18 for all the 13 crime categories. I estimate the following model:

$$y_{c,t} = \beta(Post_t \times VAW_c) + \alpha_c + \delta_t + \epsilon_{c,t} \tag{7}$$

Each observation is recorded at crime type by year level; y_{ct} is the outcome variable (arrest rate, conviction rate, etc.) for crime category c in year t; α_c is crime type fixed effects and δ_t is year fixed effects. VAW takes value 1 if the crime category c is a type of VAW and 0 otherwise. Post takes value 1 if year is between 2013-18 and 0 otherwise. $\epsilon_{c,t}$ is the idiosyncratic error term that is clustered at the level of crime type. Since there are only 13 crime types/clusters, I estimate standard errors using wild-cluster bootstrap.

Consistent with findings from the primary analysis, estimate from column (1) of Table 7 shows an increase in reported VAW (compared to GN crimes) after the shock. Columns 2-4 present results on police activity and columns 5-7 present results on judiciary activity.

I find a significant increase in arrest rates (number of arrests made per 100,000 population); an increase of nearly 31% among cases of VAW with respect to GN crimes, post-shock (see column 2). This suggests a rise in police responsiveness towards VAW; more arrests were being made possibly due to an increase in number of reported cases. The increase in responsiveness is also demonstrated through a measurable decline in case-pendency, i.e. decrease by 17% (shown in column 3). Case pendency rate refers to proportion of cases that were left pending for investigation at the end of year, out of the total number of cases registered for police investigation at the beginning of the year. It is noteworthy to find a decrease in pendency rate, despite a substantial increase in police's work-burden with the rise in reported cases post-shock.

Although, does the increase in police activity come at the cost of the quality of investigation? Following Iyer et al. (2012), I examine data on charge-sheet rate to answer this question. Charge-sheet rate refers to proportion of cases in which police's investigation is up-held by the district magistrate in the court and a formal charge is issued against the accused. Thus, a high charge-sheet rate is indicative of good investigation-quality. However, estimates from column 4 demonstrate a significant decline in charge-sheet rate among cases of VAW post-shock - an 11% decline (see column 4). This indicates that the improvement in case completion (an outcome at the extensive margin) could be at the cost of quality of investigation (an outcome at the intensive margin).

Results in columns 5-7 provide estimates on judiciary response. I find a significant increase in case pendency at courts (increase by 2%). Case pendency refers to number of cases pending for trial at the end of the year, out of the total number of cases registered for trial at the beginning of the year. The increase in pendency could possibly be due to a surge in court's work-burden, indicating that the supply-side response by the courts was not commensurate to the increase in demand for justice on cases of VAW. In a similar vein, I find a decrease in conviction rate by 16% (shown in column 6). Conviction rate refers to number of cases, which amounted in conviction out of the total number completed trials. Both these findings, i.e. increase in case-pendency and decrease in conviction rate, indicate a reduction in judicial response.

However, the interpretation of results on judicial response can be a little complicated due to considerable lag in case-disposal by courts. The average time taken for a case to get disposed by the courts is around three years and nine months (NCRB). Thus, the convictions made in given year are likely to correspond to cases that were registered approximately 4 years ago. To account for this lag, I run another analysis in which I limit the sample to years 2007-2012 and years 2016-18 (I drop years 2013-2015) and re-estimate the effect of the shock on conviction rate. The shock could have affected conviction rate for cases that were tried in or after 2016 (these correspond to cases that were registered in 2012 and after). However, it could not have influenced the conviction rate for cases that were tried in or before 2012 (these correspond to cases that were registered before 2008). Thus, by limiting the sample duration, I can cleanly divide the sample into two groups: pre-shock (2007-2012) and post-shock (2016-18). The results from the restricted sample (shown in column 7) also indicate a decrease in conviction rate; thereby, demonstrating a decline in judiciary response.

Finally, summarizing the result on mechanisms: I do not find any indication of increase in occurrence of VAW. On the contrary, I find some evidence on decrease in incidence among VAW crimes that have a low reporting bias, such as dowry deaths and sexual insult. Further, the estimated reduction in reporting-lag points to an increase in survivor disclosure. Alongside, I find moderate evidence on increase in police responsiveness at the extensive margin.

Admittedly, it is difficult to further disentangle the pathways on survivor disclosure and police responsiveness, since the crime data only includes cases that *finally got reported* and does not provide any information on *how* the case got reported, i.e. interactions between the survivor and police prior to case-registration are latent. Nonetheless, in an attempt to shed more light on the difference between these two sub-mechanisms, I run an alternative model (M4), which adds police range by year fixed effects to the preferred specification. Adding police range by year fixed effects (shown in Equation 8) controls for varying levels of police supply and stand-alone initiatives that police bureaucrats may undertake in response to an evolving crime climate. Police range is an administrative unit one level above the district. Each police range is made of three to six districts and is headed by an Additional Director General (ADG) or an Inspector General (IG). The officer-in-charge of each range has a large measure of administrative control and takes decisions relating to new appointments, postings, granting leaves, rewards and punishments.

$$y_{drt} = \beta(Exposure_d \times Post_t) + \alpha_d + \tau_t + \gamma_{rt} + \epsilon_{drt} \tag{8}$$

where y_{drt} measures rate of VAW in district d from police-range r in year t. γ_{rt} represents police-range by year fixed effects. All other variables follow same definition as Equation 2.

Estimate from column 2 in Table A.6 demonstrates that the primary effect holds even after accounting for plausible changes in police staffing. This suggests that the estimated effect cannot entirely be attributed to an increase in police responsiveness, and that the survivor disclosure channel is likely to be driving the increase in reported VAW. Overall, these results suggest that the observed rise in VAW could be viewed as a positive change; the rise in public-activism could have emboldened women to report crimes, which is an important first step towards obtaining justice and strengthening deterrence against such crimes.

6.4 Other Competing Explanations

6.4.1 Pseudo-Reporting

A competing explanation for the increase in disclosure of VAW could be a rise in pseudo-reporting, post-shock. It is possible that taking advantage of the charged atmosphere against VAW, some women may falsely implicate men and report bogus cases. While it is particularly hard to measure instances of pseudo-reporting, I examine the validity of this explanation by examining changes in false report rate, i.e. proportion of cases that were deemed false or a mistake of fact/law by the police after completion of investigation.

Figure A.6 shows that the rate of false reports, i.e. number of false reports out of the total number of investigations completed by the police, varies between 5% to 20% (depending on type of VAW). This is consistent with estimates provided by past scholarship, which indicates that the likelihood of false reporting is quite low, i.e. between 2% to 11%.[62] Importantly, Figure A.6 indicates no discernible change in the rate of false-reporting during the sample period (for most crime categories); thereby, indicating the estimated increase in VAW cannot be solely attributed to a rise in pseudo-reporting.[63]

6.4.2 Women Police Stations

Recent studies indicate that establishment of all-women police stations can increase recording of crimes against women (Amaral et al., 2018; Perova and Reynolds, 2017). Thus, another explanation for the estimated increase in disclosure could be the proliferation of all-women police stations in India during the sample period.

To check the validity of this competing mechanism, I conduct two tests. First, I conduct a restricted sample test, where all districts that had an all-women police station at baseline (i.e. in 2012) are dropped from the sample. In 2012, 294 of the 633 districts had an all-women police station. Results from panel A in Table A.7 demonstrate that the primary effect still holds. In the second test, I add a time-varying dummy control variable, which takes value 1 if a district d had an all-women police station in year t. Yet again, results from panel B in Table A.7 demonstrate that the primary effect is intact.

[62] Heenan and Murray (2006): 2.1%; Kelly et al. (2005): 2.5%; Lisak et al. (2010): 5.9%; Lonsway and Archambault (2008): 6.8%; Grace et al. (1992): 8.3%; Clark and Lewis (1977): 10.3%; Harris and Grace (1999): 10.9%

[63] Admittedly, the false report rate for kidnapping of women and girls seems to be on the higher side (i.e. 20%) and follows an upward trend after 2013. Evidence from the field suggests that the increase in false reports of kidnapping could be attributed to a rise in cases of girls eloping to marry their boyfriend; in such situations, the girl's family may *inaccurately* accuse the boyfriend and his family of kidnapping the girl. These cases are either withdrawn later or found to be a mistake of fact/law. Nonetheless, even if one had to assume that the increase in kidnapping could be attributed to a rise in false-reporting and not truthful disclosure by survivors, a similar claim cannot be made for other crime categories such as rape, sexual assault and cruelty by husband or his relatives.

7 Conclusion

This paper provides one of the first systematic analyses on how social movements can encourage disclosure of VAW via raising awareness and sensitization on VAW, alongside making the knowledge of sexual violence public. Using a difference-in-difference design, I first show that regions that were more exposed - to the 2012 rape incident and subsequent protests- witnessed a sharp increase in reported VAW (to the tune of 27%).[64] I then provide, to my knowledge, the first evidence on increase in *reporting* of VAW by measuring changes in reporting-lag. Using spatially-precise, incident-level micro-data that I compiled, I find a measurable decline in reporting-lag among cases of VAW after the incident, both at the extensive margin and the intensive margin (15% and 35%, respectively).

The study has a few key limitations. First, the crime dataset only record cases that are *formally reported* to the police; there may still be several cases that go unreported. Thus, it is likely that the obtained DiD estimates have a downward bias. Second, the evidence provided on increase in survivor disclosure is based only on data for Delhi (not all-India). Third, the 2012-incident instigated several changes: rise in protests, increase in police vigilance, legislative amends, etc. Given that all these changes took place around the same time at the national-level, it is not possible to estimate the effect of each individual change. Notably, the rise in protests was the foremost reaction to the incident, which also paved the way for subsequent reforms. Lastly, other grave cases of VAW have occurred in India after the 2012 incident (Appendix G provides details on some such incidents), which also sparked a sizable public outcry. As a result, some of the estimated increase in reported VAW, especially in later years, may be stemming from outrage associated with these incidents. While we cannot completely eliminate the possibility of this explanation, it is important to acknowledge that the social movement following the 2012-incident was the *first of its kind* and is likely to have shaped subsequent demonstrations that took off in response to other incidents.

Accounting for these caveats, the findings of this study shed light on how public activism can move the needle on disclosure norms and offers two key policy implications. First, it indicates that community-based interventions could be leveraged to overcome reporting barriers, via raising awareness on incidence and reporting of VAW in a “bottom-up” manner. Second, these results point us to another class of interventions - apart from institutional reforms - that can help in reducing under-reporting by increasing a survivor’s *intrinsic* willingness to report crimes and raising her *demand* for justice. Notably, improvements in reporting can in turn strengthen deterrence and decrease incidence of VAW.

