Majoritarian Politics and Hate Crimes Against Religious Minorities: Evidence from India, 2009–2018

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Abstract

Did the unprecedented victory of the right-wing, Hindu nationalist Bharatiya Janata Party (BJP) in the 2014 national elections in India increase hate crimes against religious minorities? I investigate this question using a difference-in-difference methodology and a novel state-level panel data set for the period 2009-18. To provide context, I offer a brief historical account of Hindu nationalism and a descriptive

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account of anti-minority hate crimes in India between 2009 and 2018. Turning to the econometric analysis, I estimate a binary treatment regression model (states where BJP won the largest plurality of votes in the 2014 national elections form the treatment group). My results show that BJP’s electoral victory in 2014 caused an increase in the incidence of hate crimes against religious minorities, especially Muslims. I test for robustness of my results by using two falsification tests and a count data model specification. I account for possible omitted variable bias and compute bias-adjusted treatment effects. I conclude that unobserved confounders are unlikely to nullify the results.

Keywords: hate crimes; religious minorities; India; difference in difference; omitted variable bias.
1 Introduction

The 2014 elections to the lower house of the national parliament (Lok Sabha) is a watershed moment in India’s post-independence history. The unprecedented victory of the right-wing, Hindu nationalist Bharatiya Janata Party (BJP) marks the rise to dominance of a majoritarian, exclusivist politics in India (Ganguly, 2014; Basu, 2015; Vanaik, 2017; Bose, 2018). A wide range of commentators in national and international media have pointed out that hate crimes against religious minorities in India started an upward trajectory in 2014 (Gowen and Sharma, 2018; Schultz, 2019; HRF, 2019). In this paper, I study the possible connection between the two, i.e. I study the question if BJP’s victory in the watershed 2014 national elections caused the observed rise in hate crimes against religious minorities?

BJP’s history and core ideology provides clues as to why its massive 2014 electoral victory might lead to an increase in anti-minority hate crimes. The BJP inherits its core political ideology of ‘Hindutva’ (roughly translated as ‘Hinduness’) from its progenitor, the all-male, right-wing organization, Rashtriya Swayamsevak Sangh (RSS). The RSS was formed in 1925 and is the primary vehicle, in Indian politics, of an exclusionary, majoritarian vision of nation-building, the key component of which is the construction of a Hindu Rashtra (Hindu nation). Its participation in the anti-colonial nationalist struggle was marginal at best, and it’s almost sole focus has been, right from

\[\text{[^1]}\text{See, for instance, the special issue of the Journal of Democracy, Volume 25, Number 4, October 2014, devoted to this topic.}\]
its inception, on the differences and conflicts between Muslims and Hindus.

The ideology of Hindutva consists of three core principles: innate unity of Hindus; 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, 2018, 2019). Founding ideologues of Hindu nationalism, like V. D. Savarkar (member and president of the Hindu Mahasabha) and M. S. Golwalkar (second sarsangchalak, or the top leader, of the RSS), envisioned the Indian nation as formed through centuries of cultural, social, and religious assimilation of the people living in the Indian subcontinent. Muslims (and Christians) are excluded, in this foundational understanding of Hindu nationalism, from the Indian nation because their religious and cultural loyalties lie elsewhere.

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 or opposition to the accommodation of lower caste aspirations - it has never compromised on its three core principles, including the perpetual ‘othering’ of Muslims (Bose, 2013; Basu, 2015; Vanaik, 2017; Bose, 2018, 2019). This is what lends credence to the hypothesis, studied empirically in this paper, that the rise to dominance of BJP in 2014 has increased attacks on religious minorities, especially Muslims. By studying this question, this paper makes two significant contributions.

First, while a large literature in history and political science has studied religious ‘riots’ between Hindus and Muslims in India (Brass, 2003; Wilkin-
son, 2004; Basu, 2015; Mitra and Ray, 2014; Iyer and Shrivastava, 2018), my study shifts the focus to a different kind of violence: religion-motivated hate crimes. An updated version of the widely used Varshney-Wilkinson data set shows a decline in the incidence of religious riots, from the highs witnessed in the early 1990s and the early 2000s (Basu, 2015, Figure 1.1, pp. 2). My study highlights that while the incidence of riots might have declined, hate crimes have taken their place. Thus, violence against religious minorities continue unabated in India, even as its form might have changed. This raises grave questions about the secular democratic nature of the Indian state.

The second significance of my paper comes from its relationship to an emerging social science literature that has been studying possible connections between the recent growth of right-wing, ethno-nationalist populism and hate crimes against marginalized social groups, like immigrants, and racial and religious minorities (Dancygier and Laitin, 2014; Muis and Immerzeel, 2017; Bonikowski, 2017; Cederman, 2019). Many studies about the US point out the link between the election of Donald Trump and the subsequent rise in hate crimes against minorities (Bursztyn et al., 2017; Edwards and Rushin, 2018; Schaffner et al., 2018; Hobbs and Lajevardi, 2019; Müller and Schwarz, 2019); many studies have highlighted the link between the Brexit vote and the rise of anti-minority hate crimes in the UK (Cuerden and Rogers, 2018; Devine, 2018; Schiliter, 2019; Williams et al., 2020); many studies have also investigated the link between the growth of the right-wing political party, Alternative for Germany (AfD), in Germany and the rise of hate crimes.
against immigrants (Müller and Schwarz, 2018; Entorf and Lange, 2019). I contribute to this emerging literature by providing evidence of the causal link between right-wing, majoritarian politics (captured by the rise to dominance of the BJP) and anti-minority hate crimes in a large developing country like India.

