

2019

# Majoritarian Politics and Hate Crimes Against Religious Minorities in India, 2009–2018

Deepankar Basu

Follow this and additional works at: [https://scholarworks.umass.edu/econ\\_workingpaper](https://scholarworks.umass.edu/econ_workingpaper)

 Part of the [Economics Commons](#)

---

# Majoritarian Politics and Hate Crimes Against Religious Minorities in India, 2009–2018

Deepankar Basu\*

August 23, 2019

## Abstract

Using a state-level panel data set on the incidence of hate crimes in India, this paper implements difference in difference (DID) and triple difference in difference (DDD) research designs to estimate the causal impact of the right-wing BJP's win in the 2014 parliamentary elections on hate crimes against religious minorities (Muslims, Christians and Sikhs). Comparing the periods 2009–13 (pre-election) and 2014–18 (post-election), I find that BJP's electoral victory caused an increase in the incidence of hate crimes against religious minorities in India.

JEL Codes: D72; D74

Keywords: minorities, hate crimes, electoral outcomes, difference in difference.

## 1 Introduction

The national parliamentary elections of 2014 is a watershed moment in India's post-independence history. The unprecedented and massive victory of the right-wing, Hindu nationalist Bharatiya

---

\*Department of Economics, University of Massachusetts Amherst, 310 Crotty Hall, 412 N. Pleasant Street, Amherst MA 01002. Email: [dbasu@econs.umass.edu](mailto:dbasu@econs.umass.edu). I would like to thank Michael Ash, Debarshi Das, Ina Ganguli, Leila Gautham, Daniele Girardi, and Kartik Misra for very helpful comments on an earlier version of this paper. The usual disclaimers apply.

Janata Party (BJP) marked the unmistakable rise to dominance of a majoritarian, exclusionist politics in India (Basu, 2015; Vanaik, 2017; Bose, 2018). Commentators in national and international media and civil society activists point to the year 2014 as also the moment, in recent history, when incidents of hate crimes against religious minorities started a disturbing upward trajectory in India (Gowen and Sharma, 2018; Schultz, 2019; HRF, 2019). This paper investigates the possible causal connection between the two.

The precursor to BJP, known as the Bharatiya Jana Sangh (BJS), was formed in 1951 at the initiative of the Rashtriya Swayamsevak Sangh (national volunteer organization; RSS). Coming out of the short-lived Janata Party experience in the late 1970s, the BJS was reorganized as the BJP in 1980. The BJS/BJP's electoral fortunes have fluctuated for most of independent India's existence - until its decisive breakthrough in the Lok Sabha (lower house of the national parliament) elections in 2014, when it won 31.34% of the popular vote and 282 of the 543 seats. In the recently concluded Lok Sabha elections in 2019, the BJP has improved its already stunning performance of 5 years ago by winning 37.36% of the popular votes and 303 parliamentary seats.<sup>1</sup>

The BJP inherits its core political ideology of 'Hindutva' (roughly translated as 'being Hindu') from its progenitor, the all-male, right-wing organization, Rashtriya Swayamsevak Sangh (RSS). The RSS was formed in 1925 and is the primary champion, in Indian politics, of an exclusionary, majoritarian vision of nationalism - in complete opposition to the secular, inclusive vision of the Indian National Congress (INC) or the Indian Left parties. Its participation in the anti-colonial national struggle was marginal, and it's almost sole focus has been, right from its inception, on the differences and conflicts between Muslims and Hindus.<sup>2</sup>

The political ideology of Hindutva has three core principles: innate unity of Hindus;

---

<sup>1</sup>Prior to 2014, BJP's best electoral performance was in the 1999 Lok Sabha elections, when it won 182 of the 543 parliamentary seats (and about 24% vote share) as part of an alliance - with 13 regional parties - known as the National Democratic Alliance (NDA). The NDA coalition government lasted at the center for the full 5-year term, but then lost in the next parliamentary elections in 2004.

<sup>2</sup>For detailed studies of the RSS, see Andersen and Damle (1987) and (Jaffrelot, 1996).

India as the land of Hindus, and not a melting pot of different cultural influences; Muslims living in India as irreconcilable enemies of Hindudom (Bose, 2019). Founding ideologues of the RSS, like V. D. Savarkar and M. S. Golwalkar, envisioned the Indian nation as formed through centuries of cultural, social, religious assimilation of the people living in the Indian subcontinent. Muslims (Christians, Jews) are excluded, in this foundational vision, from the Indian nation because their religious and cultural loyalties lie elsewhere - in the Arabian peninsula, in the Middle East (Bose, 2013, 2018).

While the BJP has been strategically flexible on certain important issues that defined it in previous decades - like economic nationalism, support for a unitary state and opposition to the accommodation of lower caste aspirations - it has never compromised on its three core principles, including the perpetual ‘othering’ of Muslims. It is with this understanding of BJP’s foundational principles that one must approach the question of the possible link between its rise to dominance and the increase in *hate crimes* against religious minorities, especially Muslims, in India over the past decade. It seems a plausible hypothesis that BJP’s spectacular victory in the 2014 Lok Sabha elections might have caused an increase in the attack on minorities, especially Muslims, because that victory is perceived as an endorsement of a politics built on othering and demonising Muslims (and other minorities). It is this hypothesis that I wish to empirically test in this paper.

For my empirical analysis, I have constructed a state-level panel data set, covering the period 2009–2018, on the incidence of hate crimes against religious minorities in India from the Citizen’s Religious Hate Crime Watch (CRHCW) website.<sup>3</sup> To investigate the causal impact of the political dominance of the right-wing Hindu nationalist party, BJP, on the incidence of hate crimes against religious minorities in India, I implement a difference in difference (DID) research design on both the level of anti-minority hate crimes and the difference in hate crimes targeting minorities and members of the majority community. I

---

<sup>3</sup>See <https://p.factchecker.in/>

conceive of BJP's spectacular victory in the 2014 Lok Sabha elections as the rise to dominance of the politics of Hindutva, and so, my primary strategy is to compare the period (in my sample) before and after 2014 in terms of: (a) *level of* hate crimes against minorities; and (b) *difference in* hate crimes between minorities and the majority (Hindus).

A simple comparison of all-India (average or total) figures before and after 2014 will only give me a biased estimate of the causal impact of BJP's rise to dominance on hate crimes against minorities. This is because the incidence of hate crimes against minorities varies substantially across states and over time, and by comparing all-India figures before and after 2014, one averages out low and high incidence states. To tease out the causal impact in a better way, therefore, I define 'treatment' and 'control' groups (of states), and (a) look at the difference in the level of hate crimes against minorities between treatment and control groups before and after 2014, and (b) look at the difference, before and after 2014, in the difference in hate crimes between minorities and the majority community (Hindus). Moreover, since I have a state-level panel data set, I am able to control for unobserved state and year effects, and also state-level trends, that might otherwise confound my results.

My definition of treatment-control groups rests on the intuition that the impact of the rise of BJP on anti-minority hate crimes will be larger in states where the party is stronger, i.e. where it has a larger organizational presence, where its ideology has wider support and acceptance among the population, where anti-minority actions by its activists will find greater support among the functionaries of the state. I use BJP's performance in the 2014 Lok Sabha elections as a measure of this support. I define the treatment group as those states where the BJP won the largest share of the popular vote in the 2014 Lok Sabha elections. By comparing the change in the incidence of anti-minority hate crimes in treatment and control groups before and after the 2014 Lok Sabha elections, I am able to identify the causal impact of the rise to dominance of BJP on hate crimes against religious minorities after controlling for unobserved state and year effects, and state-level trends. The results for my preferred

specification (in Table 5) shows that anti-minority hate crimes increased by 297% as a result of BJP's win in 2014.

One possible concern about this result might be that the DID research design is just capturing the general increase in hate crimes and mistakenly attributing it to anti-minority hate crimes. After all it is conceivable that hate crimes have increased equally for members of the minorities and the majority community (Hindus). To deal with this possible concern, I look at the *difference* in hate crimes against minorities and members of the majority community, i.e. incidents of anti-minority hate crimes *less* incidents of hate crimes against members of the majority community. The results for my preferred specification (in Table 6) shows that the difference in hate crimes against minorities increased by 98% as a result of BJP's win in 2014.

I supplement the treatment group approach with a 'treatment intensity' approach. In this second approach, I do not divide states into two groups - the treatment and control groups - but rather use the vote share won by BJP in 2014 as a measure of the 'treatment intensity'. In the first approach - the treatment group approach - the causal impact of the political dominance of right-wing Hindu nationalism on the incidence of hate crimes against religious minorities is identified by comparing the change in the incidence of hate crimes before and after 2014 for the treatment and control groups.<sup>4</sup> In the second approach - the treatment intensity approach - the same causal effect is identified with the change in the incidence of hate crimes before and after 2014 associated with a small difference in the vote share won by BJP.<sup>5</sup> My preferred specification shows that every percentage point of vote share won by the BJP in 2014 is associated with: (a) a 2.33% increase in the level of anti-minority hate crimes (in Table 7) , and (b) a 1.51% increase in the difference in hate crimes against minorities

---

<sup>4</sup>Standard DID research designs have been widely used in economics; for instance, see [Card and Krueger \(1994\)](#), [Angrist and Pischke \(2009\)](#), pp. 227–242), and [Greene \(2012\)](#), chapter 6).

<sup>5</sup>For an example of the treatment intensity approach see [Card \(1992\)](#), and [Angrist and Pischke \(2009\)](#), pp. 227–242).

over and above those faced by members of the majority community (in Table 8).

I check for the robustness of my results in various ways. First, I supplement the difference in difference research designs with a triple difference in difference methodology (Table 9). Second, I take account of the discrete nature of hate crime counts by estimating Poisson and Negative Binomial regressions (Table 10 and 11). Finally, I carry out placebo tests (Figure 4 and 5) by using different years to define the ‘After’ dummy variable (which captures the year of BJP’s electoral victory). All the robustness checks confirm my basic result: a large and significant increase in hate crimes against minorities was caused by BJP’s electoral victory in 2014.

Once the causal impact has been established, it is natural to investigate the underlying mechanisms. There might be at least two different, but related, channels through which BJP’s electoral victory in 2014 might causally impact the incidence of anti-minority hate crimes. The first channel runs through sudden unraveling of social norms due to information aggregation represented by the 2014 parliamentary elections - a mechanism studied theoretically and experimentally in (Bursztyn et al., 2017). The second channel runs through the impact of the electoral victory on law enforcement, whereby hate crimes against minorities are dealt with laxity, if at all. The weakening of law enforcement relating to anti-minority hate crimes is probably itself a result of the sudden change in social norms, and so, it is fruitful to focus on social norms.

Anti-Muslim sentiments has widespread currency among members of the majority religious community (Hindus) in India. This has deep historical roots deriving from the colonial policies of ‘divide and rule’ and its interaction with exclusivist nationalist politics - of both Hindu and Muslim varieties - in pre-independence India. The BJP’s rise to dominance since the late 1980s has largely relied on politically mobilising this latent anti-Muslim sentiment (Bose, 2018). The spectacular victory in the national parliamentary elections in 2014 - preceded by anti-Muslim rhetoric during the campaigning - represented information aggregation

regarding the prevalence of this anti-Muslim sentiment ([Bursztyn et al., 2017](#)). People holding strong anti-Muslim sentiments could now feel their viewpoint being shared by a wide section of the population. Hence, verbal and physical attacks against Muslims (and other minorities) suddenly start becoming socially acceptable. The fact that important political leaders in the government - belonging to or allied with the BJP - do not strongly condemn such attacks only reinforces the justification for them. It is hardly surprising that law enforcement officials also internalize the change in norms and hence are lax about punishing culprits. This creates a widespread culture of impunity and continues the violence against members of minorities. In this paper, I do not explicitly test for the operation of this mechanism, rather this understanding of possible mechanisms provides a theoretical scaffolding for my analysis.