[64] This refers to the estimate from binary treatment

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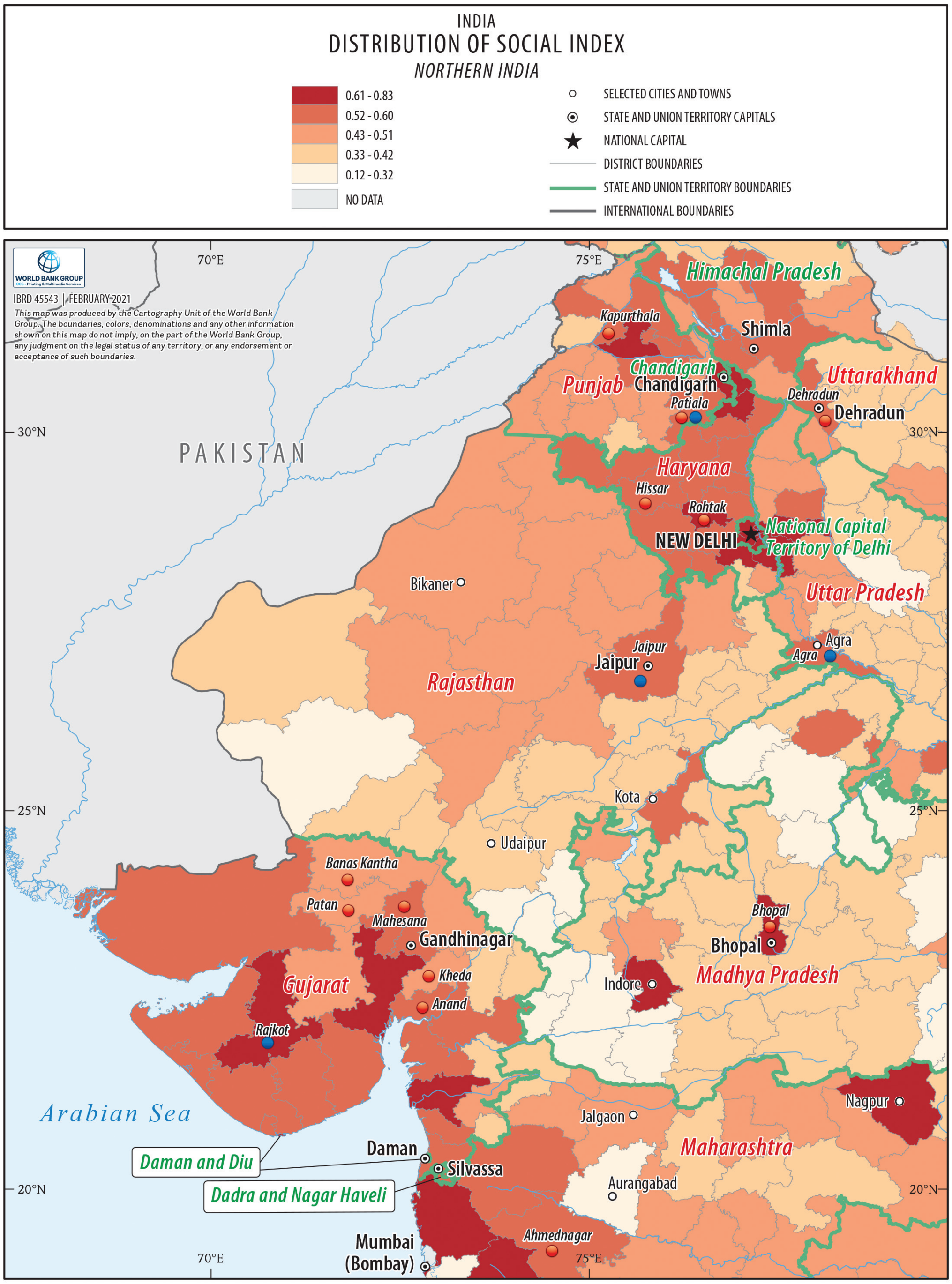
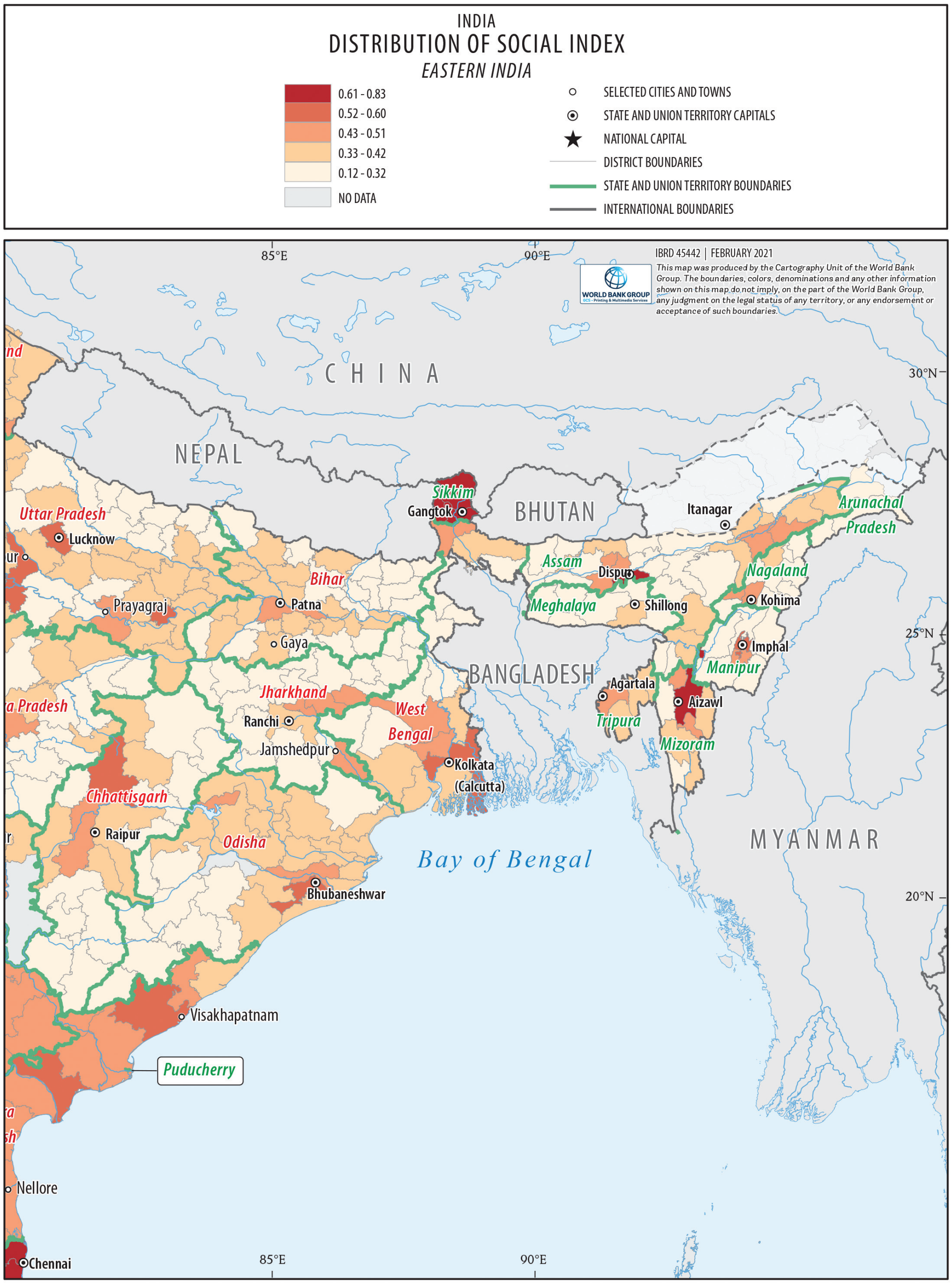
Figures

Figure 1: Treatment Map based on Exposure Index (Northwest Region)



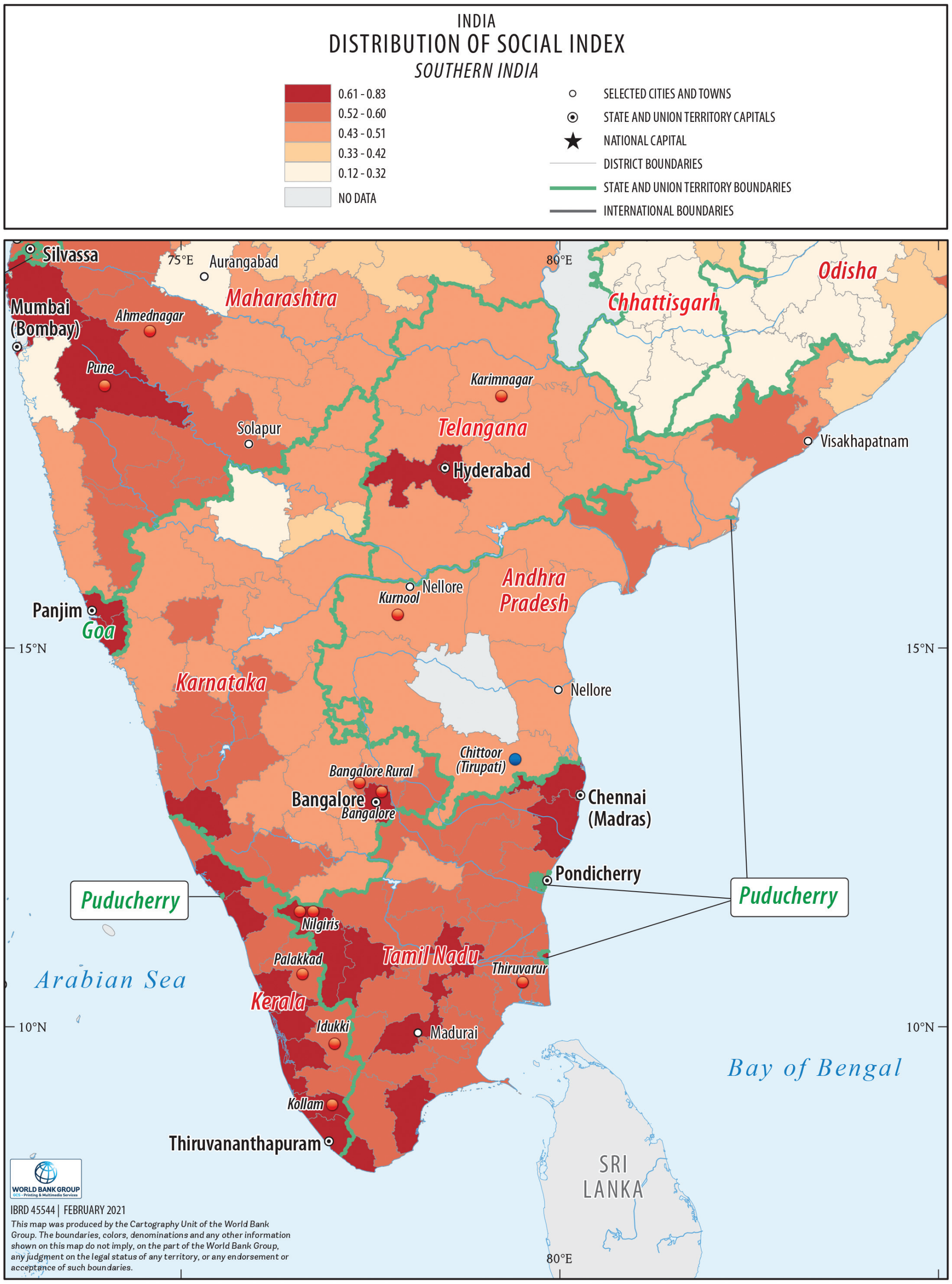
Note: This maps depicts the magnitude of exposure to the shock (i.e. level of treatment intensity) across districts in northwest India. Exposure is measured using a composite index (described in Section 4.2). Darker areas indicate districts with high exposure. This map has been created by the World Bank Map Clearance team, based on guidelines provided by the World Bank Legal Department.
Data Source: Census 2011

Figure 2: Treatment Map based on Exposure Index (East Region)



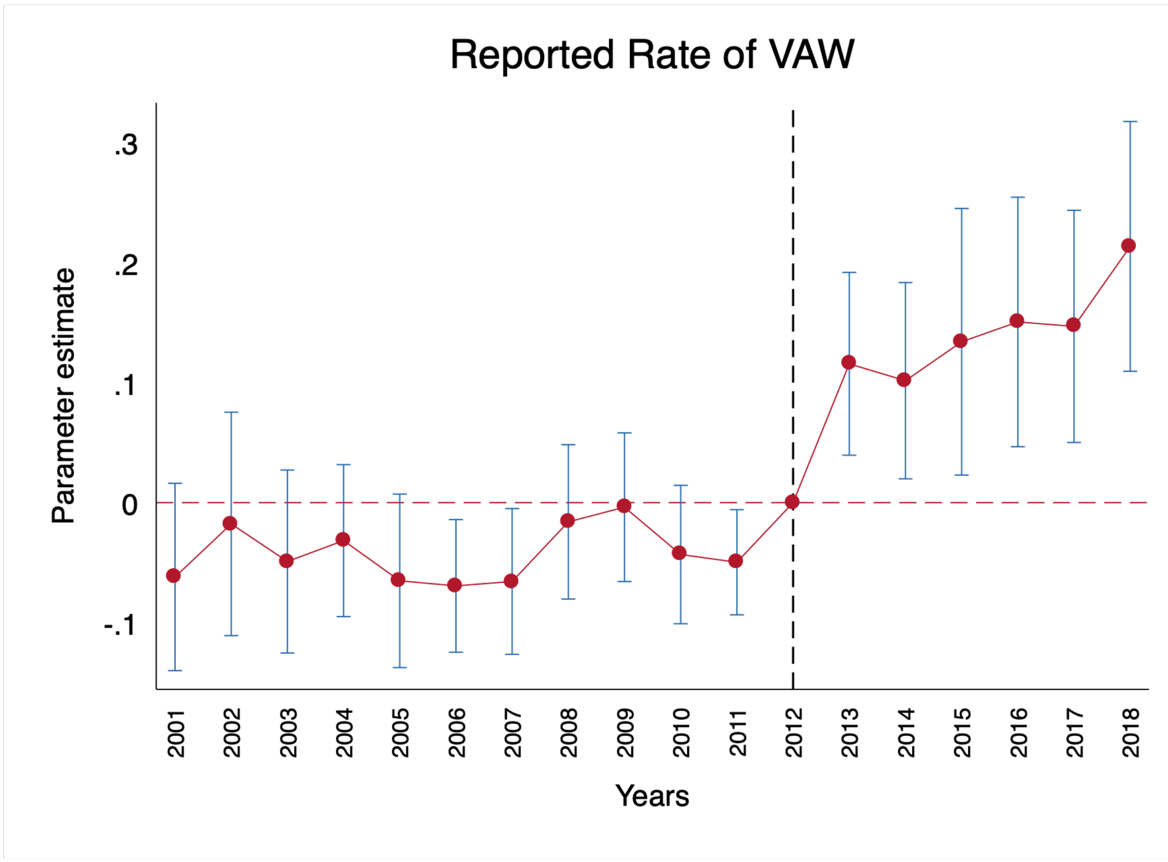
Note: This maps depicts the magnitude of exposure to the shock (i.e. level of treatment intensity) across districts in east India. Exposure is measured using a composite index (described in Section 4.2). Darker areas indicate districts with high exposure. This map has been created by the World Bank Map Clearance team, based on guidelines provided by the World Bank Legal Department.
Data Source: Census 2011