To analyse the link between BJP’s massive victory in the 2014 Lok Sabha elections and hate crimes against religious minorities, I have constructed a novel state-level panel data set, covering the period 2009–2018 (Basu, 2021a). The data on religion-motivated hate crimes were collected from the Citizen’s Religious Hate Crime Watch (CRHCW) website, and the data on electoral outcomes is from the Election Commission of India’s website. A host of other variables have been collected from different sources.\(^2\)

To investigate the causal connection between BJP’s 2014 victory and anti-minority hate crimes, I use a difference-in-difference (DD) research design. I compare the change in the incidence of anti-minority hate crimes between treatment and control groups for a ‘before’ (2009–13) and ‘after’ (2014–18) period. I define the treatment group as those states where BJP won the largest share of popular votes in the 2014 national elections; all the other states in my sample comprise the control group. I find a significantly larger change in the incidence of anti-minority hate crimes in the treatment group compared to the control group. This provides an estimate of the causal effect of BJP’s electoral victory on anti-minority hate crimes.

\(^2\)For more details about CRHCW website and the data on hate crimes, see Appendix A.
The estimate captures a causal effect only if the parallel trends assumption is satisfied, i.e. absent BJP’s victory in the 2014 national elections, the incidence of anti-minority hate crimes would have moved in a similar manner in the treatment and control group of states. I test the validity of the parallel trends assumption - that is needed for identification of the DD strategy - using visual and regression evidence. Further, I subject my analysis to two falsification tests - one using different years for defining the ‘after’ dummy, and another using hate crimes against the majority religious community group. Finally, to take account of the count data nature of hate crimes, I also estimate a quasi-Poisson regression model and find that the result is qualitatively the same: BJP’s electoral victory in 2014 increased anti-minority hate crimes.

One concern about the identification strategy in my DD research design is the possible endogeneity of treatment that can arise due to omitted variables. Two prominent candidate omitted variables come from variable reporting of hate crimes and BJP’s election campaign rhetoric. A reader who is skeptical of the results reported in this paper might argue that reporting rates of hate crimes varies over states and years in such a way that what I report is merely an artifact of this variable reporting rate, rather than a real increase in hate crimes against religious minorities. If reporting of hate crimes improved relatively in the treatment group after 2014, then my results would be biased upwards. One might also raise the concern that the anti-minority rhetoric of BJP’s campaigning before the 2014 elections could have caused an increase
both in BJP’s vote share and in the incidence of hate crimes against religious minorities after 2014, thereby biasing my results in an upward direction. To take account of omitted variable bias, I use a modified version of the methodology suggested in Oster (2019) to compute bias-adjusted treatment effects (BATE). I conclude from this investigation that unobserved confounders do not undermine my results.

The rest of the paper is organized as follows: in Section 2, I provide a brief overview of Hindu nationalism, the ideology of the BJP; in Section 3, I discuss data sources and construction of important variables; in Section 4, I provide a descriptive analysis of trends; in Section 5, I present the econometric analysis using a DD approach; in Section 6, I bias-adjusted treatment effects; finally I conclude in Section 7 with some thoughts about mechanisms and directions for future research.

2 Brief History of Hindu Nationalism

To provide context for the analysis of this paper, I would like to present a very brief history of the Hindu nationalist strand of politics - known as Hindutva - in India. Through this brief review I would like to highlight three facts that are relevant for the analysis in this paper: (a) the construction of Muslims (and Christians) as the ‘other’ of Hindu nationalist ideology; (b) BJP as the representative of Hindu nationalism in the Indian political arena; and (c) electoral outcomes in 2014 as marking a qualitative break in the
political history of Hindu nationalism in post-independence India.\textsuperscript{3}

2.1 Antecedents

The word ‘Hindu’ derives from the name of the river Indus and was used by Greeks, Romans, and Muslims, to refer to the people living beyond that river. But, so far as we know on the basis of historical research, the term was not used by the people themselves in any consistent manner. Right up to the medieval period, people living beyond the river Indus were much more likely to refer to themselves as members of specific sects than as belonging to the Hindu fold as such. While an incipient Hindu consciousness emerged in the 17-th century with Chhatrapati Shivaji and the Maratha confederacy (in Western parts of India), a much more pronounced mobilization of Hindus - as a religious group - emerged only in the 19-th century as a reaction to colonial subjugation.