My paper speaks to a large literature that has studied various aspects of Hindu-Muslim violence in India ([Varshney, 2002](#); [Wilkinson, 2004](#); [Corbridge et al., 2012](#); [Mitra and Ray, 2014](#); [Basu, 2015](#)). All these studies have investigated the Hindu-Muslim violence in colonial and post-colonial India that have taken the form of riots. An updated version of the widely used Varshney-Wilkinson data set shows a decline in the incidence of such events, from the highs witnessed in the early 1990s and the early 2000s ([Basu, 2015](#), Figure 1.1, pp. 2). Hence, what we are witnessing since 2013 is a disturbing reversal of that trend. Moreover, large scale riots is not the primary form of violence committed against religious minorities in the period of my study. Rather, it takes the form of an attack on individuals and small groups of individuals from the minority communities - often taking the form of lynching by mobs ([Bose, 2018](#); [Gowen and Sharma, 2018](#); [Schultz, 2019](#); [HRF, 2019](#)). While there has been widespread reporting in national and international media outlets on this resurgence of anti-minority violence, to the best of my knowledge, this is the first academic study of the issue.

The contribution of my paper is to show that one of the causes of the spurt in hate crimes



against religious minorities in recent years in India is the rise to dominance of the right-wing Hindu nationalist political party- the BJP. While many activists and commentators have surmised that the BJP's recent rise is a causative factor in the increasing attacks on religious minorities, this is the first study to rigorously demonstrate that that is indeed so. In providing evidence for the causal impact of the rise of majoritarian politics on anti-minority hate crimes in India, my paper is in line with the findings of a similar literature on the US, where the election of Donald Trump in 2016 also caused an increase in hate crimes on Muslims and other disadvantaged minorities (SPLC, 2017; Edwards and Rushin, 2018). Since BJP's rise in India is part of a worldwide resurgence of right-wing nationalist political parties with explicit majoritarian and exclusivist ideologies, including in the US, UK, Hungary, Germany, and other countries, my paper suggests that minorities in other countries and contexts are also at danger of attacks on them. Dealing with this problem requires not only legal changes, as is underway in some states in India, but also a wider progressive movement in society, as has been recently argued by Democratic Representative to the US Congress from Minnesota, Ilhan Omar.<sup>6</sup>

The rest of the paper is organised as follows: in section 2, I discuss my data sources and key variables; in the following section, I discuss the all-India and state-wise trends in hate crimes against religious minorities; in section 4, I discuss my empirical strategy; in section 5, I discuss the key results; and in section 6, I conclude the paper with a discussion of some possible future directions for research.

## 2 Data: Sources and Key Variables

The two key variables used in the analysis for this paper are the incidence of anti-minority hate crimes in India and the electoral performance of the BJP. The former is the outcome

---

<sup>6</sup>See <https://www.nytimes.com/2019/07/25/opinion/ilhan-omar-trump-racism.html>

variable of interest and the latter is used to construct the treatment group (of states) and treatment intensity (across states).

## 2.1 Anti-Minority Hate Crimes

I have collected data on the incidence of anti-minority hate crimes from the website: Citizen's Religious Hate Crime Watch (CRHCW).<sup>7</sup> CRHCW is an independent citizen's initiative to collect data on and highlight patterns of hate crimes against religious minorities in India. The initiative was started in 2018 and, in recognition of its stellar work, was awarded the Data Journalism Award of the Year in 2019. Data from CRHCW has been used widely by national and international media, including the Hindu, The Wire, Washington Post, New York Times, Al Jazeera, New Yorker and BBC.

The CRHCW defines a hate crime as an incident that is a *prima facie* criminal act, under the provisions of the Indian legal system, partly or wholly motivated by the religious identity of the victim. Starting from news reports about such incidents in English language online and print media, the CRHCW does a careful analysis to make sure the incident qualifies as a hate crime. A subsequent round of fact checking is done - using other media sources - to corroborate important details and uncover other aspects of the incident that might have been missed out. Using this methodology, the CRHCW has collected data on hate crimes against religious minorities in India going back to the year 2009.<sup>8</sup>

For the analysis reported in this paper, I have collected data on the number of hate crimes by state-year from the CRHCW website. I have separately recorded information about the number of hate crimes committed against the following exhaustive (and mutually exclusive) religious community groupings: Muslims, Christians, Sikhs, Hindus, and Unknown.<sup>9</sup> By

---

<sup>7</sup>I accessed <https://p.factchecker.in/> between July 10 and 15 in 2019 to put together my data set on the incidence of hate crimes in India.

<sup>8</sup>For further details about the methodology used, see <https://datajournalismawards.org/projects/hate-crime-watch/>

<sup>9</sup>In a few cases, victims included members from more than one community. In these cases, I have counted

aggregating the number of hate crimes across all these groupings, I get the total number of hate crimes for a state-year observation; and, by aggregating across Muslims, Christians and Sikhs, I get the total number of hate crimes against religious minorities for a state-year observation.

I have made one important adjustment to the hate crime count for the years 2013 and 2014. I count the number of hate crimes for the year 2014 as only those incidents that happened after the month of May in 2014; incidents that happened before May are recorded in the count for the previous year, 2013. This adjustment is motivated by the primary question investigated in this paper: the effect of the parliamentary elections on anti-minority hate crimes. Since the results of the parliamentary elections were declared in May 2014, I include incidents that occurred after May as part of the count of hate crimes for the year 2014 - to isolate the impact of the electoral outcome on subsequent hate crimes.

## 2.2 Electoral Outcome and Treatment

I use state-level outcomes of the 2014 Lok Sabha elections to construct treatment groups (states) and to measure treatment intensity (across states). I have collected state-level data on the share of popular vote won by BJP, and other political parties, for the 2014 Lok Sabha elections in India from the website of the Election Commission of India.<sup>10</sup>

Using these data, I define the treatment group as those states where BJP was the largest political party according to popular votes won in the 2014 Lok Sabha election; the control group consists of all other states in my sample. Note that in constructing this treatment dummy variable, I am comparing the vote share won by BJP with the vote share won by all

---

the incident for the category of the minority community involved. This is motivated by the understanding that minority community members are more vulnerable than their majority community counterparts. An alternative would be to count the incident under both community categories. But this latter strategy would mean that each incident be counted multiple times. Since my main outcome variable is the number of incidents and since I am mainly interested in the impact on minority communities, I have opted for the first method.

<sup>10</sup>See <https://eci.gov.in/statistical-report/statistical-reports/>

other parties. For states where the BJP emerges as the party with the largest vote share, the treatment dummy variable takes the value 1, and it takes the value 0 otherwise. This comparison-based definition of the treatment dummy means that it can take the value 1 irrespective of the magnitude of vote share won by the BJP. What matters is whether it was largest among all political parties. For instance, we can see in Table 3 that Rajasthan and Haryana are both in the treatment group - even though the vote share won by BJP in these two states were quite different: 56% in Rajasthan and 35% in Haryana.

In a standard DID research design, the population (in this case Indian states) is divided into two groups - the treatment and control group. An alternative strategy is to instead use a variable for treatment intensity. Since I have information on the share of popular vote won by the BJP, it seems intuitive to use that as a treatment intensity variable - which captures the strength of BJP's support. Hence, I will use the following definition of treatment intensity for the empirical analysis: share of popular votes won in the 2014 Lok Sabha election by BJP.

### 3 Patterns of Hate Crimes

The data used for the analysis in this paper are a state-level panel data set. My sample has data on 27 states and the national capital territory (NCT) of Delhi, which together accounted for more than 99% of the population in 2011 - the latest Census year for which data is available.<sup>11</sup> The data on hate crimes run from 2009 to 2018. Thus, my sample has a total of 280 state-year observations.

---

<sup>11</sup>I have excluded the state of Arunachal Pradesh and the 6 remaining union territories from my analysis.

### 3.1 All India Pattern

Table 1, 2 and Figure 1 summarize information about hate crimes against religious minorities, for all religious communities, and the difference in hate crimes faced by minorities and the majority (Hindus), at the all-India level for the period of analysis, 2009–2018. From Table 1 and Figure 1, we see an almost exponential increase in the incidence of hate crimes against religious minorities in India and also an equally steep increase in the difference in hate crimes faced by minorities and the majority (Hindus), especially since 2013. Thus, not only have hate crimes increased against religious minorities, it has also increased significantly in comparison to hate crimes against members of the majority community (Hindus).

In Table 2, I have summarized information on hate crimes for two periods that I will use for my econometric analysis. The first period runs from 2009 to 2013, and includes the months from January to May of 2014. Hence this first period refers to the roughly 5-year period before the 2014 Lok Sabha elections. The second period covers the period since the results for the 2014 Lok Sabha elections were declared in mid-May of 2014 and runs up to the end of 2018. Thus, in Table 2 I have information on two periods of roughly equal length, before and after the declaration of results of the 2014 Lok Sabha elections, for comparison.

For the whole period of analysis covered in this paper, there was a total of 275 religious hate crimes, of which 217, or 80 percent, were hate crimes committed against religious minorities (Muslims, Christians and Sikhs). Of the total hate crimes against religious minorities, 78.34 percent were against Muslims, 19.35 percent were against Christians and 2.3 percent were against Sikhs. In the 5-year period before the 2014 Lok Sabha elections, there were a total of 22 hate crimes against religious minorities. The incidence of hate crimes against religious minorities were distributed as follows: Muslims (36.36%), Christians (59.09%), and Sikhs (4.55%). Thus, Christians bore the main brunt of hate crimes during this period, 2009–2013. The picture changes dramatically in the next 5-year period, both in terms of the magnitude and distribution across communities.

Between June, 2014 and the end of 2018, a total of 195 hate crimes were committed against religious minorities, an increase of 786 percent from the 5-year period before the 2014 Lok Sabha elections! In this post-election period, the incidence of hate crimes against religious minorities were distributed as follows: Muslims (83.08%), Christians (14.87%), and Sikhs (2.05%). The vast majority of hate crimes are now committed against Muslims, whereas both Christians and Sikhs see a decline in the proportion of hate crimes targeting them.

While the main issue investigated in this paper is hate crimes against religious minorities, I would also like to note, for the sake of completeness, that there has been some increase in the incidence of hate crimes against the majority religious community - Hindus - too (especially between 2017 and 2018). In the period 2009–13, Hindus were victims in 4.17% of hate crimes; in the period 2014–18, 10.36% of hate crimes were committed against them. While this is certainly an increase, the actual number of incidents against Hindus fall short of those faced by Christians and are far lower than what is faced by Muslims. Only when we recall that Christians comprise 2% of India’s population (but face 11.55% of all hate crimes in the period 2014–18) and Muslims comprise 14% of India’s population (but face 64.54% of all hate crimes in the period 2014–18), can we put these numbers in proper perspective. Even as we witness a rise in hate crimes against all communities, the overwhelming majority of hate crimes target *religious minorities*.

One way to note this is to study the trend of the difference in hate crimes faced by religious minorities and the majority community (Hindus). Over the whole period, there were 190 hate crimes against minorities over and above the 27 incidents against Hindus. In the pre-election period, 2009–13, minorities faced 21 more hate crimes incidents than Hindus; in the post-election period, 2014–18, there were 169 more hate crime incidents against minorities than against Hindus. Thus, the data in Table 1 and 2 and Figure 1, show not only an increase in the overall number of hate crimes in India since 2013, but an increase in hate

crimes disproportionately targeting religious minorities.