Figure 3: Treatment Map based on Exposure Index (South Region)



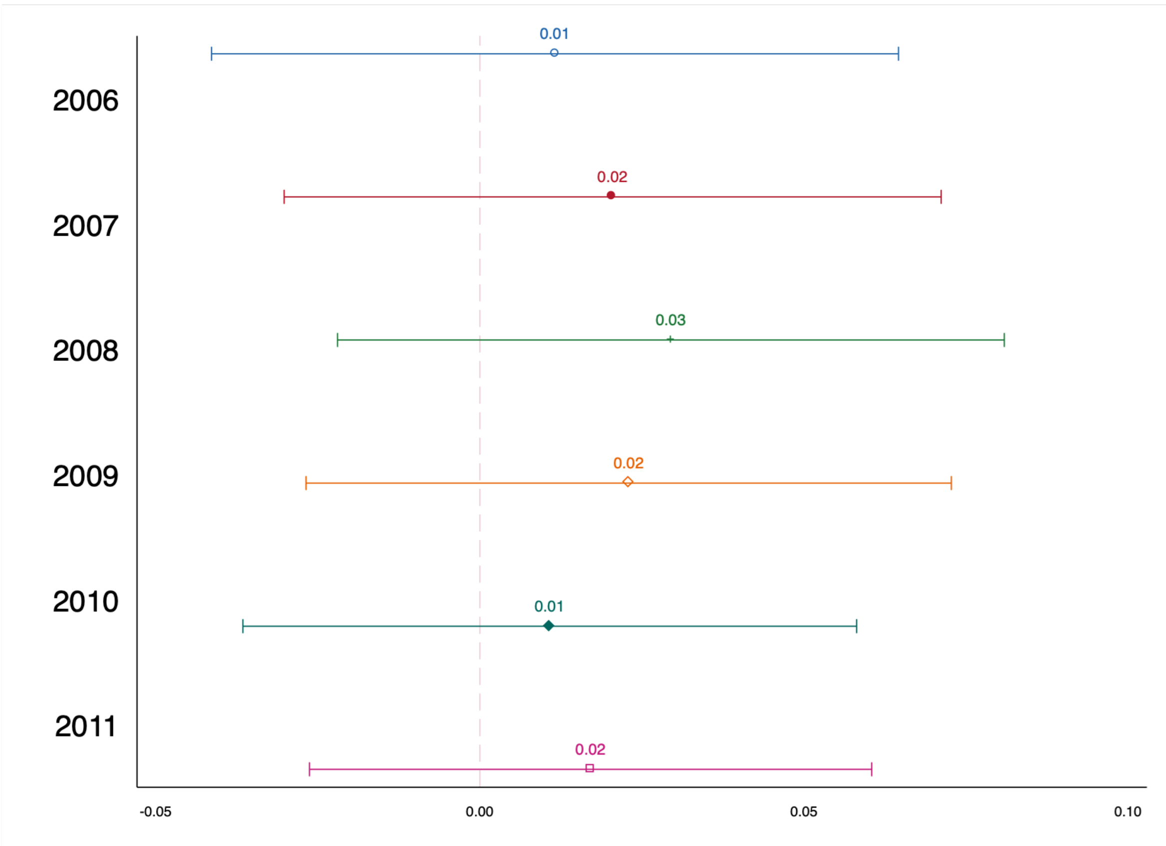
Note: This maps depicts the magnitude of exposure to the shock (i.e. level of treatment intensity) across districts in south India. Exposure is measured using a composite index (described in Section 4.2). Darker areas indicate districts with high exposure. This map has been created by the World Bank Map Clearance team, based on guidelines provided by the World Bank Legal Department.
Data Source: Census 2011

Figure 4: Test of Parallel Trends



Note: This graph plots the coefficients of the interaction terms from the event-study specification (see Equation 3). The outcome variable is reported rate of VAW per 100,000 female population. Model includes district fixed effects, year fixed effects and state by year fixed effects. Considering that the incident took place in *December 2012*and the crime data is available year-wise, I consider 2013 as the first $Post$ year. Hence, the event study graph is centered around 2012 (i.e. t-1). The figure demonstrates satisfaction of the parallel trends assumption.

Figure 5: Placebo Check: Robustness to Timing of Incident



Note: This graph plots placebo estimates from a difference-in-difference specification (similar to Equation 2). Each point estimate represents a separate regression, derived by estimating the effect of a "fake" incident in years 2006-2011, respectively. Model includes district fixed effects, year fixed effects and state by year fixed effects. Robust standard errors are clustered at the district level. The figure indicates that the placebo checks are satisfied. For reference, we recall that the primary estimate was 0.183.

Tables

Table 1: Summary of District Characteristics

District Characteristic	Mean	SD
	Media	
Coverage of Radio	0.20	0.11
Coverage of TV	0.44	0.24
Coverage of Internet	0.02	0.03
Coverage of Phone	0.60	0.19
Coverage of Newspaper	0.77	0.26
	Demography	
Hindu Population	0.74	0.27
Female Literacy	0.55	0.12
Urban Population	0.26	0.21
Young Population	0.24	0.03
	Local Transport	
Coverage of Public Bus	0.58	0.30
	Composite Index	
Exposure Index	0.43	0.14
Number of Districts	633	
Number of Observations	11215	

Table 2: Effect of Shock on Violence Against Women

	(1) M1	(2) M2	(3) M3
Post $\times$ Exposure	0.183***	0.140***	0.128***
	(0.045)	(0.038)	(0.038)
Observations	11215	11215	11043
Adjusted R^2	0.518	0.660	0.724
Pre_Shock_Mean	30.61	30.61	30.61
District FE (633)	Yes	Yes	Yes
Year FE (18)	Yes	Yes	Yes
State-Year FE (33 $\times$ 18)	Yes	Yes	Yes
District-Year Trend	No	Yes	Yes
Physical Proximity	No	No	Yes

Note: This table reports estimates from difference-in-difference specification (see Equation 2). The outcome variable is crime rate of VAW; calculated per 100,000 female population. M3 has fewer observations than M1 and M2 since data on travel time is missing for a few remote districts. Robust standard errors, clustered at district level, are reported in parentheses. * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01.

Table 3: Effect of Shock on Individual VAW Categories

	(1) Rape	(2) Kidnapping	(3) Sex.Assault	(4) Cruelty by hub.	(5) Sex.Insult	(6) Dowry Death
Post × Exposure	0.118***	0.242***	0.152***	0.134***	−0.121*	−0.078***
	(0.033)	(0.052)	(0.039)	(0.040)	(0.064)	(0.022)
Observations	11215	11215	11215	11215	11215	11215
Adjusted R^2	0.344	0.520	0.461	0.470	0.121	0.100
Pre_Shock_Mean	4.47	4.35	7.94	11.00	1.59	1.25

Note: This table reports estimates from difference-in-difference specification (see equation 2). The outcome variable is crime rate of individual categories of VAW; calculated per 100,000 female population. Definition of each crime category is provided in Appendix B. Model includes district FE, year FE and state by year FE. Robust standard errors clustered at district level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Placebo check: No effect on Gender-Neutral Crimes

	(1) GN Crimes	(2) Murder	(3) Dacoity	(4) Robbery	(5) Burglary	(6) Riots	(7) Counterfeit	(8) Breach of Trust
Post × Exposure	0.016	0.056	0.007	0.074	−0.040	−0.008	0.020	0.142
	(0.040)	(0.042)	(0.040)	(0.069)	(0.037)	(0.027)	(0.049)	(0.090)
Observations	11215	11215	11215	11215	11215	11215	11215	11215
Adjusted R^2	0.345	0.280	0.166	0.465	0.373	0.152	0.089	0.154
Pre_Shock_Mean	22.34	3.51	0.54	1.83	9.22	5.68	0.20	1.37

Note: This table reports estimates from difference-in-difference specification (see equation 2). The outcome variable is crime rate of gender neutral crimes; calculated per 100,000 population. GN crimes in column (1) refers to the sum of individual crime categories, shown in columns 2-8. Model includes district FE, year FE and state by year FE. Definition of each crime category is provided in Appendix B. Robust standard errors clustered at district level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Placebo check: Triple Difference Analysis

	(1) DD-VAW	(2) DD-GN	(3) DDD
Post × Exposure	0.117***	0.005	0.005
	(0.028)	(0.011)	(0.010)
Post × VAW × Exposure			0.112***
			(0.022)
Observations	67290	78505	145262
Adjusted R^2	0.218	0.112	0.818

Note: Column (1) and (2) show results from difference-in-difference strategy (see equation 2) for VAW and gender neutral crimes, respectively. Model includes district FE, year FE and state by year FE. Robust standard errors clustered at district level are reported in parentheses. Column (3) shows results for triple difference strategy (see equation 4). Model includes district by crime type FE, year by crime type FE and state by year by crime type FE. Robust standard errors clustered at district by crime-type level are reported in parentheses. The estimate value of Column (1) in this table differs from the estimate value in Column (1) of table 2 because the underlying data structure is different in the two specifications. In DiD analysis, observations are recorded at the district × year level and for triple difference analysis, observations are recorded at district × year × crime type panel.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of Shock on Reporting-Lag

	(1) PcLag	(2) DaysLag
Post × VAW	−0.048***	−86.853***
	(0.012)	(12.365)
Observations	17457	17457
Adjusted R^2	0.309	0.258
Pre_Shock_Mean	0.32	249

Note: This table reports estimates from difference-in-difference specification (see Equation 6). Each observation is recorded at police station × month-year × crime type level. Model includes crime type fixed effects, police station fixed effects and month-year fixed effects. Standard errors are estimated using wild cluster bootstrap procedure clustered by crime type. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of Shock on Institutional Responsiveness

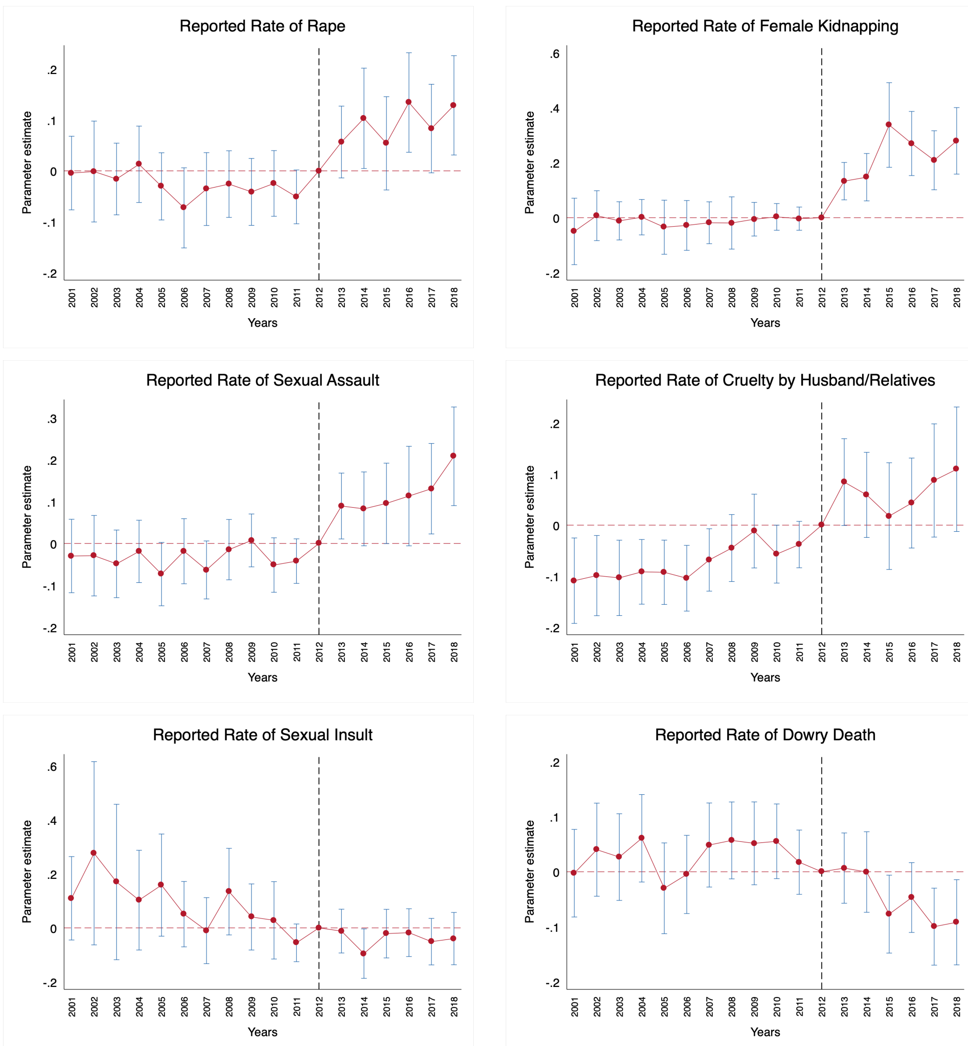
		Police Response			Judiciary Response		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Crime Rate	Arrest Rate	Police Pendency	Chargesheet Rate	Court Pendency	Conviction Rate	Conviction Rate
Post × VAW	2.296***	1.725***	−6.348**	−8.557***	1.939***	−4.467***	−5.234***
	(0.245)	(0.609)	(2.545)	(1.131)	(0.346)	(0.980)	(1.696)
Observations	156	156	156	156	156	156	117
Adjusted R^2	0.953	0.892	0.700	0.940	0.904	0.720	0.710
Pre_Shock_Mean	4.22	5.63	36.88	78.70	86.15	30.05	30.05