Contact with the British, and with Christian missionaries in particular, in the context of colonial rule, led to an ambiguous response from local (mostly upper-caste, Brahmin) elite in Bengal. While they saw in British rule a welcome development, a chance for enlightenment, they also wanted to preserve their religious practices and culture, and their hegemony in Bengali society. This ambiguous reaction first took concrete shape in the early 19-th cen-

\textsuperscript{3}For the material in this section, I primarily use \textit{Sarkar} (1984) and \textit{Jaffrelot} (2007). The former is a classic textbook on modern Indian history and the latter is an edited collection of excerpts from key writings of Hindutva leaders and ideologues, accompanied by a very informative introduction by the editor, Christophe Jaffrelot.
tury as the Hindu reform movement, symbolized most clearly by the *Brahmo Samaj* (founded in 1828 by the Hindu Brahmin, Raja Ram Mohun Roy, in the Bengal Presidency, to promote a rationalist and monotheistic religion). While acknowledging the need for reform of Hinduism, Ram Mohun Roy also constructed an image of a golden Vedic Age, pitting the spiritual superiority of this Vedic past against the scientific superiority of contemporary Britain. By the end of the century, the Hindu reform movement had transformed itself into an openly revivalist movement - with the founding of the *Arya Samaj* in Punjab in 1875 by the wandering *sanyasi* from Kathiawar, Dayanand Saraswati.

The boundaries between reform and revivalism were rather porous, so that revivalism only emphasized elements already present, perhaps in incipient forms, in the reform movement. For instance, revivalism meant emphasizing an idea already implicit in the reform movement: all problems in contemporary Hinduism that made it apparently inferior to Christianity were later day accretions to a pristine, perfect Hinduism of yore. Dayanand Saraswati developed this argument much further than Ram Mohun Roy, by adding cultural and social superiority of the Vedic Age to the spiritual superiority that Roy had emphasized. In Dayanand Saraswati’s writings, we find an early example of two key ideas that recur in contemporary Hindu nationalist discourse: (a) Hindus are the autochthonous people of sacred Bharat, the land lying beyond the Himalayas; (b) the caste system is a merit-based division of labour, rather than a hereditarily transmitted system of socio-economic
hierarchy and discrimination. In his practical work, Dayanand Saraswati developed the idea of ‘shuddhi’ (purification) - borrowing from upper caste Hindu practices - to reconvert Christians back into Hinduism, which was taken up in real earnest by his followers from 1900 onwards.

The revivalist movement found an eager audience among the non-Brahmin upper caste Hindu trading castes in Punjab - partly because of its opposition to Brahminical dominance. Two developments led to the development of an incipient organizational form and the coming together of Arya Samajists with more traditional Hindus - known as Sanatan Dhamis. The upper caste Hindu trading castes in Punjab had been rapidly acquiring land in rural Punjab from the impoverished peasantry crushed under the growing burden of indebtedness. When the colonial government passed the Punhab Alienation of Land Act in 1901 to prevent such land transfers, the trading castes saw this as an attack on their privileges. They were further antagonized by the British when, in 1906, Lord Minto (Viceroy and Governor-General of India from 1905 to 1910) promised a muslim delegation that Muslims would be granted separate electorates.\footnote{This promise became a reality in 1909 with the Morley-Minto Reform (or, the Indian Council Act of 1909), which created separate electorates for Muslims so that, in these seats, only Muslims could elect Muslims.} It is in this context that the revivalist movement took an incipient organizational shape as the Hindu Mahasabha - formed in Haridwar in 1915. But this initial organizational attempt was largely a still born baby because of sharp differences within the Hindu Mahasabha between its two primary ideological constituents, the Arya Samajists and the more traditional
Sanatan Dharmis (who were opposed to the reformist ideas championed by Arya Samajis).

2.2 Ideological and Organizational Foundations

Three developments in the 1920s signaled the founding of Hindu nationalism as an important political strand in India. First, the still born Hindu Mahasabha got revived, as the Sanatanis and Arya Samajis agreed to bury their differences and come together to face a common ‘enemy’ - the Muslims. The immediate context was large scale mobilization of Muslims in the 1920s as part of the Khilafat Movement - the movement to oppose the dismantling of the Caliphate after the defeat of the Ottoman Empire during the First World War. The Khilafat movement and the spurt in religious riots in the 1920s were perceived by the Hindu revivalist movement as a serious threat to the interests of Hindus - and mobilised them enormously. Second, in the writings of Vinayak Damodar Savarkar, Hindu nationalism found its clearest and most eloquent ideological formulation. Third, Rashtriya Swayamsevak Sangh (RSS), the organization that would give concrete shape to Hindu nationalism in the coming decades was formed in Nagpur in 1925 by Keshav Baliram Hedgewar, a Maharashtrian Brahmin like V.D. Savarkar.

In this foundational period of the 1920s, there was a subtle shift of emphasis in the definition of the ‘other’ of Hindu nationalism. In the earlier reform and revivalist phases, the primary ‘other’ was the colonial administrator and the Christian missionary - though the series of religious riots around the issue
of cow protection in the 1880s and 1890s suggests that Muslims were already an important part of the conception of the ‘other’ that was developing within Hindu nationalist discourse and consciousness (Sarkar, 1984, pp. 59–60, 79–80). In the 1920s, the emphasis shifted towards the Muslim ‘other’, who was now portrayed variously as the invader, the outsider and the prominent internal threat to the Hindu nation. While the Christian missionary did not disappear from the list of others to deal with, the Muslim became the primary ‘other’. This identification of the ‘other’ of Hindu nationalism remains in force even now - and motivates the analysis in this paper.