### 3.2 State-wise Patterns

The all-India pattern discussed above hides wide variation across states, and now I turn to a discussion of that. Using data from my sample, Table 3 summarizes two types of facts: (a) basic facts relating to hate crimes against religious minorities across Indian states, and (b) electoral performance of BJP in the 2014 Lok Sabha elections. Table 4 supplements Table 3 with data on the difference in hate crimes faced by religious minorities and members of the majority community.

The top 10 states in terms of the total number of incidents of hate crimes against religious minorities between 2009 and 2018 were, in descending order: Uttar Pradesh, Rajasthan, Karnataka, Haryana, Jharkhand, Gujarat, Maharashtra, Bihar, NCT of Delhi, and Jammu and Kashmir (and Madhya Pradesh). These states are also the top 10 states in terms of the number of hate crimes between 2014 and 2018 (the only difference being a change in the ranking of Bihar and Maharashtra), and the top states in terms of the difference in hate crimes faced by minorities and Hindus. When we turn to BJP’s electoral performance in 2014, we notice that all these states have also had significant political presence of the BJP (and its allies). Hence, this suggests a strong link between the political dominance of BJP and incidence of hate crimes against religious minorities. We can solidify this intuition further using two strategies.

For the first strategy, let us turn to Figure 2. In the top panel of the figure, I plot the average of the logarithm of 0.1 plus hate crimes against religious minorities for “treatment” and “control” groups.<sup>12</sup> In the bottom panel of the figure, I plot the average of the logarithm of 1.1 plus difference in hate crimes for “treatment” and “control” groups.<sup>13</sup> I will call states

---

<sup>12</sup>I add a small number, 0.1, before taking logarithm because many state-year observations have 0 hate crimes.

<sup>13</sup>I add 1.1, before taking logarithm because some state-year observations have  $-1$  as the difference in

belonging to the treatment group as BJP states, and those belonging to the control group as non-BJP states.

The two panels in Figure 2 show a striking trend. In the top panel, we see that while the incidence of hate crimes against minorities was moving roughly similarly in both treatment and control group states before 2014, it diverged markedly since 2014: the incidence of anti-minority hate crimes increased significantly in the treatment group after 2014 in comparison to the control group. This picture can be further strengthened by looking at the bottom panel in Figure 2, which plots the average the logarithm of 1.1 plus *difference* in hate crimes faced by minorities and Hindus. We see the same pattern as the top panel: the difference was moving similarly in both treatment and control groups before 2014, and then diverged - with the treatment group witnessing a significantly larger increase. Thus, not only was there an increase in the level of anti-minority hate crimes after the elections in the treatment group in comparison to the control group, there was an increase even in the difference in hate crimes faced by minorities and Hindus. Together, this provides strong *prima facie* evidence of a causal impact of the BJP's win in the 2014 on the increase in anti-minority hate crimes in India. In the next sections, we will investigate this link more rigorously using econometric analysis.

The second strategy takes a slightly different route. In the first strategy, I compared BJP's vote share with other political parties to decide whether it was the largest party. In the second strategy, I use BJP's vote share itself to distinguish states. A state with a higher share of the popular vote for BJP is understood as having greater political dominance of Hindutva forces - a treatment intensity approach. In the top panel of Figure 3, I present a scatter plot of the average of the logarithm of 0.1 plus hate crimes against religious minorities between 2014 and 2018 against the share of popular votes won in the 2014 Lok Sabha elections by BJP; in the bottom panel, I present a plot of the average of the logarithm of 1.1 plus hate crimes faced by minorities and Hindus.



the difference in hate crimes against religious minorities and Hindus between 2014 and 2018 against the share of popular votes won in the 2014 Lok Sabha elections by BJP. In both figures, we see a positive relationship between the two variables, as depicted by the bivariate regression line. Thus, from the relationship shown in Figure 3, we can conclude that states with higher political dominance of BJP (as measured by the share of popular vote won in the 2014 Lok Sabha elections) have witnessed higher incidence - both level and difference - of hate crimes against religious minorities between 2014 and 2018. Just as in the case of the first strategy, we will investigate this issue more rigorously in the next two sections.

## 4 Empirical Strategy

The patterns summarised in Figure 2 and 3 provide initial evidence of a positive link between the political dominance of BJP and the incidence of hate crimes against religious minorities, i.e. BJP's political dominance is associated with higher incidence of hate crimes against religious minorities. To convert this claim about association to one about causation, I will use a difference in difference (DID) research design on both the level of anti-minority hate crimes and the difference in hate crimes faced by minorities and Hindus (the majority community).

### 4.1 Difference in Difference: Level of Hate Crimes

As a first approach to the question of causation, I will estimate two variants of a standard DID model where the dependent variable is the *level* of anti-minority hate crimes. In the first variant, I will compare treatment and control groups; in the second variant, I will compare all states using a treatment intensity approach. Both will provide estimates of the causal impact of BJP's win in 2014 on the level of anti-minority hate crimes.

The first DID model of the level of anti-minority hate crimes is given as:

$$\log(0.1 + h_{st}) = \beta_1 (Treat_s \times After_t) + X'_{st}\lambda + \mu_{0s} + \mu_{1s}t + \delta_t + \varepsilon_{st} \quad (1)$$

where  $s = 1, 2, \dots, 28$  and  $t = 2009, 2010, \dots, 2018$  index states and years,  $h_{st}$  denotes the number of hate crimes against religious minorities in state  $s$  in year  $t$ ,  $Treat_s = 1$  for state  $s$  if BJP was the largest political party by popular vote in the 2014 Lok Sabha elections, and 0 otherwise,  $After_t = 1$  for all years after 2013, i.e. for  $t \geq 2014$ , and 0 otherwise,  $X_{st}$  is a vector of time-varying controls,  $\mu_{0s}$  is a state fixed effect,  $\mu_{1s}t$  denote state-specific linear time trends,  $\delta_t$  is a year fixed effect and  $\varepsilon_{st}$  is an idiosyncratic error. The coefficient of interest will be  $\beta_1$ , which will be an estimate of the causal impact of BJP's political dominance on the incidence of hate crimes against religious minorities. In this model,  $\beta_1$  is the percentage difference in the number of hate crimes in the treatment group (states where BJP is dominant) versus the control group (states where BJP is not dominant) before and after the 2014 elections.

The second DID model of the level of anti-minority hate crimes will use treatment *intensity*, instead of a treatment dummy, and is given as follows:

$$\log(0.1 + h_{st}) = \beta_2 (HVS_s \times After_t) + X'_{st}\lambda + \mu_{0s} + \mu_{1s}t + \delta_t + \varepsilon_{st} \quad (2)$$

where  $HVS_s$  is a measure of treatment intensity captured by the vote share won by BJP (the hindutva vote share, HVS) in the 2014 Lok Sabha elections, and all other variables and notation are as in equation (1). In this strategy,  $\beta_2$  is the coefficient of interest. It captures the causal impact of BJP's political dominance on the incidence of hate crimes against religious minorities:  $\beta_2$  gives the percentage change in hate crimes, between the pre and post-election periods, caused by an increase in BJP's vote share by 1 percentage point.

## 4.2 Difference in Difference: Difference in Hate Crimes

As a second approach to the question of causation, I will estimate two variants of DID model where the dependent variable is the *difference* in hate crimes faced by minorities and Hindus (members of the majority community). In the first variant, I will compare treatment and control groups; in the second variant, I will compare all states using a treatment intensity approach. Both will provide estimates of the causal impact of BJP's win in 2014 on the level of anti-minority hate crimes over and above any hate crimes faced by members of the majority community.

The DID method with the level of anti-minority hate crimes arrives at an estimate of the causal impact of BJP's electoral victory on hate crimes against minorities by comparing, before and after 2014, the increase in hate crimes against minorities in treatment versus control groups. This will give a misleading result if hate crimes against majority community members also increase over the same period. One way to deal with this concern is to use the DID method with the dependent variable defined as the difference in hate crimes against minorities and Hindus, which I discuss in this subsection. An alternative is to use a triple difference in difference research design, which I discuss in the section on robustness checks.

The first DID model on differences in hate crimes is given as:

$$\log(0.1 + dh_{st}) = \beta_3 (Treat_s \times After_t) + X'_{st}\lambda + \mu_{0s} + \mu_{1s}t + \delta_t + \varepsilon_{st} \quad (3)$$

where  $dh_{st}$  denotes the difference in the number of hate crimes against religious minorities and Hindus in state  $s$  in year  $t$ ,  $Treat_s = 1$  for state  $s$  if BJP was the largest political party by popular vote in the 2014 Lok Sabha elections, and 0 otherwise, and all other variables are as defined in (3). The coefficient of interest will be  $\beta_3$ , which will be an estimate of the causal impact of BJP's political dominance on the difference in hate crimes faced by

religious minorities and Hindus. In this model,  $\beta_3$  is the percentage difference in the number of hate crimes faced by minorities over and above those faced by Hindus in the treatment group (states where BJP is dominant) versus the control group (states where BJP is not dominant) before and after the 2014 elections.

The second DID model of differences in hate crimes will use treatment *intensity*, instead of a treatment dummy, and is given as follows:

$$\log(0.1 + dh_{st}) = \beta_4(HVS_s \times After_t) + X'_{st}\lambda + \mu_{0s} + \mu_{1s}t + \delta_t + \varepsilon_{st} \quad (4)$$

where  $dh_{st}$  denotes the difference in the number of hate crimes against religious minorities and Hindus in state  $s$  in year  $t$ ,  $Treat_s = 1$  for state  $s$  if BJP was the largest political party by popular vote in the 2014 Lok Sabha elections, and 0 otherwise,  $HVS_s$  is a measure of treatment intensity captured by the vote share won by BJP (the hindutva vote share, HVS) in the 2014 Lok Sabha elections, and all other variables and notation are as in equation (2). In this strategy,  $\beta_4$  is the coefficient of interest. It captures the causal impact of BJP's political dominance on the incidence of hate crimes against religious minorities over and above those faced by Hindus:  $\beta_4$  gives the percentage change in the difference in hate crimes faced by minorities and Hindus, between the pre and post-election periods, caused by an increase in BJP's vote share by 1 percentage point.

### 4.3 Identification

Identification of the causal effect of the intervention, in this case the rise to political dominance of BJP on anti-minority hate crimes, in all specifications used in this paper rests on a before-after comparison - of the level of anti-minority hate crimes and the difference in hate crimes faced by minorities and Hindus - between treatment and control groups. In the standard DID approach, each state belongs to either the treatment or the control group -

defined by whether BJP was the largest political party by share of popular vote in the 2014 Lok Sabha elections. On the other hand, in the treatment intensity approach, each state gets its own treatment status - defined by the BJP's vote share in the 2014 Lok Sabha elections.

Both approaches rely on the fact that absent intervention, the incidence of anti-minority hate crimes in both treatment and control groups would move in a similar manner. Thus, the estimate of the causal impact of BJP's electoral victory in 2014 comes from a comparison, before and after 2014, of the increase in anti-minority hate crimes in treatment versus control groups. Visual inspection of Figure 2 show that both groups display similar movements before the elections in 2014. Both the level of anti-minority hate crimes and the difference in hate crimes against minorities and Hindus move together in both treatment and control groups till 2013 and display an uptick in the trend for both groups after that. In a similar way, Figure 3 shows a clear positive relationship between the share of BJP's vote share in a state in 2014 and the average number of anti-minority hate crimes after 2014 - both level and difference. Hence, both figures give some preliminary evidence in support of the hypothesis that BJP's political dominance - as measured by its electoral fortunes in the 2014 parliamentary elections - is positively correlated with the incidence of anti-minority hate crimes. My empirical models - both the treatment dummy and the treatment intensity versions - deal with additional concerns about possible confounding effects in several ways.