Note: This table reports estimates from difference-in-difference specification (see equation 7). Each observation is recorded at crime type × year level. In columns (1)-(6), sample duration includes years 2007-18. In Column (7), sample includes years 2007-12 and 2016-18. Model includes crime type fixed effects and year fixed effects. Standard errors are estimated using wild cluster bootstrap procedure clustered by crime type. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendices

A Additional Tables and Figures

Figure A.1: Test of Parallel Trends for Individual VAW Categories

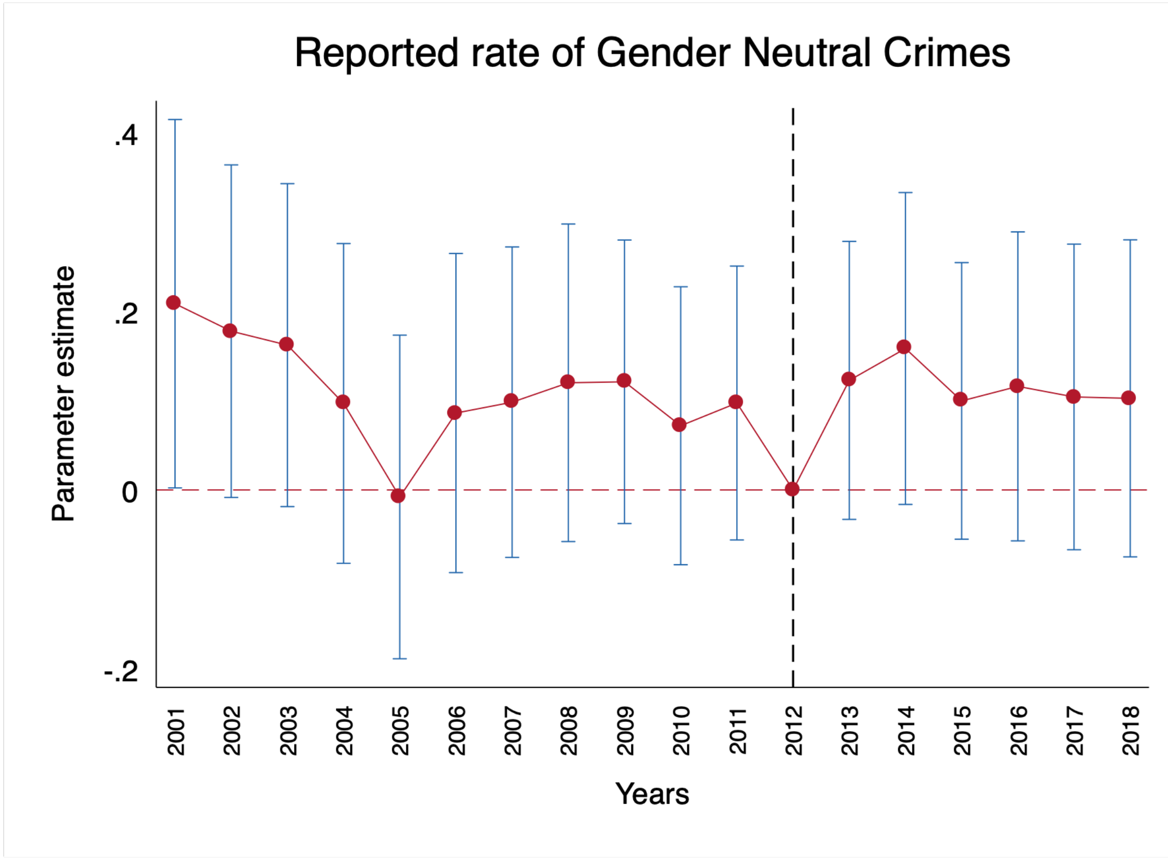


Note: Each sub-graph plots the interaction term coefficients from the event-study specification (Equation 3). The outcome variable represents rate of individual VAW crime categories (per 100,000 female population). Model includes district fixed effects, year fixed effects and state by year fixed effects. Robust standard errors are clustered at district level.

Figure A.2: Police Supply at all-India level

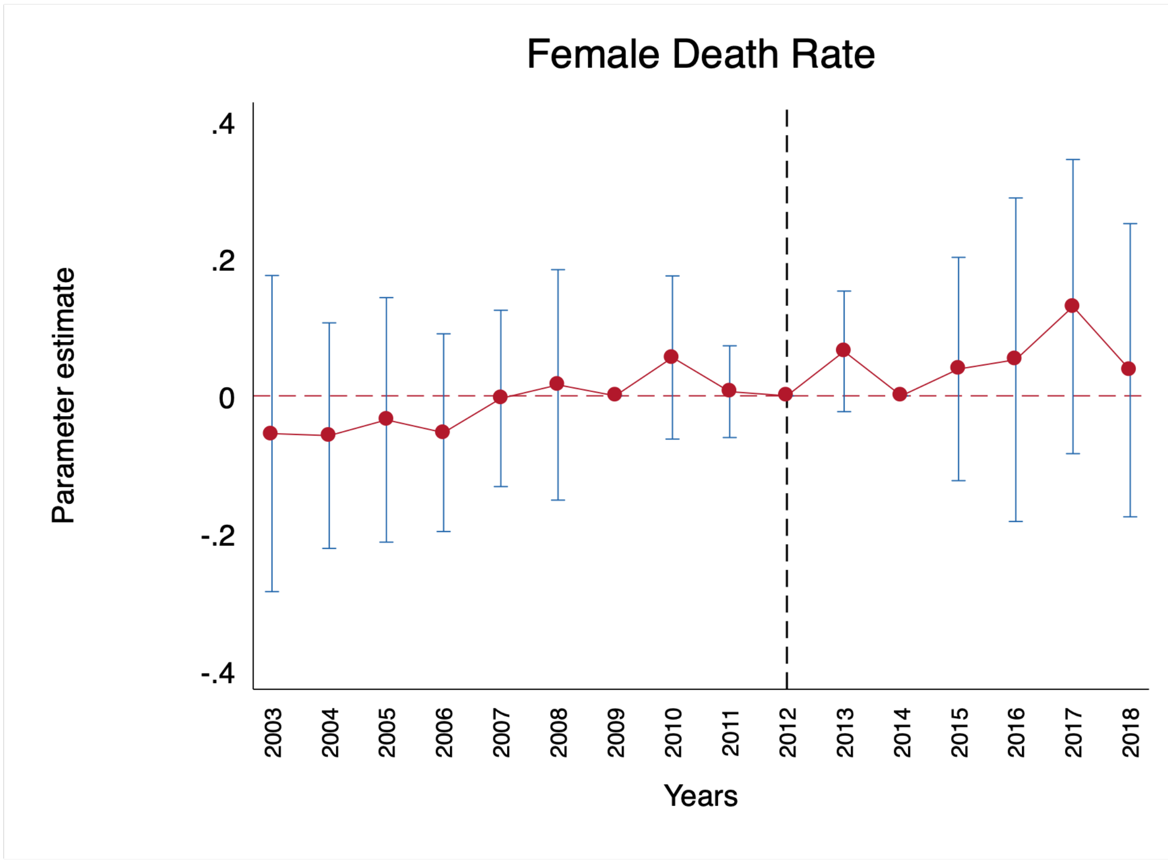
These figures plot changes in the level of police supply at the all-India level during the sample period. Police supply is measured using three indicators, namely population per policeman ratio, police population ratio, and police-area ratio. These plots depict that police supply was fairly stable during the sample period. Data Source: Bureau of Police and Research Development (2007-17), Chapter 1 (Basic Police Data)

Figure A.3: Placebo Check: No change in Gender Neutral Crime



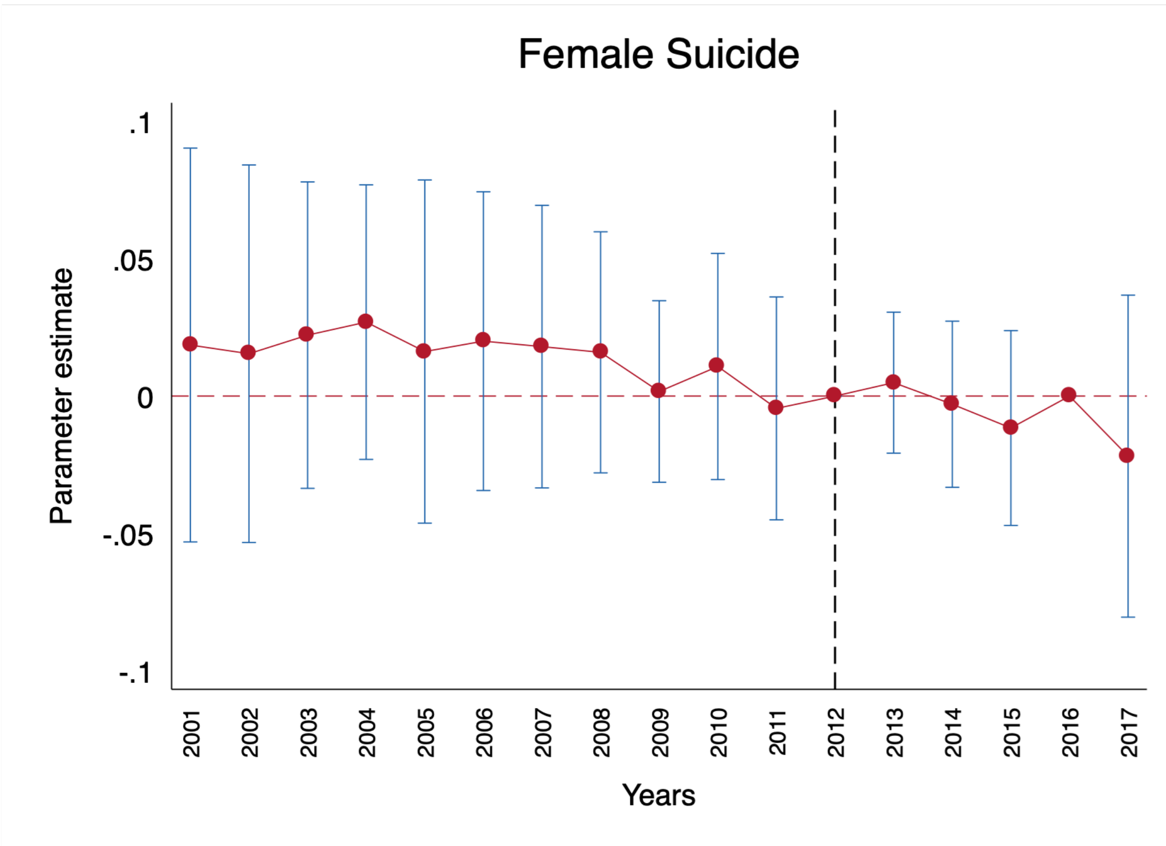
Note: This figure plots the coefficients of interaction terms from the event-study specification (see Equation 3). Gender neutral crime rate refers to the sum of murder, dacoity, robbery, burglary, riot, counterfeit, and breach of trust per 100,000 population. Model includes district fixed effects, year fixed effects and state by year fixed effects. Robust standard errors are clustered at district level.