The idea of the Hindu Rashtra (Hindu nation), the establishment of which is the goal of Hindu nationalism, was most cogently formulated in the 1923 book by V. D. Savarkar, *Hindutva: Who is a Hindu?* For Savarkar, who wrote this book while in prison for his anti-colonial, revolutionary activity, and much before he joined the Hindu Mahasabha or became its president, Hindutva (roughly translated as Hinduness) is the ideology of the Hindu nation. Savarkar conceives of the nation in cultural terms, giving impetus to the cultural nationalism that animates Hindu nationalism to this day. Savarkar lays down four criteria that will determine whether a person belongs to the Hindu nation: Hindu religion, Hindu culture, Hindi (or Sanskrit) language and looking at Bharat as a sacred territory. He is clear why Muslims and Christians cannot belong to the Hindu nation, why they are the perpetual other:

In the case of some of our Mohammedan or Christian countrymen
who had originally been forcibly converted to a non-Hindu religion and who consequently have inherited along with Hindus, a common Fatherland and a greater part of the wealth of a common culture - language, law, customs, folklore, history - are not and cannot be recognized as Hindus. For though Hindusthan to them is Fatherland as to any other Hindus, yet it is not to them a Holyland too. Their Holyland is far off in Arabia or Palestine. Their mythology and Godmen, ideas and heroes are not the children of this soil. Consequently their names and their outlook smack of a foreign origin. Their love is divided. (In V. D. Savarkar, *Hindutva: Who is a Hindu?*).

While Savarkar formulated the ideology of Hindu nationalism, its translation into concrete activity was to be carried out most consistently and effectively by the RSS - formed by K. B. Hedgewar in 1925. For the first few decades, the RSS and the Hindu Mahasabha co-existed as two important organizational forms of Hindu nationalism - with subtle differences between the two - but after independence, and the tragic death of S. P. Mookherjee (the president of the Hindu Mahasabha) in 1953, the RSS completely eclipsed the Hindu Mahasabha and became the pre-eminent organization of Hindu nationalism. Over the years, the RSS has spawned a whole series of organizations, which are together known as the Sangh Parivar (roughly translated as the family of the Sangh), and which permeates the social and political life

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of the country. This includes the student front, Akhil Bharatiya Vidyarthi Parishad (ABVP), formed in 1948; the tribal movement, Vanvasi Kalyan Ashram (VKA), formed in 1952; the trade union, Bharatiya Mazdoor Sangh (BMS), formed in 1955; the world council of Hindus, Vishwa Hindu Parishad (VHP), formed in 1964; the Vidya Bharati, formed in 1977 to coordinate a network of schools first developed in the 1950s; among many others.

[Figure 1 about here]

2.3 Hindu Nationalism in the Political Arena

Hindu nationalism found expression in the political arena with the formation in 1951, just before the first general elections in independent India, of the Bharatiya Jana Sangh (BJS). The BJS was formed by the RSS, and in its initial years, accommodated political strands coming both from the Hindu Mahasabha and the RSS. But after the death of S. P. Mookherjee in 1953 (the president of the Hindu Mahasabha), the BJS was completely dominated by the RSS. The BJS was active in electoral politics from 1951 to 1977. It merged with the Janata Party in 1977. When the Janata Party experiment collapsed due to contradictions between its constituent parts (the socialists and the RSS members), former BJS members regrouped as the Bharatiya Janata Party (BJP) in 1980. From 1980, the BJP has been the political representative of Hindu nationalism in Indian politics.

To gauge the strength of its presence in the political arena, let us turn
to Figure 1, which plots the share of seats and share of popular votes won by the Hindutva strand of politics, i.e. BJS before 1977 and BJP after 1980, in the Lok Sabha elections in post-independence India.\footnote{All figures in this paper have been created with the package \texttt{ggplot2} in R (Wickham, 2016).} From the figure, we can see that the rise to political dominance of Hindutva displays a two-step pattern. The BJS was a marginal presence in the electoral landscape, never able to cross 10\% of the popular votes cast, or seats contested, in Lok Sabha elections. Hindutva’s political rise only begins in its incarnation as the BJP. We can see that BJP’s electoral fortunes takes two significant leaps. In the early 1990s, the BJP won more than 20\% of seats in the Lok Sabha for the first time. It consolidated its position further and increased its political presence significantly in 2014 by winning more than 30\% of the popular votes and a majority of seats in the Lok Sabha - for the first time in its history.