First, I check to see if the incidence of hate crimes against religious communities in the period 2009–13 have any predictive power about the electoral performance of BJP in the 2014 Lok Sabha elections. I have conceived of the 2014 elections as an intervention and have studied its impact on the incidence of hate crimes in subsequent years. If past hate crimes were able to predict the outcomes of the 2014 elections, then the validity of my empirical strategy would be in question. When I ran a bivariate state-level regression of BJP's vote share in the 2014 Lok Sabha elections on the logarithm of  $0.1 +$  the average number of hate crimes in the period 2009–13, I got a coefficient estimate of 0.326 that was insignificant

(p-value: 0.95) and a very small r-squared (essentially 0). This suggests that previous hate crimes did not significantly affect the electoral outcomes in 2014.

Second, I include a full set of state fixed effects. Hence, my model controls for state-level unobserved factors that do not change over the 10-year period of analysis, like historical legacies of communal violence, demographic composition of the population, geographical aspects, rural-urban divisions, etc. Third, I include a full set of year fixed effects. Hence, I control for unobserved national events that might have affected all states, like common economic shocks or national level political events.

Even after I have controlled for unobserved state-specific and year-specific factors, there might be concerns that each (or different groups of) state(s) have had different trends in the incidence of hate crimes. There is some substance in this idea because studies of Hindu-Muslim violence by historians and political scientists show some states as the main location of such incidents (Mitra and Ray, 2014; Basu, 2015). To address this concern, I include a full set of state-specific linear time trends. This is the key method by which I address any possible contamination of my results due to pre-existing trends in hate crimes across states.

Finally, based on the extant literature, I include two additional time-varying controls. Many scholars of communal violence in India have pointed to the important role of the State-level government in preventing such events (Basu, 2015). Hence, I include a dummy variable in my model that takes the value 1 if BJP or one of its key allies is part of the state government. Some scholars who focus on the economic dimension of conflicts have also found some role for economic growth as a predictive variable (Jha, 2013). Hence, I include 1-lag of the growth rate of per capita net state domestic product as an additional control.

With controls for state-specific and year-specific unobserved effects, state-specific linear trends, and the two control variables, it is likely that the DID models give reliable estimates of the *causal* impact of BJP's political rise on the incidence of hate crimes against religious

minorities.<sup>14</sup>

## 5 Results

The main results of the DID research design of this paper are presented in Tables 5 through 8, which show results, in turn, for the basic DID model with treatment dummy, and the DID model with treatment intensity; robustness checks are presented in Table 10 and 11 for Poisson and Negative Binomial regressions, and placebo tests are shown in Figure 4 and 5. All analyses were conducted in R (R Core Team, 2019).

### 5.1 Main Results

Tables 5 and 6 present results of estimating DID models with a treatment dummy given in (1) and (4). All specifications include a full set of state and year fixed effects, and I report the coefficient on the interaction of the treatment and after dummy variables. In Table 5, the dependent variable is the logarithm of 0.1 plus the level of anti-minority hate crimes. We see that the coefficient on the interaction term is positive and significant in all specifications in both tables.

Using estimates in Table 5, we see that the coefficient on the interaction term is 1.455 in the basic DID model (column 1), is 1.405 when we add the two control variables - 1 lag of growth in the per capita net state domestic product and a dummy variable for whether BJP was in the governing coalition in the State government - and becomes 1.378 when we include state-specific linear time trends (column 3). This coefficient suggests the causal impact of BJP's political dominance on the incidence of hate crimes against religious minorities is very large, at about 300% ( $100 * [\exp(1.378) - 1] = 297$ ). This means that the difference in

---

<sup>14</sup>While there might be some measurement error in the incidence of hate crimes, this is a less serious problem because it is the dependent variable in the econometric model. Moreover, unless there is a time-varying source of measurement error that varies systematically across states, the inclusion of state and year fixed effects would take care of the problem.

increase in the incidence of hate crimes against religious minorities between BJP-dominant states and the rest is about 300%!

Turning to the estimates in Table 6, where the dependent variable is the logarithm of 1.1 plus the difference in hate crimes faced by minorities and Hindus (majority community), we see that all specifications have a positive and significant causal impact. Our preferred specification is the last column - which includes state and year fixed effects, controls and state-specific time trends. The estimate shows that hate crimes against minorities increased by 98% ( $100 * [\exp(0.681) - 1] = 97.58$ ) more than against Hindus (the majority community).

While the results of the basic DID model (with a treatment dummy) present evidence linking BJP's political dominance with the rise in hate crimes against religious minorities, we can strengthen this result with a DID model with treatment intensity (Card, 1992). Table 7 and 8 present estimates from the treatment intensity models in (3) and (4). In the former table, the dependent variable is the logarithm of 0.1 plus the level of anti-minority hate crimes, and in the latter, it is the logarithm of 1.1 plus the difference in hate crimes against minorities and Hindus.

From the results in Table 7, we see that the coefficient on the interaction of HVS (BJP's vote share in 2014) and the 'After' dummy variable is positive and statistically significant. In the basic specification (column 1), the estimate is 0.029; when I add controls, it becomes 0.028; and on controlling for state-specific linear trends, the coefficient becomes 0.023. This coefficient can be interpreted as showing that each percentage point rise in BJP's popular vote is associated, on average, with an increase of 2.33% in the number of hate crimes against religious minorities ( $100 * [\exp(0.023) - 1] = 2.33$ ) after 2014, compared to the 5-year period before the elections. From the results in Table 8, we see a similar result: the difference in hate crimes faced by minorities and Hindus has increased significantly with BJP's vote share in 2014. My preferred specification in column 3 shows that every percentage point increase in BJP's vote share is associated with a 1.51% increase in the differential incidence of hate



crimes against minorities.

## 5.2 Robustness Checks

Tables 9, 10, 11 and Figures 4 and 5 present robustness checks. I conduct three types of robustness checks. First, I estimate triple difference in difference (DDD) models with both treatment dummy and treatment intensity. Second, I take account of the fact that the dependent variable is a count variable and has a large number of zeros. To take account of the possibility of nonlinearities that come about because of this, I estimate my DID model with treatment intensity using Poisson and Negative Binomial regressions (Greene, 2012, chapter 18). Third, I use placebo tests by using different years to define the ‘after’ dummy for the original DID models.

### 5.2.1 Triple Difference in Difference

So far, all the results in the paper for causal estimates of BJP’s electoral victory on anti-minority hate crimes come from difference in difference models. In these models, the treatment group consists of the states where BJP was strong, and the control group consists of all other groups. Hence, the estimate of the causal impact comes from a comparison of the increase in anti-minority hate crimes after 2014 in treatment versus control groups. A valid concern about this method is that this comparison might be confounded by time-varying unobservable factors that vary for minorities and the rest (Hindus). One way to address this concern is to compare the difference in hate crimes between minorities and the majority - as I have done in the models in (3) and (4). An alternative is to use a triple difference in difference (DDD) model, where the comparison group is Hindus in control states. Thus, in the DDD model, the estimate of the causal impact comes from taking the difference before and after 2014 of the difference in the incidence of hate crimes between minorities and Hindus in treatment versus control groups. This method is robust to the presence of time-varying

unobservable factors by community (minority and majority).

In Table 9, I report results of estimating two triple difference in difference models. The first DDD model is the following:

$$\log(0.1 + h_{cst}) = \beta_5 (MAJ_c \times Treat_s \times After_t) + X'_{st}\lambda + \mu_{0s} + \mu_{1s}t + \delta_t + \varepsilon_{st} \quad (5)$$

where  $c = 0, 1$  is the index for community,  $s, t$  index states and year,  $h_{cst}$  is the number of hate crimes committed against community  $c$ ,  $MAJ_c = 1$  if the observation is for the majority community (Hindus) and  $MAJ_c = 0$  if the observation is for the religious minorities. All other variables have the same interpretation as in (3). The second DDD model I estimate is a treatment intensity variant of the above:

$$\log(0.1 + h_{cst}) = \beta_5 (MAJ_c \times HV S_s \times After_t) + X'_{st}\lambda + \mu_{0s} + \mu_{1s}t + \delta_t + \varepsilon_{st} \quad (6)$$

where  $HV S_s$  is the vote share won by BJP in the 2014 parliamentary elections, and all other variables have the same interpretation as in (5).

The first column in Table 9 gives the estimate on the triple interaction term in (5). It is negative and significant, showing that the causal impact of BJP's electoral victory in 2014 was significantly higher hate crimes against religious minorities. The magnitude of the estimate suggests that minorities BJP's electoral victory in 2014 caused a 244% increase in hate crimes against minorities. The second column in Table 9 gives the estimate on the triple interaction term in (6) and confirms the earlier findings. In terms of the magnitude, the second columns - with a treatment intensity model - shows that every percentage point increase in BJP's vote share in 2014 caused a 2.5% increase in hate crimes against minorities.

### 5.2.2 Poisson and Negative Binomial Models

In Table 10, I present results of Poisson and Negative Binomial regressions where the dependent variable is the level of anti-minority hate crimes. I present results for both the DID model with treatment dummy and DID model with treatment intensity. These models are specified exactly as the model in (1) and (2), other than the fact that now the dependent variable is treated not as a continuous random variable but as a discrete random variable, either with a Poisson or a Negative Binomial distribution (Greene, 2012, chapter 18). The model parameters are estimated by the method of maximum likelihood, and standard errors are computed from the outer product of gradient matrix. The estimates in Table 10 are all positive and significant, much along the lines of the linear model discussed thus far. In Table 11, I report results of Poisson and Negative Binomial regression model where the dependent variable is the difference in hate crimes committed against minorities and Hindus. The estimates are, again, all positive and significant, thus confirming the results of the linear specification used earlier in this paper.

### 5.2.3 Placebo Tests for Difference in Difference Models

In Figures 4 and 5, I return to the linear model used in this paper and present results of placebo tests. In Figure 4, I plot the value of the estimate (with a 95% error band) of the causal effect of interest from the DID model. The top panel uses the model in (1), where the dependent variable is the logarithm of 0.1 plus the level of anti-minority crimes; the bottom panel uses the model in (2), where the dependent variable is the logarithm of 1.1 plus the difference in hate crimes faced by minorities and Hindus (the majority community). On the far left, I use the year 2011 to define the ‘After’ dummy; in the next estimate, I use 2012, and go all the way to using the year 2016 to define the ‘After’ dummy on the far right. The figure shows that the estimate is negative or close to zero when I use 2011 or 2012 to define the ‘After’ dummy, but becomes positive and significant for the year 2013. For years after

2013, the effect is positive but its statistical significance declines. This holds for models with both the level and difference in hate crimes against minorities. Hence, these placebo tests confirm that there was a significant increase in both the level and difference in hate crimes against minorities in 2014 - which is the year in which BJP emerged as the dominant political force at the national level in India. In Figure 5, I report placebo test results for the treatment intensity models (3) and (4). The set-up is similar to those underlying Figure 4. We also see similar results: the placebo tests confirm that there was a significant increase in both the level and difference in hate crimes against minorities in 2014 using a treatment intensity approach.