Figure A.4: Criminal Behavior: No change in Female Death Rate



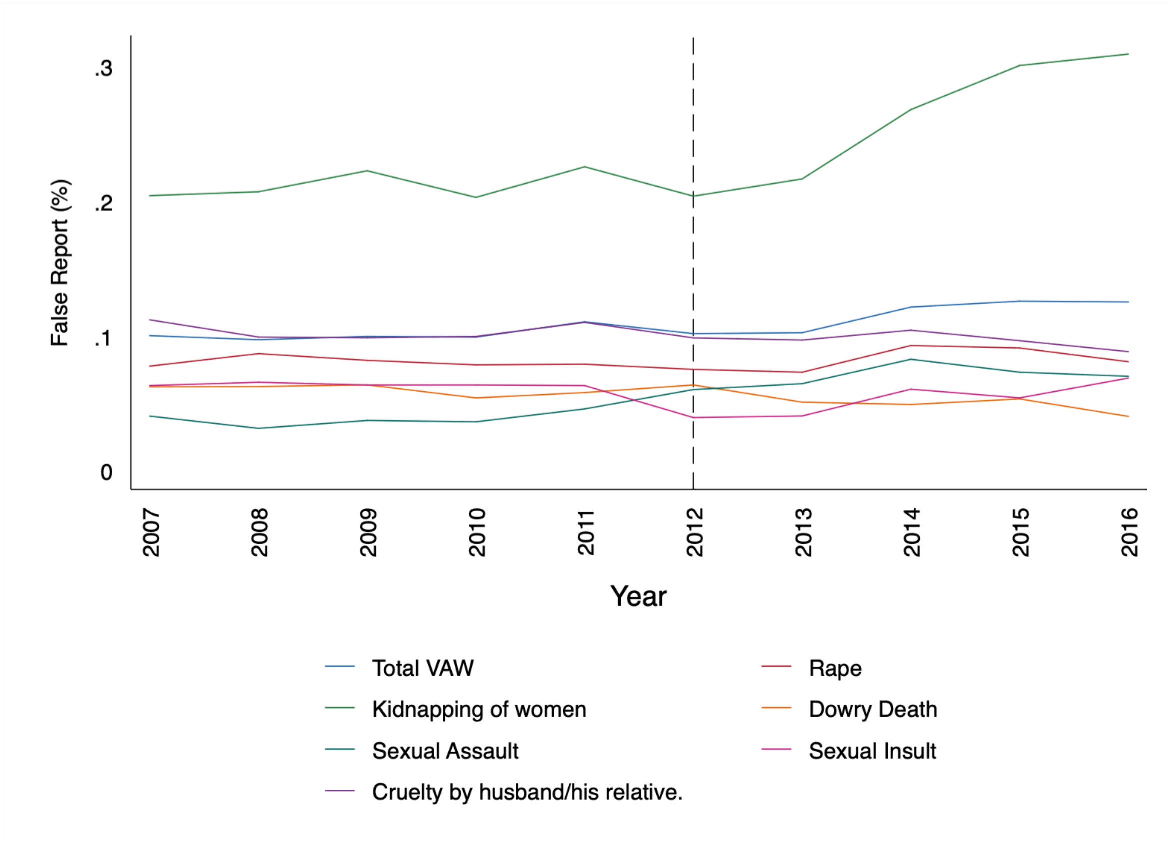
Note: This figure plots the coefficients of interaction terms from the event-study specification (see Equation 5). Female death rate refers to number of female deaths per 100,000 female population. Robust standard errors are clustered at the state level. Data for years 2009 and 2014 is missing. Data Sources: Sample Registration System (SRS).

Figure A.5: Criminal Behavior: No change in Female Suicides



Note: This figure plots the coefficients of interaction terms from the event-study specification (see Equation 5). The outcome variable records total number of female suicides. Robust standard errors are clustered at the state level. Data Sources: Accidental Deaths and Suicides in India, National Crime Records Bureau.

Figure A.6: Pseudo Reporting: Changes in False Report Rate



Note: This figure plots the rate of false reports over time. False report rate is proportion of reports that were found to be false or a mistake of fact/law on completion of police investigation, out of the total number of cases investigated by the police. Data on false report rate is only available at the national level. Therefore, the figure tracks raw changes in false report rate, devoid of any fixed effects or control variables. These plots indicate little change in false report rate for most VAW categories (except kidnapping). Data Source: National Crime Records Bureau

Table A.1: Composition of Exposure Index

Variable	**Description**	**Data Source**
	Media	
Newspaper	Percentage of villages in a district that have daily newspaper supply	District Census Handbook
Television	Percentage of households that own a TV	HH asset ownership module
Phone (mobile phone or landline)	Percentage of households that own a phone	HH asset ownership module
Internet	Percentage of households that own a computer with Internet	HH asset ownership module
	Demography	
Female Literacy Rate	Percentage of women who are literate among total women population	Primary Census Abstract
Religion	Percentage of population who identify themselves as Hindu	Primary Census Abstract
Urban population	Percentage of population who reside in urban areas	Primary Census Abstract
Young population	Percentage of people in age-group 18-30 years old out of total population	Primary Census Abstract
	Transport	
Public-bus	Percentage of villages in a district that have public-buses	District Census Handbook

Table A.2: Robustness to Alternative Sample Restrictions

	(1)	(2)	(3)
Panel A: Dropping Major Cities			
	(1)	(2)	(3)
	M1	M2	M3
Post × Exposure	0.166***	0.123***	0.110***
	(0.049)	(0.040)	(0.040)
Observations	11035	11035	10863
Adjusted R^2	0.509	0.654	0.720
Pre_Shock_Mean	30.41	30.41	30.41
Panel B: Dropping State Capitals			
	(1)	(2)	(3)
	M1	M2	M3
Post × Exposure	0.169***	0.116***	0.098**
	(0.048)	(0.045)	(0.045)
Observations	10639	10639	10467
Adjusted R^2	0.512	0.650	0.718
Pre_Shock_Mean	30.32	30.32	30.32
Panel C: Dropping Delhi			
	(1)	(2)	(3)
	M1	M2	M3
Post × Exposure	0.181***	0.136***	0.124***
	(0.045)	(0.038)	(0.038)
Observations	11053	11053	10881
Adjusted R^2	0.463	0.620	0.690
Pre_Shock_Mean	30.18	30.18	30.18

Note: This table reports estimates from difference-in-difference specification (see Equation 2). Sample in panel A excludes 10 major cities from the sample, namely, Ahmadabad, Bangalore, Chennai, Hyderabad, Jaipur, Kolkata, Mumbai, New Delhi, Pune and Surat. Sample in panel B excludes all state capitals. Sample in panel C excludes all districts in Delhi. Robust standard errors, clustered at district level, are reported in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Robustness to Alternative Construction of Exposure Index (dropping each indicator sequentially)

Rate of VAW (per 100,000 female pop.)	(1) M1	(2) M2	(3) M3
Exposure index constructed excluding:			
		Media Factors	
Coverage of Radio	0.194***	0.147***	0.133***
	(0.0465)	(0.0392)	(0.0399)
Coverage of TV	0.181***	0.139***	0.126***
	(0.0447)	(0.0373)	(0.0378)
Coverage of Newspaper	0.180***	0.150***	0.138***
	(0.0443)	(0.0383)	(0.0385)
Coverage of Internet	0.175***	0.126***	0.113***
	(0.0451)	(0.0378)	(0.0383)
Coverage of Phone	0.188***	0.150***	0.138***
	(0.0447)	(0.0375)	(0.0379)
		Demographic Factors	
Female literacy	0.180***	0.139***	0.127***
	(0.0458)	(0.0383)	(0.0388)
Young Population	0.183***	0.138***	0.128***
	(0.0451)	(0.0380)	(0.0383)
Hindu Population	0.187***	0.137***	0.127***
	(0.0445)	(0.0372)	(0.0373)
Urban Population	0.185***	0.134***	0.124***
	(0.0473)	(0.0398)	(0.0402)
		Local Transport	
Coverage of public-bus	0.160***	0.132***	0.121***
	(0.0427)	(0.0357)	(0.0359)

Note: This table reports estimates from difference-in-difference specification (see Equation 2). Robust standard errors, clustered at district level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A.4: Robustness to Alternative Construction of Exposure Index (PCA and Ranking Method)

	(1)	(2)	(3)
Panel A: PCA Method			
	(1)	(2)	(3)
	M1	M2	M3
Post × PCA Exposure	0.187***	0.151***	0.139***
	(0.044)	(0.037)	(0.037)
Observations	11215	11215	11043
Adjusted R^2	0.519	0.660	0.724
Panel B: Ranking Method			
	(1)	(2)	(3)
	M1	M2	M3
Post × Rank Exposure	0.158***	0.113***	0.093***
	(0.042)	(0.036)	(0.035)
Observations	11215	11215	11043
Adjusted R^2	0.517	0.659	0.723

Note: This table reports estimates from difference-in-difference specification (see Equation 2). Robust standard errors, clustered at district level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Robustness to Alternative Treatment Assignments

	(1) Treatment Intensity	(2) Binary Treatment	(3) Discrete Treatment
Post ×Exposure	0.183***	8.278***	
	(0.045)	(2.005)	
Post×HighExposure			12.65***
			(2.978)
Post×MediumExposure			6.688***
			(2.526)
Post×LowExposure			0.0739
			(2.035)
Observations	11215	11215	11215
Adjusted R^2	0.518	0.516	0.518

Note: Model includes district fixed effects, year fixed effects and state by year fixed effects. Robust standard errors, clustered at district level, are reported in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Comparing Sub-Mechanisms: Survivor Disclosure Vs. Police Responsiveness

	(1)	(2)
	M1	M4
Post Incident × Exposure	0.183***	0.276***
	(0.045)	(0.080)
Observations	11215	10335
Adjusted R^2	0.518	0.554
Pre_Shock_Mean	30.61	30.61
District fixed effects (633)	Yes	Yes
Year fixed effects (18)	Yes	Yes
State-Year fixed effects (33 × 18)	Yes	No
Police range-Year fixed effects (193 × 18)	No	Yes

Note: Columns 1 and 2 reports estimates from difference-in-difference specification, i.e. equations 2 and 8. The outcome variable is crime rate of VAW; calculated per 100,000 female population. Column 2 has fewer observations because data on police range is missing for two Indian states, i.e. Madhya Pradesh and Maharashtra. Robust standard errors, clustered at district level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Competing Explanation: All-Women Police Stations

	(1)	(2)	(3)
Panel A: Dropping districts with women police station			
	(1)	(2)	(3)
	M1	M2	M3
Post × Exposure	0.174**	0.211***	0.196***
	(0.078)	(0.061)	(0.063)
Observations	5961	5961	5825
Adjusted R^2	0.493	0.642	0.728
Pre_Shock_Mean	33.95	33.95	33.95
Panel B: Controlling for presence of women police station			
	(1)	(2)	(3)
	M1	M2	M3
Post × Exposure	0.156***	0.096***	0.085**
	(0.042)	(0.037)	(0.036)
Observations	8154	8154	8028
Adjusted R^2	0.546	0.705	0.709
Pre_Shock_Mean	32.04	32.04	32.04
Women PS Control	Y	Y	Y

Note: This table reports estimates from difference-in-difference specification (see equation 2). Sample in panel A excludes all districts that had an all-women police station at baseline, i.e. 294 districts. Panel B includes all 633 districts, with an additional control for presence of an all-women police station. Data on women police station is only available for years 2005-2017. Robust standard errors clustered at district level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B Crime Definitions

Table B.1: Definition of Crime Categories (Indian Penal Code)