![Figure 1 about here](image)

The electoral outcome in 2014 marks a turning point, a qualitative shift, in the political history of Hindu nationalism. While the BJP had emerged as the largest political party in the Lok Sabha in the 1996 elections, it did not come even close to winning a majority of parliamentary seats. This meant that it had to form alliances with other parties to govern at the Central level - which it did for five years between 1999 and 2004 - and thus could not pursue its core agenda items. It is only in 2014 that the BJP won, for the
first time, a majority of seats in the Lok Sabha, dispensing with the need to rely on allies to run the central government.

3 Data: Sources and Key Variables

To investigate the possible impact of the 2014 national election results on anti-minority hate crimes, I have constructed a state-level panel data set with information on 28 states (27 states and the nation capital territory of Delhi) for the years 2009 to 2018, giving me a total of 280 state-year observations.\(^7\) The two key variables in my data set are the incidence of religion-motivated hate crimes (outcome variable) and the electoral performance of the BJP (treatment variable).\(^8\)

3.1 Outcome Variable

Many countries in the world have been collecting data on different aspects of hate crimes through its official agencies since the late 1980s (Green et al., 2001). Unfortunately, the Indian government does not collect data on hate crimes. Hence, I had to turn to an unofficial source for the data on anti-

\(^7\)The 28 states included in my sample together accounted for more than 99% of India’s population in 2011. I have excluded the state of Arunachal Pradesh and the 6 remaining union territories from my analysis. The state of Telengana was formed out of Andhra Pradesh in June, 2014. For the years 2014 and after, I have absorbed Telengana’s data into the composite state of Andhra Pradesh to facilitate comparison over time. Where relevant, I have used population weighted values of variables for Telengana and Andhra Pradesh to compute the corresponding numbers for the composite state of Andhra Pradesh.

\(^8\)The data and code files are available for download from a Harvard Dataverse repository; see Basu (2021a).
minority hate crimes in India, the Citizen’s Religious Hate Crime Watch (CRHCW) website.\footnote{I accessed the CRHCW website, 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. The data is no longer available in the public domain. It was reported in the media that the website had been pulled down on September 1, 2019 (Scroll, 2019). For further details, see Appendix A.} CRHCW is an independent citizen’s initiative that was formed 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 religion-motivated hate crime in the way that is standard in the extant literature. In particular, a religion-motivated hate crime is an incident with two characteristics: (1) it is a \textit{prima facie} criminal act, under the provisions of the Indian legal system; (2) it is partly or wholly motivated by prejudice towards the religious identity of the victim. The main source of data on religion-motivated hate crimes recorded by the CRHCW are news reports in the national media. Starting from reports about such incidents in English language online and print media, the CRHCW did a careful analysis - with the help of legal experts - to make sure an incident qualifies as a hate crime. A subsequent round of fact checking was done - using other media, especially vernacular, sources - to corroborate important details and uncover other aspects of the incident that might have been missed out. Us-

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ing this methodology, the CRHCW collected data on religion-motivated hate

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.\(^\text{11}\) In India, Hindus are the majority religious community, and Muslims, Christians and Sikhs are the main minority religious communities. By aggregating the number of hate crimes across all these religious groups, I get the total number of religion-motivated 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

\(^{10}\text{For further details about the methodology used, see Appendix A.}\)

\(^{11}\text{In a few cases, victims included members from more than one community. In these cases, I have counted the incident for the category of the minority community involved. This is motivated by the understanding that minority community members are more vulnerable than their majority community counterparts.}\)
2014, I include incidents that occurred after May as part of the count of hate crimes for the year 2014. This allows me to isolate the impact of the electoral outcome on subsequent hate crimes.

I would like to highlight two issues about the data on hate crimes. First, it is important to note the difference between hate crimes, which I study in this paper, and religious riots, which have been extensively studied in the history and political science literature. During riots a relatively big group of members of some religious community witness large scale violence directed against it. The resultant direct loss of life and property is relatively large. Prominent examples of religious riots in India are: riots during the partition of the country in 1946–47; Gujarat riots in 1969; the 1992 riots (after the demolition of the Babri Masjid); the Gujarat riots of 2002; the Muzaffarnagar riots of 2013.\footnote{For detailed studies of riots, see Brass (2003); Wilkinson (2004); Basu (2015).}

Religion-motivated hate crimes, on the other hand, are instances of targeted mob violence directed against an individual or a family. The direct loss of life and property in an incident of hate crime is far smaller than in the case of riots. But the psychological impact on the victim and the community she belongs to is probably equally damaging because hate crimes are often intended to terrorize and humiliate the whole community of the victim (Ray, 2007). To highlight the phenomenon studied in this paper, the following list gives some prominent examples of religion-motivated hate crimes that occurred over the past few years.
• On the night of June 17 June, 2019, in Saraikela, Jharkhand, a 24 year old Muslim man named Tabrez Ansari was beaten by a mob for allegedly being a thief. He was humiliated and forced to chant “Jai Shri Ram”. He died in hospital a few days later.\textsuperscript{13}

• On 22 June, 2017, a 16 year old Muslim boy, Junaid Khan, was stabbed on a Delhi-Mathura train. He bled to death on the platform in Asoti railway station, Faridabad.\textsuperscript{14}