## 6 Conclusion

In the Indian parliamentary elections in 2014, the right-wing Hindu nationalist BJP won a massive and unprecedented victory - an absolute majority of parliamentary seats for the first time in independent India's history. The year 2014 has also seen a marked rise in hate crimes against religious minorities. Since BJP's core politics is unmistakably majoritarian and exclusivist in orientation, it is natural to ask if the two - BJP's rise to dominance and an increase in hate crimes against religious minorities - are causally linked. In this paper, I have investigated this question empirically with a unique data set constructed from a recently formed citizen's religious hate crime watch website. Using a difference in difference research design, I find that BJP's rise to political dominance caused a significant increase in the incidence of hate crimes against religious minorities.

My sample has information on 28 states (27 states and the national capital territory of Delhi) over the period 2009–2018, giving me a total of 280 state-year observations. For the empirical analysis, I conceive of the 2014 Lok Sabha elections as the moment when BJP's political dominance at the national level in India was cemented. By all accounts, the BJP

replaced the Indian National Congress as the dominant national political party (Bose, 2018). Therefore, to tease out the causal impact of BJP's rise to political dominance on hate crimes against religious minorities, I compare 5-year periods before and after the 2014 election. I use the variation in BJP's ideological and organization reach across states to define treatment and control groups, and also to define treatment intensity. These are meant to capture the strength of the possible effect of BJP's dominance on hate crimes against religious minorities. States where BJP is relatively stronger will, I conjectured, see a higher effect of its rise to dominance on anti-minority hate crimes, if that effect exists.

My empirical analysis suggests that this is indeed the case. The estimates from my difference in difference research design shows that BJP's rise to political dominance - signaled by its spectacular victory in the parliamentary elections in 2014 - increased the level of anti-minority hate crimes by 300% and increased the difference in hate crimes against minorities and Hindus (the majority community) by 98%. Using the treatment intensity approach, I find that if BJP's support - as measured by the share of popular vote won in the 2014 parliamentary elections - increased by 1 percentage point, the level of hate crimes against religious minorities increased by 2.33%, and the difference in hate crimes against minorities and Hindus (the majority community) increased by 1.51%.

What is the mechanism that links BJP's electoral victory in 2014 to the spurt of anti-minority hate crimes after that? While I have not presented any evidence for the operation of mechanisms, my analysis has relied on recent work - both theoretical and experimental - which provides some plausible hypotheses that work through rapid changes in social norms. An election is a way in which information about attitudes, in this case anti-Muslim attitudes, can be thought to be aggregated. Thus, BJP's spectacular electoral victory in 2014 sent a signal to those holding strong anti-Muslim sentiments that such sentiments were widely held in society. Since the election campaigns by key BJP leaders had demonised and vilified Muslims, its victory made it acceptable to verbally and physically attack Muslims. Since key

political leaders did not strongly condemn such attacks and law enforcement officials were lax, it reinforced the attacks on Muslims by creating and sustaining a culture of impunity. It is this social atmosphere that encouraged violent, and often lethal, attacks on Muslims across India.

While an analysis of different mechanisms could be an avenue for future research, there are other issues as well that call for careful scholarly attention. First, it is clear that the phenomenon studied in this paper is a worldwide one - marginalized minorities have been under attack in many countries across the world. Hence, a comparative analysis across countries might throw light on some of the important dimensions of the problem. Second, what we are witnessing in India today has obvious parallels to the phenomenon of lynching seen in other parts of the world in earlier periods, like early 20-th century USA and South Africa. Hence, the comparative lens might be fruitfully extended to cover not only other countries today but in earlier periods as well. Third, a very recent literature has started studying the role of social media in encouraging and sustaining anti-minority violence ([Müller and Schwarz, 2019](#)). Since BJP's political campaigns rely on the widespread use of social media, its role needs to be investigated in the context of anti-minority violence in India. Fourth, the social and political impact of anti-minority violence on members of the larger minority community needs to be studied. There is some evidence that right-wing rhetoric against Muslims in the US has had chilling effects on the community, and they have withdrawn from the public sphere ([Hobbs and Lajevardi, 2019](#)). Is the same phenomenon of Muslims retreating from the public sphere also happening in India?

In this paper, I have limited my analysis to the end of 2018 to study comparable period before and after the 2014 elections. But incidents of anti-minority hate crimes have continued occurring in 2019 in an equally disturbing manner as in the previous 5-year period. In fact, since the end of the 2019 Lok Sabha elections, which the BJP won in an even more decisive manner, the country has seen a spurt of hate crime incidents. A list of such incidents has

been compiled in Table 12. Within a period of about 90 days, the country has witnessed 14 horrific incidents of hate crimes, 13 of which were exclusively against Muslims. It seems that the rate of occurrence of hate crimes against Muslims that had declined between 2017 and 2018 (see Table 1) is about to reverse itself.

Taking note of the growth in the disturbing phenomena of mob violence, cow vigilantism and lynching of minorities, the Supreme Court of India in 2018 had directed the Central and State governments to enact measures to put an end to what it called “horrendous acts of mobocracy”.<sup>15</sup> A year on, the Supreme Court’s directive has only been followed by the state of Manipur. In July 2019, the Law Commission of the state of Uttar Pradesh published a *suo motto* report and a draft bill to deal with the phenomenon of lynching.<sup>16</sup> Recently, the Congress government in the state of Madhya Pradesh has made some changes in existing laws to deal more firmly with cow vigilantism,<sup>17</sup> and the Congress government in Rajasthan has promised to enact fresh legislation to check mob lynching and hate crimes.<sup>18</sup> Expressing concern at the rising wave of anti-minority lynching, many prominent people and celebrities in India recently wrote to the Prime Minister of the country to take decisive and swift action.<sup>19</sup> While these legislative actions are necessary, it must be complemented with efforts to strengthen the progressive movement in society to deal with such a serious problem that is gravely undermining the democratic republic of India.

---

<sup>15</sup>Source: The Washington Post, 17 July, 2018 (internet edition). ([link](#))

<sup>16</sup>Source: The Wire, 12 July, 2019. ([link](#))

<sup>17</sup>Source: The Hindustan Times, 27 June, 2019 (internet edition). ([link](#))

<sup>18</sup>Source: The Hindustan Times, 17 July, 2019 (internet edition). ([link](#))

<sup>19</sup>Source: The Times of India, 24 July (internet edition). ([link](#))

## References

- Andersen, W. K. and Damle, S. D. (1987). *The Brotherhood in Saffron: The Rashtriya Swayamsevak Sangh and Hindu Revivalism*. Westview Press, Boulder, CO.
- Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, New York.
- Basu, A. (2015). *Violent Conjunctions in Democratic India*. Cambridge University Press, New York, NY.
- Bose, S. (2013). *Transforming India: Challenges to the World's Largest Democracy*. Harvard University Press, Cambridge, MA.
- Bose, S. (2018). *Secular States, Religious Politics*. Cambridge University Press, Cambridge, UK.
- Bose, S. (2019). Modi and the other idea of india. *The Open Magazine*. Published on 21 June. Available here: <https://www.openthemagazine.com/article/essay/modi-and-the-other-idea-of-india> (accessed 25 July, 2019).
- Bursztyn, L., Egorov, G., and Fiorin, S. (2017). From extreme to mainstream: How social norms unravel. *NBER Working Paper 23415*. Retrieved from National Bureau of Economic Research website: <http://www.nber.org/papers/w23415> (accessed 21 August, 2019).
- Card, D. (1992). Using regional variation in wages to measure the effects of the federal minimum wage. *Industrial and Labor Relations Review*, 46(1):22–37.
- Card, D. and Krueger, A. B. (1994). Minimum wages and employment: A case study of the fast-food industry in new jersey and pennsylvania. *American Economic Review*, 84(4):772–793.



- Corbridge, S., Kalra, N., and Tatsumi, K. (2012). The search for order: Understanding hindu-muslim violence in post-partition india. *Pacific Affairs*, 85(2):287–311.
- Croissant, Y. (2017). *pglm: Panel Generalized Linear Models*. R package version 0.2-1.
- Croissant, Y. and Millo, G. (2018). *Panel Data Econometrics with R: the plm package*. Wiley.
- Edwards, G. S. and Rushin, S. (2018). The effect of president trump’s election on hate crimes. Available here: <https://ssrn.com/abstract=3102652> (Accessed 22 August, 2019).
- Gowen, A. and Sharma, M. (2018). Rising hate in india. *The Washington Post*. Published on 31 October. Available here: [https://www.washingtonpost.com/graphics/2018/world/reports-of-hate-crime-cases-have-spiked-in-india/?utm\\_term=.c6db6bd3e457](https://www.washingtonpost.com/graphics/2018/world/reports-of-hate-crime-cases-have-spiked-in-india/?utm_term=.c6db6bd3e457) (accessed 23 July, 2019).
- Greene, W. H. (2012). *Econometric Analysis*. Prentice Hall, seventh edition.
- Hobbs, W. and Lajevardi, N. (2019). Effects of divisive political campaigns on the day-to-day segregation of arab and muslim americans. *The American Political Science Review*, 113(1):270–276.
- HRF (2019). *Violent Cow Protection in India: Vigilante Groups Attack Minorities*. Human Rights Watch, Washington DC.
- Jaffrelot, C. (1996). *The Hindu Nationalist Movement and Indian Politics: From 1925 to the 1990s*. Hurst & Co, London.
- Jha, S. (2013). Trade, institutions, and ethnic tolerance: Evidence from south asia. *The American Political Science Review*, 107(4):806–832.

- Mitra, A. and Ray, D. (2014). Implications of an economic theory of conflict: Hindu-muslim violence in india. *Journal of Political Economy*, 122(4):719–765.
- Müller, K. and Schwarz, C. (2019). From hashtag to hate crime: Twitter and anti-minority sentiment. Available here: <https://ssrn.com/abstract=3149103> (Accessed 22 August, 2019).
- R Core Team (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.
- Schultz, K. (2019). Murders of religious minorities in india go unpunished, report finds. *The New York Times*. Published on 18 February. Available here: <https://www.nytimes.com/2019/02/18/world/asia/india-cow-religious-attacks.html?smid=tw-nytimes&smtyp=cur> (accessed 23 July, 2019).
- SPLC (2017). *Update: 1,094 Bias-Related Incidents in the Month Following the Election*. Southern Poverty Law Center, Alabama, USA.
- Vanaik, A. (2017). *The Rise of Hindu Authoritarianism*. Verso, London.
- Varshney, A. (2002). *Ethnic Conflict and Civic Life: Hindus and Muslims in India*. Yale University Press, New Haven, CT.
- Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York.
- Wilkinson, S. (2004). *Votes and Violence: Electoral Competition and Ethnic Riots in India*. Cambridge University Press, New York, NY.