Crime Category	**Description**
Rape	Unlawful sexual activity and usually sexual intercourse carried out forcibly or under threat of injury against a person's will or with a person who is beneath a certain age or incapable of valid consent because of mental illness, mental deficiency, intoxication, unconsciousness, or deception
Kidnapping and Abduction of Women and Girls	Kidnapping, abducting or inducing woman to compel her into marriage or intercourse
Sexual Assault	Assault or criminal force to woman with intent to outrage her modesty. Sexual harassment including advances involving unwelcome and explicit sexual overtures or demanding sexual favors [354A]. Assault or use of criminal force to woman with intent to disrobe [354B]. Voyeurism involving watching or capturing the image of a woman engaging in a private act without her knowledge [354C]. Stalking involving attempts to contact a woman to foster personal interaction repeatedly despite a clear indication of disinterest [354D]
Sexual Insult	Uttering words, making gestures or acting in a way intended to insult the modesty of a woman with the intention to be heard and subsequently intrude upon the privacy of such woman
Cruelty by husband or his relatives	Any unwilful conduct that is likely to drive the woman to commit suicide or to cause grave injury or danger to life, limb or health (whether mental or physical) of the woman. Harassment with a view to coercing a woman or any person related to her to meet any unlawful demand for any property or valuable security or is on account of failure by her or any person related to her to meet such demands
Dowry Deaths	Causing death of a woman by criminal means within seven years of her marriage where it is shown that soon before her death she was subjected to cruelty or harassment by her husband or any relative of her husband for, or in connection with, any demand for dowry
Murder	The act by which death is caused and done with intent
Robbery	Theft or attempted theft along with causing death, hurt or wrongful restraint
Rioting	Force or violence used by an unlawful assembly
Dacoity	Five or more persons conjointly committing or attempting to commit a robbery; the number includes persons committing, attempting or aiding the crime
Counterfeiting	Fraudulent activity, impersonation including counterfeiting a document, property marks,

	currency, instruments etc.
Breach of Trust	Dishonest misappropriation of property
Burglary	House-breaking by night with the intent to commit felony

C Chronology of Delhi Rape

Table C.1: Chronology of Events in the Delhi Rape Case

Date	**Event**
December 16, 2012	Gang rape. 23-year-old physiotherapy student is gang raped on a moving bus in Delhi
December 17, 2012	First four accused arrested
December 18, 2012	Protest outside Vasant Vihar police station (Southwest Delhi district)
December 19, 2012	Male victim testifies in court
December 19, 2012	Protest at India Gate and North Block (Central Delhi district)
December 20, 2012	Two of the accused confess to crime
December 20, 2012	Students protest outside Delhi Chief Minister' residence (Central Delhi district)
December 21, 2012	Sixth Accused Arrested
December 21, 2012	Protest at Rashtrapati Bhawan (Central Delhi district)
December 22, 2012	Protest at India Gate and Raisina Hill (Central Delhi district)
December 23, 2012	Protests continue at India Gate – Constable Subhash Tomar of Delhi Police seriously injured
December 23, 2012	Ride for Law and Order at India Gate
December 25, 2012	Constable Subhash Tomar succumbs to injuries
December 26, 2012	Protest at Jantar Mantar (New Delhi district)
December 29, 2012	Victim dies; accused are charged with murder
December 30, 2012	Protest at Jantar Mantar (New Delhi district)
January 3, 2013	Delhi Police filed charge sheet in Magisterial Court
January 5, 2013	Magisterial Court takes cognizance charge sheet
January 9, 2013	Gag Order prohibiting media from reporting on court proceedings
January 17, 2013	Case Committed to fast track court

January 23, 2013	Verma Committee Report released
January 24, 2013	Arguments begin
February 2, 2013	Accused plead Not guilty
February 5, 2013	Trial begins.
March 5, 2013	Police testify in Court.
March 11, 2013	Ram Singh (one of the accused) found dead in jail cell.
March 15, 2013	Accused charged with robbery (35 yr old carpenter lured into the bus and robbed few hours before the assault)
March 21, 2013	Criminal Law (Amendment) Act, 2013 passed by both houses in the Parliament
March 25, 2013	Media’s Gag removed (allowed in court proceedings)
April 3, 2013	Criminal Law (Amendment) Bill, 2013 came into force
April 21, 2013	Protests over 5-year-old Gudiya who was raped.
May 6, 2013	Vinay Sharma (one of the accused) taken to hospital, suspect he was poisoned in jail.
September 10, 2013	Four men found guilty by Delhi High Court
September 13, 2013	Four men sentenced to death by Delhi High Court
March 13, 2014	Supreme court stayed the execution of two of the four accused who appealed against their conviction
June 2, 2014	Remaining two accused also appealed against their conviction
July 14, 2014	Supreme court stayed execution of remaining accused
August 27, 2015	All 4 convicted of robbery
May 5, 2017	Supreme Court upheld the death sentence of the all 4 accused
July 9, 2018	Supreme Court rejected a review petition filed by 3 of the 4 accused
January 7, 2020	Delhi High Court issues death warrant against all four accused; to be hanged on January 22
January 19, 2020	One of the accused moved a curative plea in the Supreme Court seeking commutation of his death penalty to life imprisonment.
February 28, 2020	Death warrant re-issued against all four convicts; to be hanged on March 3.
March 4, 2020	Fourth death warrant was issued by court with the execution date as 20 March 2020 at 5:30 a.m.
March 20, 2020	All four convicts were executed by hanging at Tihar Jail in New Delhi

D Checks for Alternative Strategies and Samples

1. Difference in Difference (by crime type and time)

1.1 Replication of Primary Results

I estimate the effect of the shock on reported VAW using the following specification:

$$CrimeRate_{c,t} = \beta(Post_t \times VAW_c) + \gamma_c + \delta_t + \epsilon_{c,t} \tag{D.1}$$

Each observation is recorded at crime type-year level; y_{ct} is the crime rate for a given crime category c in year t. Crime rate for VAW is calculated as number of crimes per 100,00 female population. Crime rate for gender neutral crimes is calculated as number of crimes per 100,000 population. γ_c is crime type fixed effects and δ_t is year fixed effects. VAW takes value 1 if the crime category c is a type of VAW and 0 otherwise. Types of VAW include rape, sexual assault, sexual insult, cruelty by husband or his relatives, dowry deaths and kidnapping of women and girls. Gender neutral crimes include murder, dacoity, burglary, robbery, riot, counterfeiting and criminal breach of trust. Post takes value 1 if year is between 2013-18 and 0 otherwise. $\epsilon_{c,t}$ is the idiosyncratic error term that is clustered at the level of crime type, using wild cluster bootstrap procedure (Cameron et al., 2008).

Estimates from Table D.1 show an increase in reported VAW (compared to gender-neutral crimes) post-shock, both for all-India sample (column 1) and only-Delhi sample (column 2).[65]

1.2 Identification Check

I conduct an event study analysis to test if the alternative DiD strategy upholds the parallel trends assumption. Figure D.1 demonstrates satisfaction of the parallel trends and thereby lends credibility to the results obtained on survivor disclosure (Table 6) and police responsiveness (Table 7).

$$CrimeRate_{ct} = \gamma_c + \delta_t + \sum_{\tau=2}^{m} \mu_{-\tau}(VAW_c \times T_{t-\tau}) + \sum_{\tau=0}^{q} \mu_{+\tau}(VAW_c \times T_{t+\tau}) + \epsilon_{ct} \tag{D.2}$$

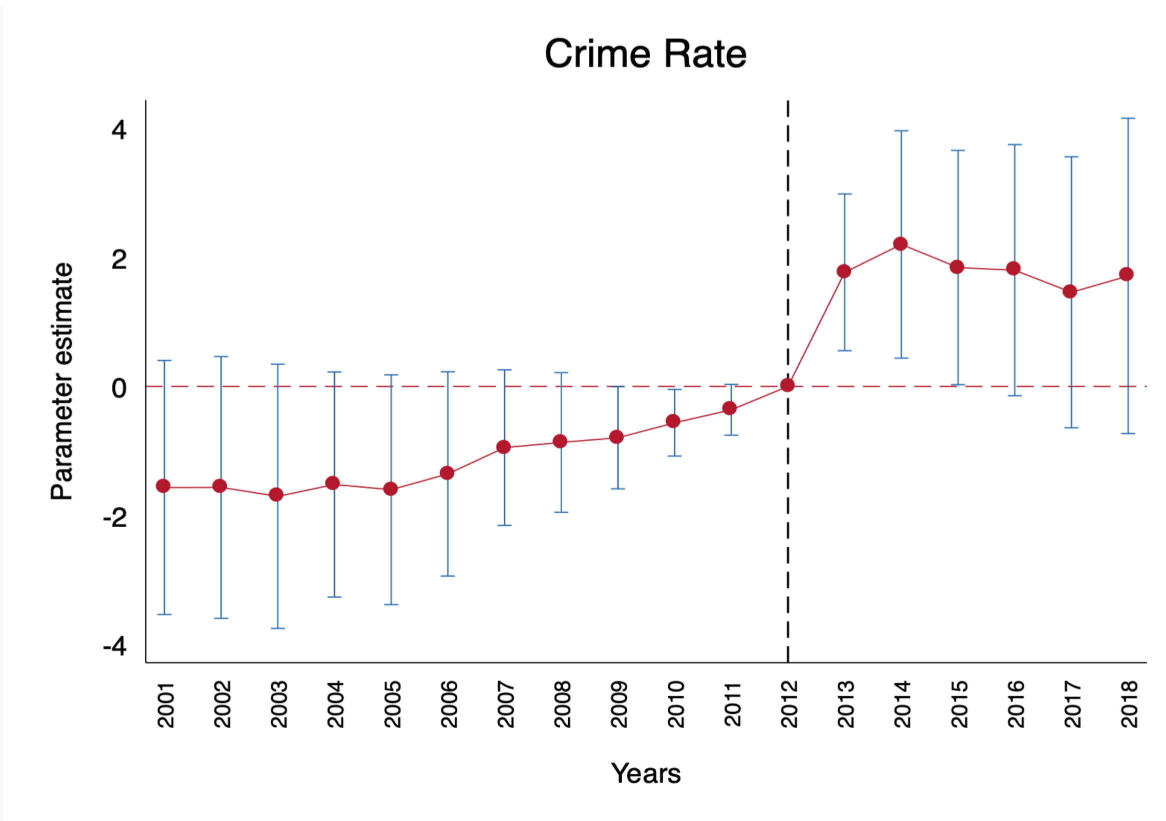
[65] Notice that the crime rate in Delhi is higher than the national average.

Table D.1: Effect of Shock on Crime (DiD by crime type and time)

	(1) CrimeRate	(2) CrimeRate
Post × VAW	3.073***	9.865***
	(0.314)	(2.335)
Observations	234	234
Adjusted R^2	0.917	0.679
Pre_Shock_Mean	4.02	6.08
Sample	All-India	Only Delhi

Note: This table reports estimates from the difference in difference specification (see Equation D.1). Outcome is crime rate, calculated as crimes per 100,000 female population for VAW crimes and crimes per 100,000 population for gender neutral crimes. Model includes crime type fixed effects and year fixed effects. Standard errors are estimated by wild-cluster bootstrap technique clustered by crime type. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure D.1: Test of Parallel Trends (DiD by crime type and time)



Note: This graph plots coefficients of the interaction terms from Equation D.2. Outcome variable is crime rate (per 100,000 population). Model includes crime type fixed effects and year fixed effects. Standard errors are clustered by crime type. This figure demonstrates that the alternative empirical strategy satisfies the parallel trends assumption.

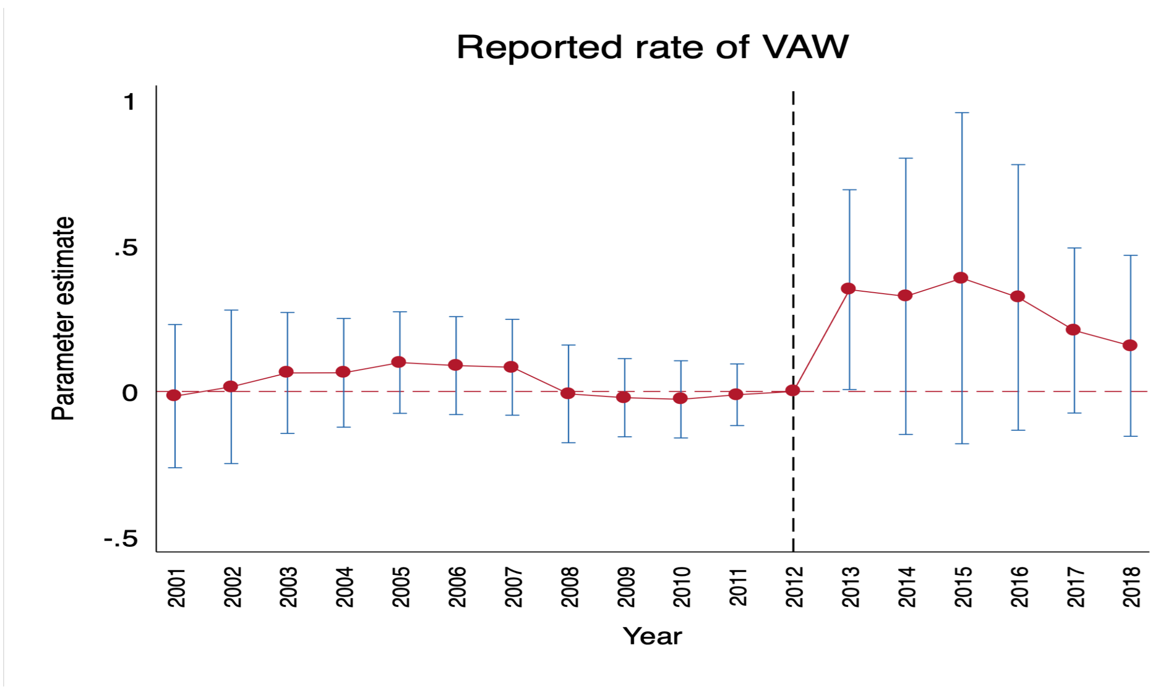
2. Difference in Difference (based on state-level exposure)

Given that the data on a few outcomes such as female death rate and female suicides are only available at the state level (not district), I use a variant of the primary empirical strategy, in which district level exposure is aggregated at the state level. I check whether this tweak in the empirical strategy satisfies the identification check and yields similar results as the primary effect.