• On 1 April, 2017, in Alwar, Rajasthan, 55 year old cattle trader, Pehlu Khan, and his sons were beaten by a cow vigilante mob when they were transporting cattle from a weekly cattle market in Jaipur. Pehlu Khan died in hospital two days later.\textsuperscript{15}

• On 28 September 2015, in Dadri, Uttar Pradesh, a mob attacked a 52 year old Muslim man, Mohammad Akhlaq, and killed him over beef rumours.\textsuperscript{16}

The second issue relates to the limitations of the data on hate crimes. While there is a long tradition in the social sciences of using data collected from newspaper reports, especially those related to violence against marginalized social groups, there is no doubt that such data come with many problems (Krueger and Pischke, 1997; Mitra and Ray, 2014). Since the data only in-

\textsuperscript{13}See the reports in Scroll and The Indian Express (accessed 24 November, 2019).
\textsuperscript{14}See the report in NDTV
\textsuperscript{15}See report in The Hindustan Times
\textsuperscript{16}See report in Al Jazeera.
cludes cases that are reported in the media, this is different from the actual number of incidents that might have occurred. After all, not all incidents get reported in the news media. There might also be issues of differential coverage and reporting across states and years. Ideally, one would have liked to check trends from the CRHCW data with trends generated by official data - as was done in Krueger and Pischke (1997) - but official data on religion-motivated hate crimes is not available in India. Hence, while I am aware of the limitations of my data on hate crimes, I would like to emphasize that this is the only data set that is currently available for the purpose of my study.17

3.2 Treatment Variable and Other Covariates

I use state-level outcomes of the 2014 national elections to construct treatment groups (of states). The key electoral outcome variable that I have used is the share of popular votes won by BJP, and other political parties, for the 2014 national elections in India.18 I have downloaded this data from the website of the Election Commission of India. 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 (I call these

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17It is also worth recalling that in studies of religious riots in India, the primary data set is the Varshney-Wilkinson data set, which was itself constructed from reports in the Bombay (Mumbai) edition of the leading English language daily, The Times of India; for details, see Mitra and Ray (2014).

18In this paper, I analyze the impact of the 2014 national elections on the incidence of anti-minority hate crimes. State-level electoral outcomes are likely to have significant impacts on anti-minority hate crimes. But that is not the question under investigation in this paper. That is why I do not use any data on state-level electoral outcomes.
the ‘BJP states’); the control group consists of all other states in my sample (I call these the ‘non-BJP states’).

To facilitate comparisons between treatment and control groups (of States), I need to ensure that they are reasonably similar. To do so, I include the following covariates as control variables in my regression models.\(^{19}\)

- Incidence of crime (number): This variable gives the incidence (number) of crimes covered by the Indian Penal Code (IPC).

- Estimated mid-year population (lakhs).

- Per capita net state domestic product (PCNSDP) at 2011-12 prices (rupees)

- Literacy rate in 2011 (%): The literacy rate is defined as the ratio of the literate population aged 7 years and above divided by the total population aged 7 years and above.

- Share of urban population in 2011 (%).

- Share of Muslim population in 2011 (%).

### 4 Descriptive Analysis

I begin my analysis by discussing overall trends - both at the all-India level and at state-levels - about the prevalence of hate crimes against religious

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\(^{19}\)For details of data sources, and summary statistics, see Appendix B.
minorities between 2009 and 2018. Figure 2, and Table 1, summarize information about hate crimes for the period of analysis, 2009–2018. From Figure 2, we see a significant 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 religious community (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 1, 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 1, I have information on two periods of roughly equal length, before and after the declaration of results of the 2014 Lok Sabha elections.

[Table 1 about here]

For the whole period of analysis covered in this paper, 2009–2018, there were 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, which were distributed across religious groups as follows: Muslims (36.36%), Christians (59.09%), and Sikhs (4.55%). Thus, Christians mainly bore the brunt of hate crimes during this period, 2009–2013.

[Figure 2 about here]

The picture changes dramatically in the next 5-year period, both in terms of the magnitude and distribution of hate crimes 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 were now committed against Muslims, whereas both Christians and Sikhs saw a decline in the proportion of hate crimes targeting them.

To get a sense of magnitudes involved, it is useful to compare the incidence of religion-motivated hate crimes with the incidence of Hindu-Muslim riots using the updated Varshney-Wilkinson data set (Mitra and Ray, 2014). Between 1950 and 1995, there were a total of 1200 riots. Between 1950 and 1981, the average number of riots in India was 16 per year; this increased
to more than 48 per year between 1982 and 1995 (Mitra and Ray, 2014, pp. 734). Between 2014 and 2018, the average number of hate crimes against religious minorities was 39 per year. Thus, the incidence of hate crimes against religious minorities and Hindu-Muslim riots for the two periods that saw high incidence of both - 2014-18 for the former and 1982-95 for the latter - are comparable.