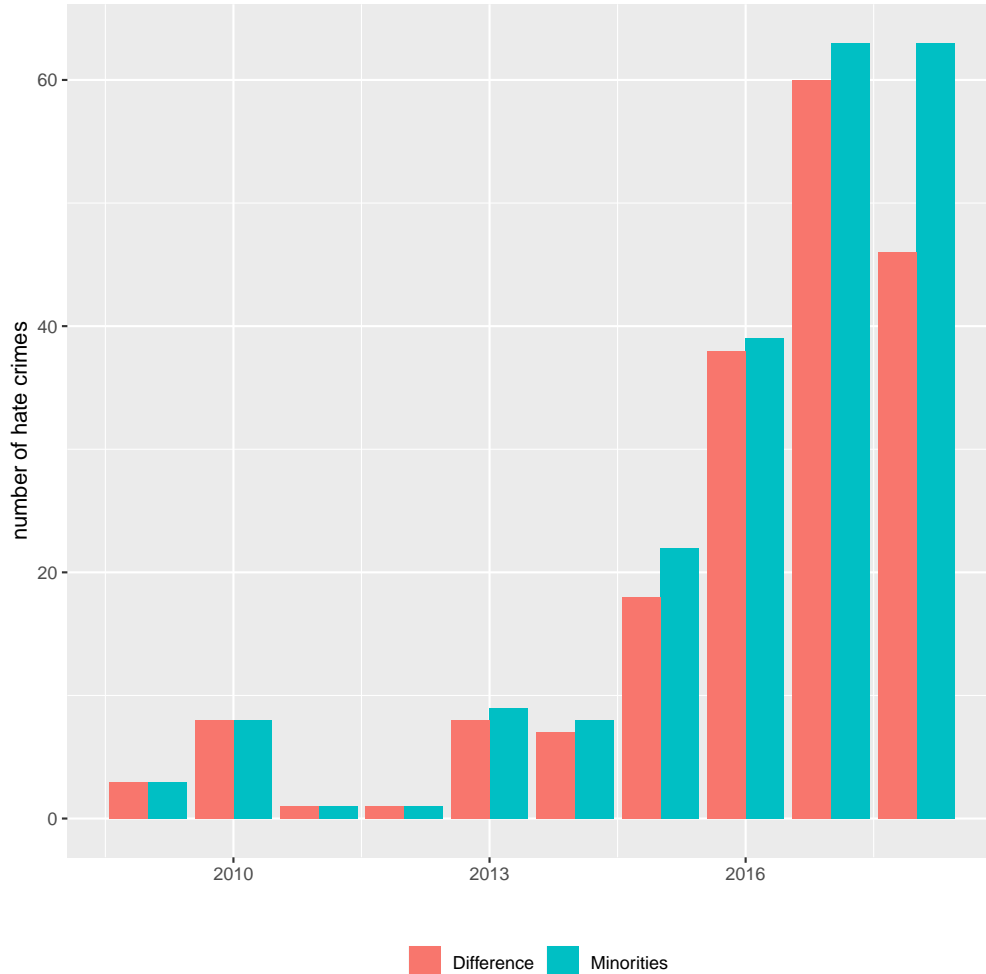


Figure 1: *The variable ‘Minorities’ measures the total number of hate crimes against all religious minorities (Muslims, Christians, and Sikhs) in India, 2009–2018; the variable ‘Difference’ is the total number of hate crimes committed against minorities less those against members of the majority community (Hindus) in India, 2009–2018. Source: Author’s calculation from data accessed from the following website: <https://p.factchecker.in/>. I have used the package `ggplot2` in R for creating the graphics (Wickham, 2016).*

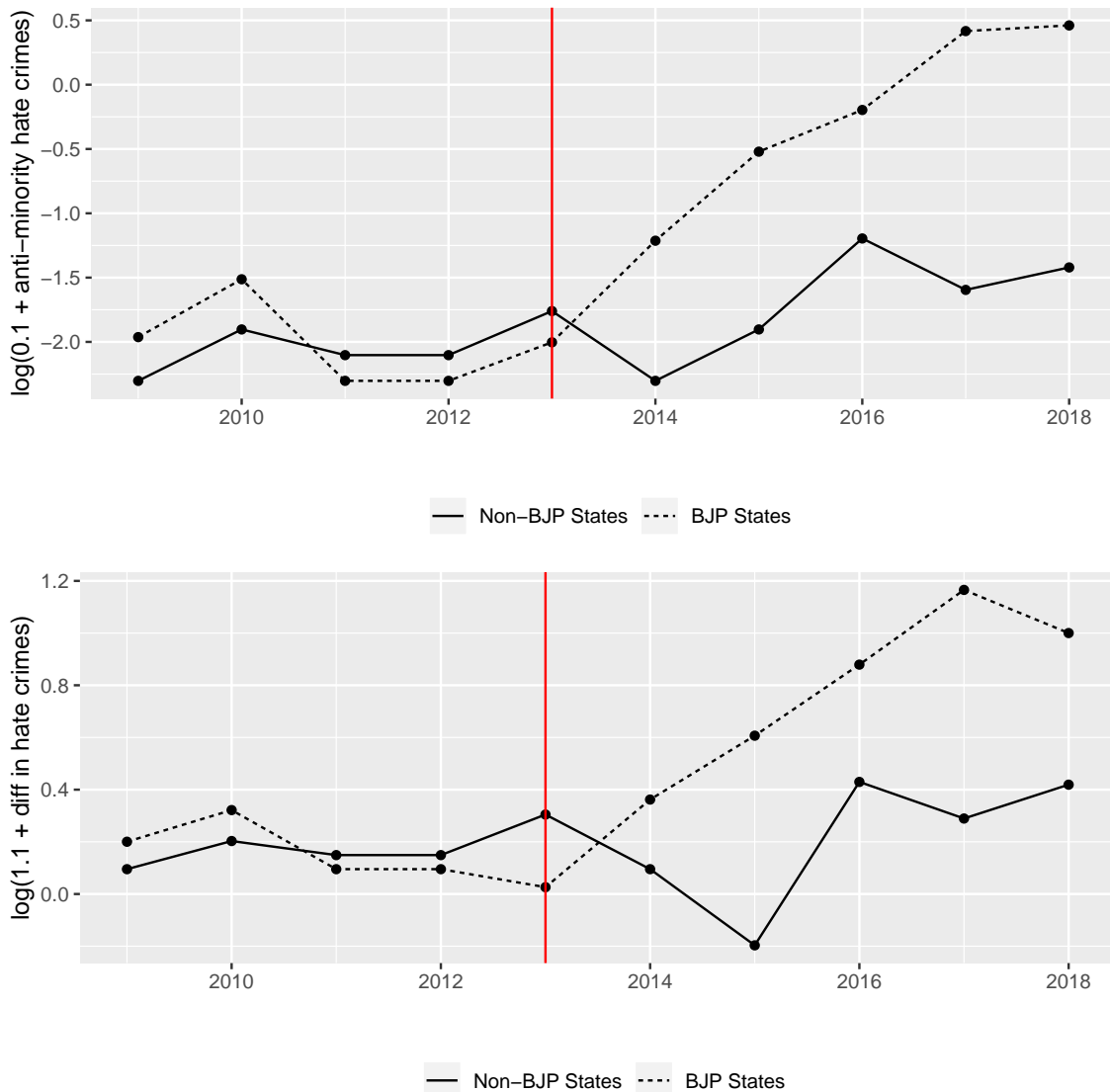


Figure 2: The top panel plots the average of  $\log(0.1 + \text{anti-minority hate crimes})$  per year in the treatment group (BJP states; dotted line) and the control group (non-BJP states; solid line) between 2009 and 2018; the bottom panel plots the average of  $\log(1.1 + \text{diff in hate crimes})$ , where the difference is the incidents of anti-minority hate crimes less hate crimes against the majority community (Hindus). The treatment group consists of states where BJP was the largest political party by share of the popular vote in the Lok Sabha elections of 2014; the control group consists of all other states. The red vertical line represents the year 2013, and demarcates the pre-election and post-election periods. I have used the package `ggplot2` in R for creating the graphics (Wickham, 2016).

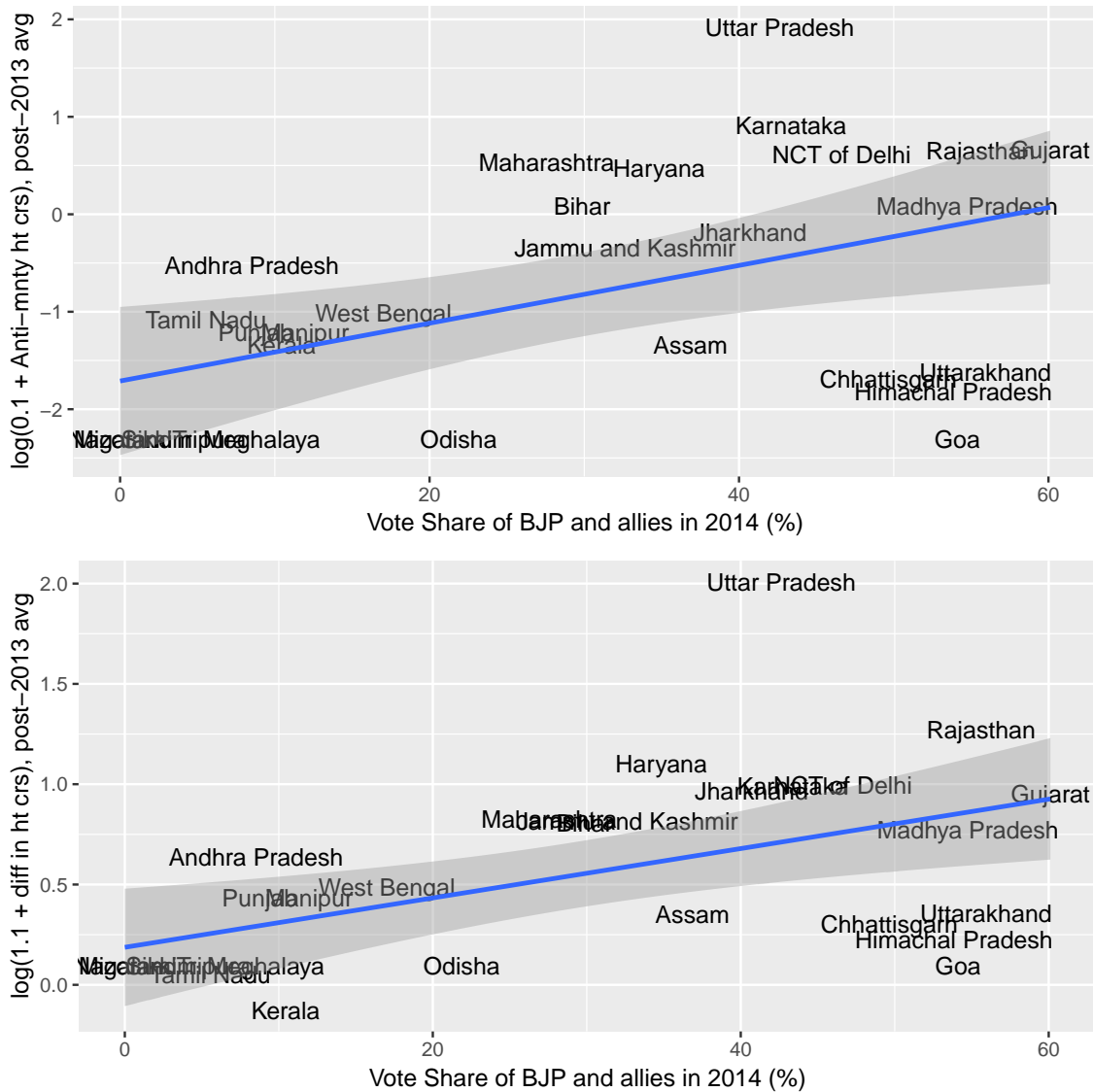


Figure 3: The top panel gives the scatter plot of average of  $\log(0.1 + \text{anti-minority hate crimes})$  across Indian states between 2014 and 2018 versus BJP's vote share in the 2014 Lok Sabha elections; the bottom panel gives the scatter plot of average of  $\log(1.1 + \text{difference in hate crimes})$  across Indian states between 2014 and 2018 versus BJP's vote share in the 2014 Lok Sabha elections (where difference in hate crimes is the total hate crimes against minorities less the number of hate crimes against the majority community). A bivariate regression line with 95% confidence interval included. I have used the package `ggplot2` in R for creating the graphics (Wickham, 2016).