To test this, I conduct an event study analysis (Equation D.3). I find that there was no significant difference in the trend of reported VAW between more and less exposed states before the shock, but after the shock the more exposed states witnessed an increase - although not significantly so- in reported VAW (shown in Figure D.2).

$$y_{st} = \gamma_s + \delta_t + \sum_{\tau=2}^{m} \mu_{-\tau}(AvgExp_s \times T_{t-\tau}) + \sum_{\tau=0}^{q} \mu_{+\tau}(AvgExp_s \times T_{t+\tau}) + \epsilon_{st} \qquad \text{(D.3)}$$

Figure D.2: Test of Parallel Trends (state-level exposure)



Note: This figure plots the coefficient of the interaction terms in Equation D.3. The treatment intensity variable, originally assigned at the district-level, is aggregated to yield average treatment intensity at state level. Outcome is reported rate of VAW per 100,000 female population. Model includes state fixed effects, year fixed effects and standard errors are clustered at the state level. There are 33 states in the sample.

E Unpacking the Exposure Index

In the primary analysis, treatment was assigned based on a composite exposure index that was made of ten indicators across three components. In this section, I unpack the composite index and re-assign treatment based on the 10 individual indicators, such that there are 10 distinct variables of treatment intensity.

I first check if the parallel trends assumption holds for each model by conducting event study analyses, similar to Equation 3. Figures E.1 and E.2 suggest that the identifying assumption is satisfied for almost all indicators.[66] In the subsequent regression analysis, I consider three specifications:

In the first specification, I estimate the effect of the shock using each treatment intensity variable in a separate regression, i.e. yielding ten distinct regressions:

$$y_{d,s,t} = \beta_j(IndvExposure_{j,d} \times Post_t) + \alpha_d + \delta_t + \gamma_{s,t} + \epsilon_{d,s,t} \tag{E.1}$$

where, subscript j refers to each individual indicator. It ranges between 1 to 10 and a separate regression is run for each j.

In the second specification, I conduct an analysis using all 10 treatment intensity variables simultaneously in one regression. Estimates from this specification can shed light on the relative strength of the effects measured using individual components of the exposure index.

$$y_{d,s,t} = \sum_{j=1}^{10} \beta_j(IndvExposure_{j,d} \times Post_t) + \alpha_d + \delta_t + \gamma_{s,t} + \epsilon_{d,s,t} \tag{E.2}$$

where, subscript j refers to each individual indicator.

In the third specification, I sequentially run a model where treatment is based on each individual indicator along with the treatment based on the composite exposure index. This analysis helps in identifying the strength of each individual indicator, conditional on the composite measure.

$$y_{d,s,t} = \theta(ExposureIndex_d) + \beta_j(IndvExposure_{j,d} \times Post_t) + \alpha_d + \delta_t + \gamma_{s,t} + \epsilon_{d,s,t} \tag{E.3}$$

where, subscript j refers to each individual indicator. It ranges between 1 to 10 and a separate regression is run for each j.

[66] Admittedly, the evidence for treatment based on newspaper, radio and public-bus is relatively weak.

Table E.1 summarizes the results for all three specifications. Columns (1), (2) and (3) present the results for the first, second and third specification, respectively. Three indicators surface as salient factors - coverage of Internet, female literacy and coverage of public-bus. While the finding on coverage of Internet is robust across all three models, those for coverage of public-bus and female literacy is robust only for models 1 and 2. While not necessarily causal, these estimates elicit strong correlations that are worth exploring.

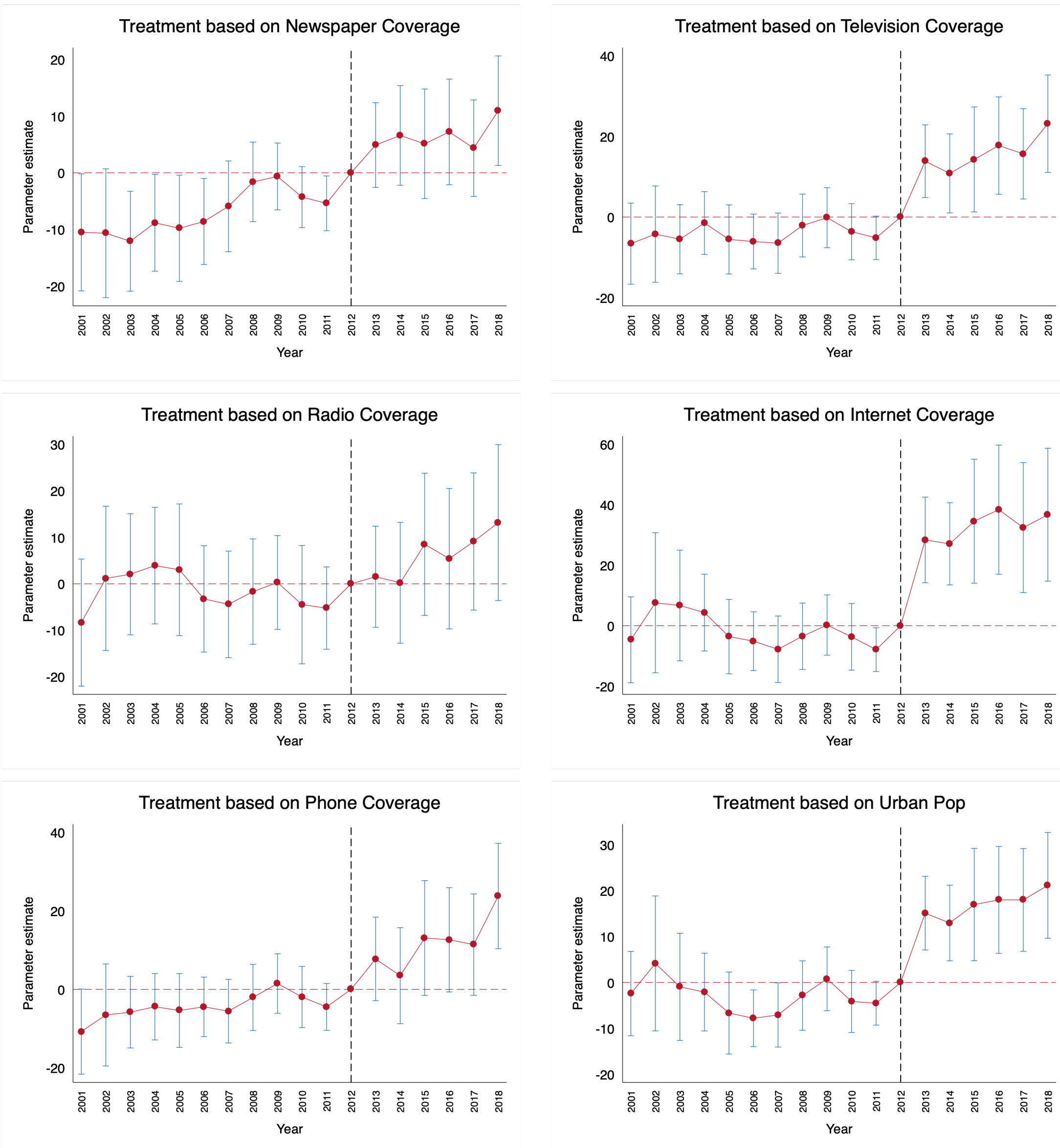
Districts with higher Internet coverage witnessed a significant increase in reported VAW, compared to districts with lower Internet coverage after the shock. This is somewhat expected; media played an important role in disseminating information about the incident and the associated protests.[67] Receipt of this information is the first touch-point of exposure to the incident. Further, among the various forms of media, Internet is the fastest-growing mode and can overcome boundaries of time and space of traditional media.

Similarly, districts with high female literacy witnessed higher rates of reported VAW post-incident. This indicates that empathy and connectedness through literacy is important; regions with high female literacy are likely to share greater empathy with the victim of this incident and thereby witnessed a higher response to this shock.

Finally, districts with greater coverage of public-buses witnessed a higher reported rate of VAW. As discussed previously, regions where people rely more on public transport and claim public spaces are likely to relate more with the circumstances of the gang-rape incident, compared to regions with lower presence of public transport.

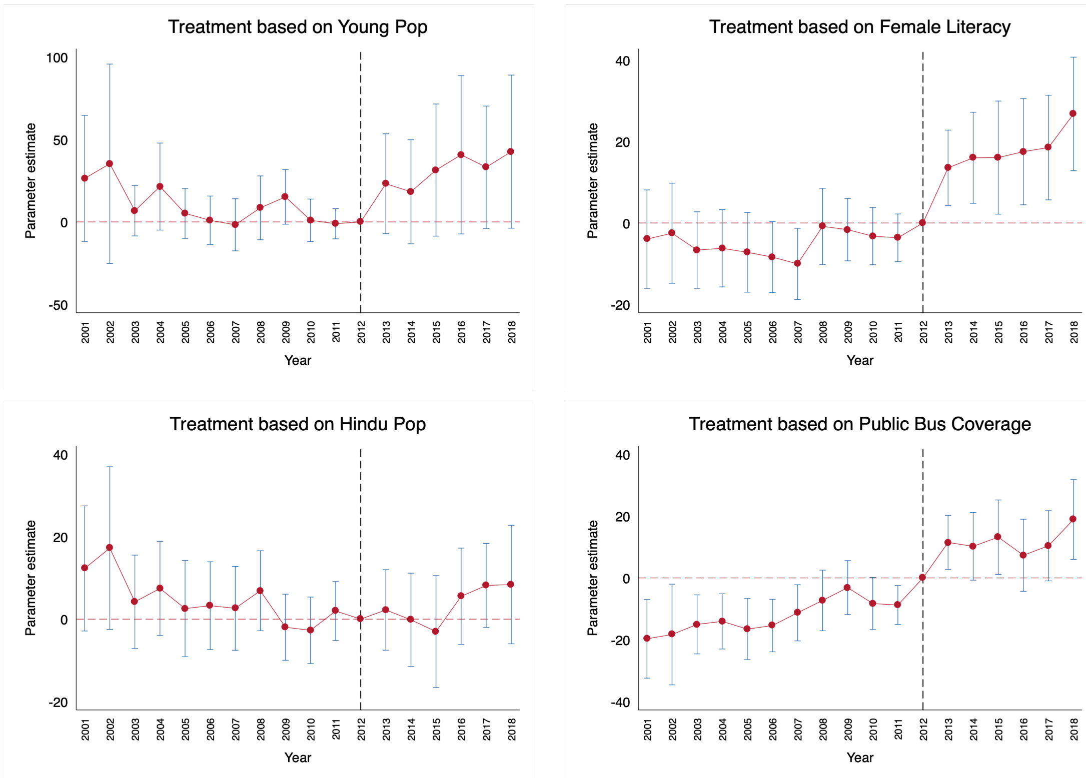
[67] A media content-analysis paper by Phillips et al. (2015) demonstrates that 40% of published media reports on the gang-rape incident were about the protests and outrage over the incident.

Figure E.1: Event Study Graphs (Single Component Exposure - Set 1)



Note: Each sub-graph plots the interaction term coefficients from event-study specification for each individual treatment intensity variable (estimating equation is similar to Equation 3). The outcome variable is reported rate of VAW per 100,000 female population. Model includes district fixed effects, year fixed effects and state by year fixed effects. Robust standard errors are clustered at district level. These sub-figures demonstrate satisfaction of the parallel trends assumption for all individual components of exposure.