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, Figure 3 shows that there is a positive correlation between BJP’s 2014 vote share and the increase in hate crimes against religious minorities between 2009-13 and 2014-18. This suggests a possible link between the political dominance of BJP and incidence of hate crimes against religious minorities. I investigate the evidence in favour of this possible link in the rest of the paper. Figure 3 is useful because it also identifies a clear outlier at the top-right of the chart: Uttar Pradesh. In the econometric analysis, I estimate models with and without Uttar Pradesh to ensure that results are not driven by this one outlier.

5 Empirical Analysis

To investigate the causal impact of BJP’s electoral performance in the 2014 Lok Sabha elections on the incidence of anti-minority hate crimes, I use a
difference-in-difference (DD) research design.

5.1 Binary Treatment Regression

5.1.1 The Empirical Model

In the first strategy I use a binary treatment variable, $BJP_s$, and estimate the following regression model,

$$h_{st} = \beta_1 (BJP_s \times \text{AFTER}_t) + \mu_s + \delta_t + X_s'\lambda + \varepsilon_{st}, \quad (1)$$

where $s = 1, 2, \ldots, 28$ and $t = 2009, 2010, \ldots, 2018$ index states and years, respectively, $h_{st}$ denotes the count of hate crimes against religious minorities in state $s$ in year $t$, $BJP_s = 1$ for state $s$ if BJP was the largest political party by popular vote in the 2014 Lok Sabha elections, and 0 otherwise, $\text{AFTER}_t = 1$ for $t \geq 2014$, and 0 otherwise, $X_s$ is a vector of controls, $\mu_s$ is a state fixed effect, and $\delta_t$ is a year fixed effect. The coefficient of interest is $\beta_1$, which will be an estimate of the causal impact of BJP’s electoral victory on the incidence of hate crimes against religious minorities. In this model, $\beta_1$ measures the differential increase in expected anti-minority hate crime counts in BJP versus non-BJP states after 2014.

To choose control variables for the regression I draw on the existing literature on religious conflicts in India (Jha, 2013; Mitra and Ray, 2014; Iyer and Shrivastava, 2018). This literature suggests the following variables: per capita net state domestic product (PCNSDP), population, literacy rate, ur-
banization rate, population share of Muslims, and the incidence of crime. In using some of these control variables, I face some data limitations. While data on per capita net state domestic product and population are available for all years, I have data on urbanization rate, literacy rate and population share of Muslims only for the latest Census year, 2011. Hence, when I include urbanization rate, literacy rate and population share of Muslims in the regression models, I interact them with the $After_t$ dummy variable.

The crime incidence variable is especially important for my analysis. If hate crimes are rising along with general crimes, then it will be difficult to ascribe the rise in the former to the 2014 electoral outcomes. Hence, it is important to control for the evolution of the incidence of general crimes. It can capture important trends in the treatment and control groups, as far as the incidence of hate crimes is concerned, that is necessary to control for the validity of the DD approach. The problem I face with this variable is that it is not available for 2017 and 2018 - which reduces the sample size.

### 5.1.2 DD Results

Table 2 presents results of estimating the DD model in (1) using the least squares dummy variable (LSDV) estimator. I report the coefficient on the interaction of the treatment dummy, $BJP_s$ (whether BJP won the largest share of popular votes in the 2014 Lok Sabha elections in state $s$) and the ‘After’ dummy variable. In the first specification (column 1), the model includes state and year fixed effects. State fixed effects control for unobserved
state-specific time-constant factors, like history of Hindu-Muslim violence (see Mitra and Ray (2014, Table I)), and year fixed effects control for common year shocks to all states (like changes in reporting of hate crimes in media outlets). In the second specification (column 2), I add two time-varying controls (log PCNSDP, log population); in the third specification (column 3), I add three pre-2014 controls (share of urban population, population share of Muslims, and literacy rate, all measured in the Census year 2011) interacted with the $After_t$ dummy variable; in the fourth specification (column 4), I add log incidence of crime; in column 5, I report results for the sample without Uttar Pradesh (the clear outlier identified in Figure 3); and in column 6, I drop the five North Eastern states. Standard errors are always clustered by state to address possible problems of inference arising from within-state serial correlations of the error term (Bertrand et al., 2004). Since the number of clusters is relatively small, I also report wild cluster boostrapped p-values in the last row of Table 2.

In Table 2 we see that the estimates of the treatment effect are positive and significant in all specifications (not only with cluster-robust standard errors but also with wild cluster boostrapped p-values), including the restricted sample without the outlier, Uttar Pradesh (column 5), and the sample without the five North Eastern states. The magnitude of the coefficient of 0.964 in column 4, my preferred specification, suggests that the causal impact of
BJP’s political dominance on the incidence of hate crimes against religious minorities is significant and large. The average number of anti-minority hate crimes between 2009 and 2013 was 0.157. Hence, the coefficient of 0.964 means that, on average, anti-minority hate crimes increased by 514%, compared to the pre-2014 mean, in states where BJP won the largest share of popular votes in the 2014 Lok Sabha elections.

5.1.3 Parallel Trends Before 2014?

In the DD research design, identification of causal effects rests on the parallel trends assumption. This translates to the claim that absent intervention, in this case BJP’s electoral victory in 2014, the incidence of anti-minority hate crimes in both treatment and control groups would evolve in a similar manner. In effect the non-BJP states (the control group) provide the counterfactual trajectory of the incidence of anti-minority hate crimes. While there is no way to test this directly, it is possible to provide some indirect evidence for this.