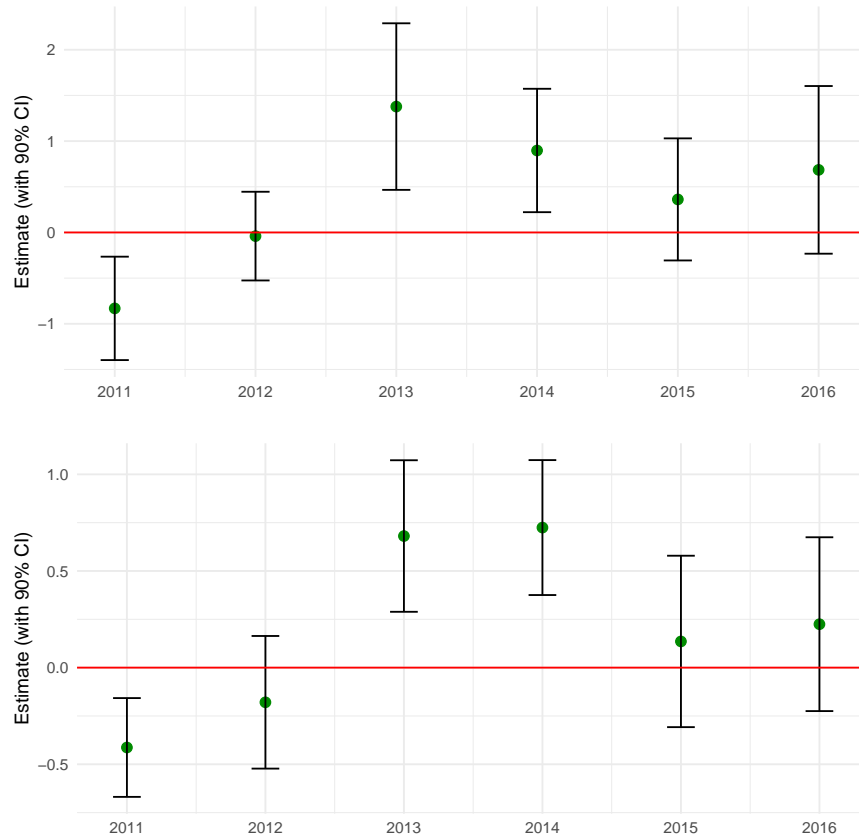


Figure 4: *Placebo tests for the causal effect from DID model, where the dependent variable is  $\log(0.1 + \text{anti-minority hate crimes})$  in the top panel, and the dependent variable is  $\log(1.1 + \text{difference in hate crimes})$  in the bottom panel. The treatment group consists of states where BJP was the largest political party by share of the popular vote in the Lok Sabha elections of 2014. The x-axis gives the year that was used to define the ‘After’ dummy. Thus, the year corresponding to 2013 is the correct definition of the ‘After’ dummy, and the other years serve as placebo tests. I have used the package `ggplot2` in R for creating the graphics (Wickham, 2016).*

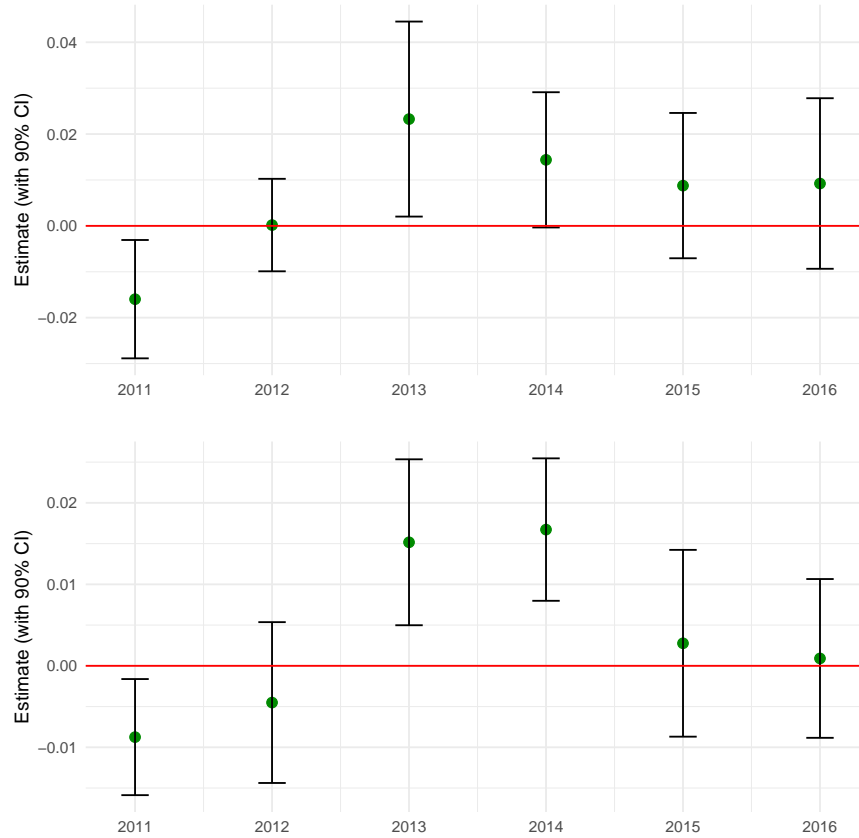


Figure 5: *Placebo tests for the causal effect from the treatment intensity model, where the dependent variable is  $\log(0.1 + \text{anti-minority hate crimes})$  in the top panel, and the dependent variable is  $\log(1.1 + \text{difference in hate crimes})$  in the bottom panel. The treatment intensity is measured by the share of popular votes won by BJP in the Lok Sabha elections of 2014. The x-axis gives the year that was used to define the ‘After’ dummy. Thus, the year corresponding to 2013 is the correct definition of the ‘After’ dummy, and the other years serve as placebo tests. I have used the package `ggplot2` in R for creating the graphics (Wickham, 2016).*

Table 1: Number of Religion-motivated Hate Crimes by Community of Victims in India, 2009–18<sup>a</sup>

	Community of Victims					All Minorities	All Minorities Less Hindus
	Muslim	Christian	Sikh	Hindu	Unknown		
2009	1	2	0	0	0	3	3
2010	3	5	0	0	0	8	8
2011	0	1	0	0	0	1	1
2012	0	0	1	0	0	1	1
2013	4	5	0	1	1	9	8
2014	6	2	0	1	7	8	7
2015	21	1	0	4	4	22	18
2016	28	9	2	1	2	39	38
2017	58	5	0	3	5	63	60
2018	49	12	2	17	12	63	46

<sup>a</sup> This table gives total number of hate crimes by community of victim for all years in my sample, 2009–2018. In this table, religious minorities include Muslims, Christians and Sikhs. Hindus are the majority religious community. Source: Author’s calculation from data accessed from the following website: <https://p.factchecker.in/>



Table 2: Number of Religion-motivated Hate Crimes in India, 2009–18<sup>a</sup>

	2009–2013	2014–2018
<hr/>		
<u>Religious Community of Victims</u>		
Muslim	8	162
Christian	13	29
Hindu	1	26
Sikh	1	4
Unknown	1	30
All Religious Minorities	22	195
Minorities less Hindus	21	169

<sup>a</sup> This table reports basic facts pertaining to the incidence of anti-minority hate crimes in India between 2009 and 2018. The number for 2014 only counts incidents that occurred after May, 2014; incidents that occurred between January and May 2014 are included in the number for 2013. This facilitates a clean comparison before and after the results for the 2014 Lok Sabha elections were declared in May 2014. Source: Author’s calculation from data accessed here <https://p.factchecker.in/>

Table 3: Hate Crimes Against Religious Minorities across Indian States, 2009–18<sup>a</sup>

	State	Hate Crimes (2009–13)	Hate Crimes (2014–18)	BJP Vote Sh, 2014 (%)	BJP Largest Party, 2014?
1	Uttar Pradesh	2	45	42.63	1
2	Rajasthan	2	20	55.61	1
3	Karnataka	3	15	43.37	1
4	Haryana	1	13	34.84	1
5	Jharkhand	0	13	40.71	1
6	Gujarat	0	11	60.11	1
7	Bihar	0	10	29.86	1
8	Maharashtra	2	10	27.56	1
9	NCT of Delhi	0	10	46.63	1
10	Jammu and Kashmir	0	8	32.65	1
11	Madhya Pradesh	0	8	54.76	1
12	Andhra Pradesh	8	6	8.52	0
13	Tamil Nadu	0	5	5.56	0
14	West Bengal	1	5	17.02	0
15	Manipur	0	3	11.98	0
16	Punjab	1	3	8.77	0
17	Uttarakhand	0	3	55.93	1
18	Assam	0	2	36.86	1
19	Chhattisgarh	0	2	49.66	1
20	Kerala	1	2	10.45	0
21	Himachal Pradesh	1	1	53.85	1
22	Goa	0	0	54.12	1
23	Meghalaya	0	0	9.16	0
24	Mizoram	0	0	0	0
25	Nagaland	0	0	0	0
26	Odisha	0	0	21.88	0
27	Sikkim	0	0	2.39	0
28	Tripura	0	0	5.77	0

<sup>a</sup> This table reports basic facts pertaining to the incidence of hate crimes against religious minorities across Indian states between 2009 and 2018. The number for 2014–18 counts all incidents that occurred after May, 2014; incidents that occurred between January and May 2014 are included in the number for 2009–13. This facilitates a clean comparison before and after the results for the 2014 Lok Sabha elections were declared. In the last two columns, I report the share of popular votes won by BJP and whether it was the largest political coalition by popular vote in the 2014 Lok Sabha elections.

Table 4: Hate Crimes Against Religious Minorities *less* those Against the Majority Community across Indian States, 2009–18<sup>a</sup>

	State	Diff Hate Cr (2009–13)	Diff Hate Cr (2014–18)	BJP Vote Sh, 2014 (%)	BJP Largest Party, 2014?
1	Uttar Pradesh	2	38	42.63	1
2	Rajasthan	2	18	55.61	1
3	Jharkhand	0	13	40.71	1
4	Haryana	1	12	34.84	1
5	Karnataka	3	11	43.37	1
6	Bihar	0	9	29.86	1
7	NCT of Delhi	0	9	46.63	1
8	Gujarat	0	8	60.11	1
9	Jammu and Kashmir	0	8	32.65	1
10	Maharashtra	2	8	27.56	1
11	Madhya Pradesh	-1	7	54.76	1
12	Andhra Pradesh	8	5	8.52	0
13	Tamil Nadu	0	4	5.56	0
14	West Bengal	1	4	17.02	0
15	Manipur	0	3	11.98	0
16	Punjab	1	3	8.77	0
17	Uttarakhand	0	3	55.93	1
18	Assam	0	2	36.86	1
19	Chhattisgarh	0	2	49.66	1
20	Himachal Pradesh	1	1	53.85	1
21	Kerala	1	1	10.45	0
22	Goa	0	0	54.12	1
23	Meghalaya	0	0	9.16	0
24	Mizoram	0	0	0	0
25	Nagaland	0	0	0	0
26	Odisha	0	0	21.88	0
27	Sikkim	0	0	2.39	0
28	Tripura	0	0	5.77	0

<sup>a</sup>This table reports the average incidence of hate crimes against religious minorities less those against the majority community (Hindus) across Indian states between 2009 and 2018. The number for 2014–18 counts all incidents that occurred after May, 2014; incidents that occurred between January and May 2014 are included in the number for 2009–13. This facilitates a clean comparison before and after the results for the 2014 Lok Sabha elections were declared. In the last two columns, I report the share of popular votes won by BJP and whether it was the largest political coalition by popular vote in the 2014 Lok Sabha elections.