Figure E.2: Event Study Graphs (Single Component Exposure - Set 2)



Note: Each sub-graph plots the interaction term coefficients from event-study specification for each individual treatment intensity variable (estimating equation is similar to Equation 3). The outcome variable is reported rate of VAW per 100,000 female population. Model includes district fixed effects, year fixed effects and state by year fixed effects. Robust standard errors are clustered at district level. These sub-figures demonstrate satisfaction of the parallel trends assumption for almost all individual components of exposure, except public-bus.

Table E.1: Effect of Shock on VAW (Exposure based on Single Component)

Rate of VAW (per 100,000 female pop.)	(1) M1	(2) M2	(3) M3
Post × Exposure	X	X	0.082
			(0.057)
Post × Internet	0.167***	0.172***	0.117**
	(0.041)	(0.061)	(0.053)
Post × Exposure	X	X	0.209***
			(0.048)
Post × Radio	0.040	−0.055	−0.052
	(0.035)	(0.036)	(0.033)
Post × Exposure	X	X	0.224**
			(0.093)
Post × Television	0.179***	−0.041	−0.052
	(0.048)	(0.085)	(0.094)
Post × Exposure	X	X	0.192***
			(0.058)
Post × Newspaper	0.120***	0.032	−0.015
	(0.046)	(0.052)	(0.058)
Post × Exposure	X	X	0.266***
			(0.058)
Post × Phone	0.117***	−0.035	−0.102*
	(0.045)	(0.052)	(0.053)
Post × Exposure	X	X	0.196***
			(0.046)
Post × Hindu Pop.	−0.006	−0.022	−0.064
	(0.056)	(0.052)	(0.056)
Post × Exposure	X	X	0.151***
			(0.057)
Post × Female literacy	0.145***	0.093**	0.041
	(0.036)	(0.038)	(0.040)
Post × Exposure	X	X	0.126*
			(0.073)
Post × Urban Pop.	0.137***	−0.046	(0.073)
	(0.035)	(0.058)	(0.055)
Post × Exposure	X	X	0.183***
			(0.045)
Post × Young Pop.	0.039	−0.005	−0.002
	(0.029)	(0.013)	(0.012)s
Post × Exposure	X	X	0.124*
			(0.070)
Post × Public Bus	0.244***	0.179**	0.118
	(0.056)	(0.078)	(0.087)

Note: Column (1) shows β estimates from Equation E.1; each row depicts estimates from separate regressions. Column (2) shows elements of β estimate vector from Equation E.2; all estimates come from the same regression. Column (3) shows θ and β estimates from Equation E.3; each block depicts estimates from separate regressions. Robust standard errors are clustered at district level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F FIR Data Caveats

Given that cases of VAW are of a *sensitive* nature and anonymity of the victim is crucial, there are limitations on public viewing of individual level crime data. The Delhi Police uploads FIR reports for all cases on its website, except those categorized as “sensitive” by the Deputy Commissioner of Police (DCP) of the concerned district (in compliance with a Writ Petition issued by the Delhi High Court in 2010).

To understand the exact criterion for identifying a case as sensitive, I conducted in-depth interviews with DCPs of five police districts in Delhi and their team of data entry operators who are responsible for uploading the FIRs. From these interviews, I find that the criteria for classifying cases as sensitive is somewhat *loosely* defined and may vary across districts. While some DCPs reported that cases of rape, sexual assault and kidnapping of minors are not available for public viewing, others reported that only cases that fall under juvenile justice and Protection of Children from Sexual Offences (POCSO) Act are not uploaded online. During another interview, a data entry operator mentioned that cases against civil servants are not uploaded online. Such variation in responses demonstrates little systematic pattern in how uploading decisions are taken. While the decision-making process is not completely random, given that it is based on the discretion of few fixed-tenure officials, it is as-good-as-random conditional on district and time fixed effects.[68] Further, evidence from the qualitative interviews does not suggest any change in the uploading criterion during the sample period. It is also noteworthy that there may be little *strategic* incentive for DCPs to under-upload FIRs, since the full set of district-level aggregated crime figures need to be submitted to NCRB, which is later published in the public domain.

Nevertheless, while interpreting estimates on reporting-lag (Table 6), it is pertinent to acknowledge plausible under-representation of VAW cases in the FIR data. Specifically, we need to check two issues. First, does under-representation of VAW cases change systematically over-time, i.e. are more cases being *uploaded* by the police post-shock? Second, is the under-representation of VAW cases systematically correlated with lag in reporting, i.e. is the police “selectively’ uploading cases with lower reporting lag, post-shock?

I try to investigate these questions by triangulating the FIR data and NCRB data. The NCRB data used in the primary analysis serves as the benchmark database. As discussed before, the NCRB data are aggregated from individual FIR reports and published at the district level

[68] Notably, while conducting analysis using the FIR data, I use more granular fixed effects, i.e. police station (one administrative level below district) and month-year fixed effects.

and the state level, annually.[69] For adequate comparison, I re-structure the FIR and NCRB datasets such that each observation is recorded at the level of crime type $\times$ year, consistent with the empirical strategy used to examine reporting-lag.[70]

To measure representation of the FIR dataset, I construct a variable (i.e. PcRep) which yields the quotient of number of cases reported by the FIR dataset and the number of cases reported under the NCRB dataset, for a given year and crime category. To test the first concern, I estimate the following OLS equation.

$$PcRep_{c,t} = \beta_0 + \beta_1 Post_t + \beta_2 VAW_c + \beta_3 (Post_t \times VAW_c) + \epsilon_{c,t} \tag{F.1}$$

Estimates are presented in Table F.1. Expectedly, under-representation is significantly higher for cases of VAW compared to gender neutral crimes (indicated by negative and statistically significant β_2). Although, reassuringly there is no systematic difference in this under-representation over time - β_3 is statistically insignificant; thereby, addressing our first concern.

Similarly, to check the second concern on whether cases with *lower-lag* were being selectively uploaded, I estimate the following equation:

$$\begin{aligned} PcRep_{c,t} = \beta_0 + \beta_1 Post_t + \beta_2 VAW_c + \beta_3 PcLag_{c,t} + \beta_4 (Post_t \times VAW_c) + \\ \beta_5 (VAW_c \times PcLag_{c,t}) + \beta_6 (Post_t \times PcLag_{c,t}) + \\ \beta_7 (Post_t \times VAW_c \times PcLag_{c,t}) + \epsilon_{c,t} \end{aligned} \tag{F.2}$$

Ass defined in section 6.2, PcLag is the proportion of cases reported with a lag. Estimates are presented in Table F.2. Insignificance of β_7 indicates that there is no systematic change in correlation between under-representation and reporting-lag among cases of VAW before and after the shock; thereby, suggesting that the competing explanation for reduction in

[69]Although, it is pertinent to reiterate that the NCRB Statistics department follows the 'Principle Offence Rule' to classify crimes under separate categories, i.e. if a case is registered under multiple offences, then only the most heinous crime (maximum punishment) will be considered as a counting unit. For example, murder with rape, is counted as murder. This counting rule has been followed by NCRB throughout the sample period. Consequently, even if it were the case that all FIR reports were uploaded, the count of each crime head may differ from the NCRB data. With this caveat in mind, I compare the two datasets and check whether concerns pertaining to the FIR data can be alleviated.

[70]Since the FIR data are only available for four full years (data for 2015 are only reported till June), the restructured dataset records 52 observations, 13 crime categories tracked over 4 years.

reporting-lag after the shock is unlikely.

Table F.1: Changes in Uploading

	(1) PcRep
Post	0.724
	(1.190)
VAW	-1.654***
	(0.464)
Post × VAW	-0.919
	(1.194)
Observations	52
Adjusted R^2	0.143

This table presents estimates Equation F.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F.2: Relation between Uploading and Lag in Reporting

	(1) PcRep
Post	1.680
	(1.979)
PcLag	1.945
	(1.402)
VAW	-1.108
	(0.741)
Post × PcLag	-4.286
	(3.509)
Post × VAW	-1.928
	(1.990)
VAW × PcLag	-2.328
	(1.451)
Post × VAW × PcLag	4.427
	(3.541)
Observations	52
Adjusted R^2	0.096

This table presents estimates Equation F.2. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G Other Major Incidents of Crimes Against Women

Despite several changes that took place after the 2012 gang-rape incident, cases of VAW (rape in particular) are still occurring in India. Below are few such cases that gained substantial public attention.

- Gudiya case: In April 2013, a 5-year-old was brutally raped and held captive by her neighbor in Delhi. The incident gained public attention, especially due to delays in registration of crime (relatives of the victim alleged that the police offered them a bribe to not register the complaint). After the case was registered, investigation began and the two accused were arrested from their native homes in Bihar.

- Shakti Mills gang-rape case: In July-August, 2013, a 22-year old journalist was attacked and raped in an abandoned mill in Central Mumbai. The accused threatened that her photos would be posted online if she complained. An 18-year-old alleged being raped in the same premises on July 13. Three of five men who were convicted were held guilty of both crimes and sentenced to death. Two other accused were minors who were tried and sentenced to three years in a juvenile detention facility by the Juvenile Justice Court in Mumbai.

- Kamaduni case: On 7 June 2013, a 20-year-old college student was abducted, gang-raped and murdered in Kamduni village in West Bengal. The victim, a college student, was walking home along the Kamduni BDO Office Road in the afternoon, when she was abducted and taken inside a factory where she was gang-raped by eight men. After raping her, the perpetrators slit her throat and dumped her body into a nearby field. After the victim's family discovered her body, a case was reported to the local police. Eight men were taken into police custody. The incident sparked large protests by Kamduni residents, human right groups, student bodies, eminent intellectuals, and different Naxalite factions.

- Birbhum gang-rape case: In January 2014, a 20-year old from a tribal region in Birbhum district of West Bengal was gang-raped by a group of people, as a punishment ordered by Salishi Sabha, a village kangaroo court, for having an affair with a boy of a different community. The girl's family reported the case to the police. A trial was conducted in September 2014; 13 persons were found guilty and were sentenced to 20 years of imprisonment. The incident received international media coverage. The superintendent of police was removed after this incident and the state governor called for a ban on such courts by all state governments.

- Badaun gang-rape case: In May 2014, two teenage girls in Badayun district of Uttar Pradesh were gang-raped and murdered. The girls were found hanging from a tree. The incident was widely reported in the national as well as international media. The investigation was initially conducted by Central Bureau of Investigation (a national level investigating agency of India), which concluded that there was no gang-rape. However, later the court on Protection of Children Against Sexual Offences (POCSO) rejected CBI's report. The girls' families and several activists rejected the CBI report as a cover-up "to avoid international shame and acceptance of the dismal law and order situation". They also charged the local police of covering-up the case and not taking adequate action, as the family belonged to a lower caste. This case garnered considerable attention from national and international bodies, including the United Nations, Save the Children and All India Democratic Women's Association; both because of the severity of the incident and the alleged irresponsible and biased response from redressing agencies. This incident, in particular, highlighted how VAW is being used as a political and social weapon against marginalized communities.

- Unnao case: In June 2017, a member of the ruling political party allegedly raped a 17-year-old girl. The victim registered her complaint but she was not allowed to name her assailants. On the other hand, supporters of the assailant attacked the victim's father and framed him in a case, due to which he was arrested and kept in judicial custody. In protest and demand for justice, the victim attempted to immolate herself in front of the Chief Minister's residence, while her father died in judicial custody. The death and immolation attempt sparked widespread protests. As a result of which, an FIR was finally registered against the politician.

- Kathua case: In January 2018, an 8-year-old girl was abducted, raped and murdered in a village in Kathua district, Jammu and Kashmir. The accused included a temple priest, son and nephew of the priest, 2 police officers, a head constable and a sub-inspector in the police. The rape and murder drew widespread condemnation. The complaint filed by the police stated that the abduction of the victim was planned in an attempt to get personal revenge by the accused and to intimidate her community into moving out of the area. The incident also generated substantial communal tension, especially since the victim (who belonged to a Muslim community) was held captive in a Hindu temple.

- Hyderabad case: In November 2019, a 26-year old veterinary doctor was gang-raped and murdered in Shamshabad, near Hyderabad. The incident elicited outrage in several parts of the country. Protests and public demonstration against rape were organized nationwide after the incident, with the public demanding stricter laws against rape and rapists. Four men were arrested based on evidence from nearby CCT cameras and the victim's phone. The accused were in police-custody and were later killed in a police encounter in December 2019. According to the police, the suspects were taken to the location for a reconstruction of the crime scene, where two of them allegedly snatched guns and attacked the police. In the ensuing shootout, all four suspects were shot dead. While some accused the police of extra-judicial execution, thousands of people celebrated the men's deaths.

Appendix References

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