Table 5: Basic DID Model for Level of Anti-minority Hate Crimes<sup>a</sup>

	Logarithm of (0.1 + Hate Crimes)		
	(1)	(2)	(3)
After X TREAT	1.455*** (0.282)	1.405*** (0.287)	1.378** (0.554)
Observations	280	273	273
State FE	Y	Y	Y
Year FE	Y	Y	Y
Controls		Y	Y
State Specific Trends			Y

<sup>a</sup> This table reports results of estimating a difference in difference model, where the dependent variable is  $\log(0.1 + \text{anti-minority hate crimes})$ . *After* is a dummy variable that takes the value 1 for years after 2013. *Treat* is a dummy variable that takes the value 1 for states where the BJP was the largest party (or coalition) by popular votes in the 2014 Lok Sabha (lower house of parliament) elections. Two control variables have been used: 1-lag of the growth rate of per capita net state domestic product, and a dummy variable indicating whether the BJP (or its major allies) was part of the state government in any year. Standard errors, clustered at the state level, appear in parentheses below the estimates. \*\*\*Significant at the 1 percent level; \*\*significant at the 5 percent level; \*significant at the 10 percent level. I use the `p1m()` function in R for the econometric analysis (Croissant and Millo, 2018).

Table 6: Basic DID Model for Difference in Hate Crimes Against Minorities and Hindus (Majority Community)<sup>a</sup>

	Logarithm of (0.1 + Hate Crimes)		
	(1)	(2)	(3)
After X TREAT	0.628*** (0.118)	0.616*** (0.115)	0.681*** (0.238)
Observations	280	273	273
State FE	Y	Y	Y
Year FE	Y	Y	Y
Controls		Y	Y
State Specific Trends			Y

<sup>a</sup> This table reports results of estimating a difference in difference model, where the dependent variable is  $\log(1.1 + \text{difference in hate crimes})$ , where difference in hate crimes is total hate crimes against minorities less number of hate crimes against majority community members (Hindus). *After* is a dummy variable that takes the value 1 for years after 2013. *Treat* is a dummy variable that takes the value 1 for states where the BJP was the largest party (or coalition) by popular votes in the 2014 Lok Sabha (lower house of parliament) elections. Two control variables have been used: 1-lag of the growth rate of per capita net state domestic product, and a dummy variable indicating whether the BJP (or its major allies) was part of the state government in any year. Standard errors, clustered at the state level, appear in parentheses below the estimates. \*\*\*Significant at the 1 percent level; \*\*significant at the 5 percent level; \*significant at the 10 percent level. I use the `plm()` function in R for the econometric analysis (Croissant and Millo, 2018).

Table 7: Treatment Intensity Model for Level of Anti-minority Hate Crimes<sup>a</sup>

	Logarithm of (0.1 + Hate Crimes)		
	(1)	(2)	(3)
After X HVS	0.029*** (0.009)	0.028*** (0.008)	0.023* (0.013)
Observations	280	273	273
State FE	Y	Y	Y
Year FE	Y	Y	Y
Controls		Y	Y
State Specific Trends			Y

<sup>a</sup> This table reports results of estimating a DID model with treatment intensity, where the dependent variable is  $\log(0.1 + \text{anti-minority hate crimes})$ . *HVS* denotes Hindutva vote share - which functions as a treatment intensity. It is measured as the share of popular votes won by the BJP in the 2014 Lok Sabha elections. *After* is a dummy variable that takes the value 1 for years after 2013. Two control variables have been used: 1-lag of the growth rate of per capita net state domestic product, and a dummy variable indicating whether the BJP (or its major allies) was part of the state government in any year. Standard errors, clustered at the state level, appear in parentheses below the estimates. \*\*\*Significant at the 1 percent level; \*\*significant at the 5 percent level; \*significant at the 10 percent level. I use the `p1m()` function in **R** for the econometric analysis (Croissant and Millo, 2018).

Table 8: Treatment Intensity Model for Difference in Hate Crimes Against Minorities and Hindus (Majority Community)<sup>a</sup>

	Logarithm of (1.1 + Diff in Hate Crimes)		
	(1)	(2)	(3)
After X HVS	0.014*** (0.003)	0.013*** (0.003)	0.015** (0.006)
Observations	280	273	273
State FE	Y	Y	Y
Year FE	Y	Y	Y
Controls		Y	Y
State Specific Trends			Y

<sup>a</sup> This table reports results of estimating a DID model with treatment intensity, where the dependent variable is  $\log(1.1 + \text{difference in hate crimes})$ , with the difference in hate crimes defined as the total hate crimes against minorities less the number against members of the majority community (Hindus). *HVS* denotes Hindutva vote share - which functions as a treatment intensity. It is measured as the share of popular votes won by the BJP in the 2014 Lok Sabha elections. *After* is a dummy variable that takes the value 1 for years after 2013. Two control variables have been used: 1-lag of the growth rate of per capita net state domestic product, and a dummy variable indicating whether the BJP (or its major allies) was part of the state government in any year. Standard errors, clustered at the state level, appear in parentheses below the estimates. \*\*\*Significant at the 1 percent level; \*\*significant at the 5 percent level; \*significant at the 10 percent level. I use the `p1m()` function in R for the econometric analysis (Croissant and Millo, 2018).

Table 9: Triple Difference Model for Anti-Minority Hate Crimes<sup>a</sup>

	Log (0.1 + Anti-minority hate crimes)	
	(1)	(2)
MAJ X After X Treat	-1.236*** (0.303)	
MAJ X After X HVS		-0.025*** (0.007)
Observations	546	546
State FE	Y	Y
Year FE	Y	Y
Controls	Y	Y
State Specific Trends	Y	Y

<sup>a</sup> This table reports results of estimating a DDD model with treatment dummy and treatment intensity, where the dependent variable is  $\log(1.1 + \text{anti-minority in hate crimes})$ . *MAJ* is a dummy variable that takes the value 1 for Hindus and 0 religious minorities (Muslims, Christians, and Sikhs). *Treat* is a dummy variable that takes the value 1 for states where the BJP was the largest party (or coalition) by popular votes in the 2014 Lok Sabha (lower house of parliament) elections. *HVS* denotes Hindutva vote share - which functions as a treatment intensity. It is measured as the share of popular votes won by the BJP in the 2014 Lok Sabha elections. *After* is a dummy variable that takes the value 1 for years after 2013. Two control variables have been used: 1-lag of the growth rate of per capita net state domestic product, and a dummy variable indicating whether the BJP (or its major allies) was part of the state government in any year. Standard errors, clustered at the state level, appear in parentheses below the estimates. \*\*\*Significant at the 1 percent level; \*\*significant at the 5 percent level; \*significant at the 10 percent level. I use the `p1m()` function in R for the econometric analysis (Croissant and Millo, 2018).



Table 10: Poisson and Negative Binomial Regression for Level of Anti-minority Hate Crimes<sup>a</sup>

	Dep Var: Number of Anti-Minority Hate Crimes			
	Poisson		Negative Binomial	
	(1)	(2)	(3)	(4)
After X Treat	1.964*** (0.479)		1.907*** (0.532)	
After X HVS		0.054*** (0.014)		0.051*** (0.015)
Log Likelihood	-146.88	-147.57	-145.05	-145.51
Observations	280	280	280	280
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

<sup>a</sup> This table reports maximum likelihood estimates of poisson and negative binomial regression models where the dependent variable is the number of hate crimes against minorities. Columns 1 and 3 use the DID model with treatment defined as states where BJP won the largest proportion of popular votes in 2014; columns 2 and 4 use the treatment intensity model, where BJP's vote share in 2014 is the measure of treatment intensity. Standard errors, computed from the outer product of gradient matrix, appear in parentheses below the estimates. \*\*\*Significant at the 1 percent level; \*\*significant at the 5 percent level; \*significant at the 10 percent level. I use the `pglm()` function in R for the econometric analysis (Croissant, 2017).

Table 11: Poisson and Negative Binomial Regression for Difference in Hate Crimes Against Minorities and Hindus (Majority Community)<sup>a</sup>

	Dep Var: Diff in Number of Hate Crimes			
	Poisson		Negative Binomial	
	(1)	(2)	(3)	(4)
After X Treat	1.862*** (0.484)		1.717** (0.552)	
After X HVS		0.050*** (0.015)		0.046*** (0.016)
Log Likelihood	-147.04	-147.89	-144.12	-144.42
Observations	277	277	277	277
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

<sup>a</sup> This table reports maximum likelihood estimates of poisson and negative binomial regression models where the dependent variable is the difference in hate crimes against minorities and members of the majority community (Hindus). Columns 1 and 3 use the DID model with treatment defined as states where BJP won the largest proportion of popular votes in 2014; columns 2 and 4 use the treatment intensity model, where BJP's vote share in 2014 is the measure of treatment intensity. Standard errors, computed from the outer product of gradient matrix, appear in parentheses below the estimates. \*\*\*Significant at the 1 percent level; \*\*significant at the 5 percent level; \*significant at the 10 percent level. I use the `pglm()` function in R for the econometric analysis (Croissant, 2017).

Table 12: Religion-motivated Hate Crimes in India since the 2019 Lok Sabha Elections<sup>a</sup>

	State	Date	Victims	Description
14	Uttar Pradesh	28 July	Muslim	Muslim youth kidnapped and set ablaze for refusing to chant ‘Jai Shri Ram’ in Chandauli - the person died in hospital two days later.
13	Maharashtra	21 July	Muslim	Two Muslim men assaulted and forced them to chant ‘Jai Shri Ram’ in Aurangabad.
12	Maharashtra	19 July	Muslim	Muslim man assaulted and forced them to chant ‘Jai Shri Ram’ in Aurangabad.
11	Uttar Pradesh	16 July	Muslim	Mob from Behta village torched a madrasa after beef was recovered from the premises.
10	Uttar Pradesh	11 July	Muslim	Three Muslim teenagers were beaten for refusing to chant ‘Jai Shri Ram’ in Unnao.
9	Assam	4 July	Muslim	Three Muslim youths thrashed and forced to chant ‘Jai Shri Ram’ in Barpeta district.
8	NCT Delhi	30 June	Muslim, Hindu	Temple vandalized by a Muslim mob after a dispute over parking in Hauz Qazi area.
7	Uttar Pradesh	28 June	Muslim	A Muslim youth was allegedly thrashed in Kanpur for refusing to chant ‘Jai Sri Ram’.
6	Maharashtra	23 June	Muslim	Three men beat up a 25-year-old Muslim cab driver and forced him to chant ‘Jai Shri Ram’ on the outskirts of Mumbai.
5	West Bengal	20 June	Muslim	23-year-old Muslim man, an Arabic teacher at a Madrasa in Hooghly, was beaten & pushed off a local train in Kolkata.
4	Uttar Pradesh	19 June	Hindu	Farmer Gangaram Thakur was beaten to death by his Muslim neighbours after he filed a complaint against them when his daughter went missing, police said.
3	Jharkhand	17 June	Muslim	A 24-year-old welder, Tabrez Ansari, was tied to a pole and beaten with sticks for over 18 hours before being handed over to the police. Ansari died four days later.
2	Uttar Pradesh	1 June	Muslim	Four Muslim laborers beaten for allegedly eating beef in an area consider ‘sacred’ to Hindus.
1	Bihar	25 May	Muslim	Mohammed Qasim, a detergent salesman, shot at after revealing his identity as a Muslim.

<sup>a</sup> This table gives basic information about hate crimes in India since the announcement of the results of the 2019 parliamentary elections on 23 May, 2019. Description of the incidents has been abbreviated to save space. For full details, refer to the source of this data: <https://p.factchecker.in/>.