[Figure 4 about here]

The first piece of evidence of parallel trends is visual and is summarized in Figure 4, which has time series plots of the average of $hc_{st}$, where $hc_{st}$ is the count of anti-minority hate crimes in state $s$ in year $t$, for the treatment and control groups. A vertical line at year 2014 separates out the pre-election and post-election 5 year periods. From the figure we see that the average of
moved similarly in both groups before 2014. While there is an increase in hate crimes in both groups from 2014, the treatment group (BJP States) shows a relatively larger increase. From this visual evidence, we can conclude that the parallel trend assumption is satisfied.

I complement the visual evidence with regression results to test the parallel trends assumption. Following Muralidharan and Prakash (2017), I estimate the following regression model on the sample for 2009–2013 (pre-election years),

\[ h_{st} = \alpha (\text{YEAR}_t \ast \text{BJP}_s) + \mu_s + \delta_t + X_{st}' \lambda + \epsilon_{st}, \] (2)

where \( \text{YEAR}_t \) is a linear time trend, and all other variables are the same as in (1). My interest is in the coefficient, \( \alpha \), which will allow us to test if average anti-minority hate crimes in the treatment group (BJP states) is growing faster than in the control group (non-BJP states) for the period before the 2014 elections, i.e. 2009–2013.

Table 3 presents estimates of \( \alpha \). In column 1 of Table 3, the model includes state and year fixed effects; in column 2, I add time-varying controls; in column 3, I add the log of crime incidence. The parameter estimates in all the columns are negative but not statistically significant even at the 10% level. This suggests that the incidence of anti-minority hate crimes was growing at roughly the same rate in the treatment and control groups. This implies that the parallel trends assumption that justifies the DD research
design is satisfied.

5.1.4 Placebo Tests with Different Definitions of ‘After’

I have argued in this paper that the BJP’s electoral victory in 2014 is the crucial event that has increased hate crimes against religious minorities. If this is true, then a before-after comparison with years before 2014 should not give me any effect. I test this by running placebo tests. I estimate the model in (1) for 6 definitions of the \( After_t \) dummy variable, and index each version of the model with the year I use to define the \( After_t \) dummy variable. For instance, in Model-2011, \( AFTER_t = 1 \) if year >= 2011, and 0 otherwise; in Model-2012, \( AFTER_t = 1 \) if year >= 2012 and 0 otherwise; and so on.

![Figure 5 about here]

In Figure 5, I plot the estimate of \( \beta \) for the placebo tests. Each model is indexed by the year that defines the ‘After’ dummy. In this figure, we see that the effect is statistically insignificant for comparisons with years before 2014, is highest when the comparison uses 2014 to define the ‘After’ dummy, and falls thereafter. Therefore, Figure 5 confirms our expectation about the effect being non-existent before the crucial national elections in 2014.

5.1.5 Placebo Tests with the Majority Religious Group

Since BJP’s politics targets and demonizes religious minorities, especially Muslims, I should not find any effect if I use hate crimes against Hindus (who
are members of the *majority* religious community) as the dependent variable in the basic DD model. Such falsification tests are regularly recommended to test the validity of DD research designs (Green and Spry, 2014). To test this I run a placebo test again, i.e. I estimate the following binary treatment model,

\[
hch_{st} = \beta (BJP_s \times AFTER_t) + \mu_s + \delta_t + X'_{st}\lambda + \varepsilon_{st}, \tag{3}
\]

where \(hch_{st}\) is number of hate crimes against Hindus (majority religious community in India) in state \(s\) in year \(t\), and everything else is the same as in the basic binary treatment model in (1). Table 4 presents estimates of \(\beta\) in the model in (3) for four different specifications. We see that the coefficient is positive but statistically insignificant in all specifications with controls (columns 2 through 4). This means that in states where BJP emerged as the largest political party in 2014, the incidence of hate crimes against members of the majority religious community did not change after 2014. The nonexist-ent effect of BJP’s electoral victory on hate crimes against Hindus stands in stark contrast to the increase in hate crimes against religious minorities. But this is exactly what one would expect given that BJP has a majoritarian vision of nationalism and its ideology is built on attacking religious minorities, especially Muslims.

[Table 4 about here]

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5.2 Quasi-Poisson Regression

The dependent variable in my regressions, i.e. number of hate crimes against religious minorities, is a count variable. To take account of the count data nature of the dependent variable, I report results from estimating a Poission regression model.

\[
\ln E(h_{st}) = \beta_1 (BJPs \times AFTERt) + \mu_s + \delta_t + X_{st}'\lambda. \tag{4}
\]

One restrictive feature of a Poisson regression model is that it forces the mean and variance of the count variable to be equal. In many cases this is unrealistic because the count variable has more variation than can be captured by the mean - a situation known as ‘overdispersion’. A common way to deal with overdispersion is a quasi-Poisson approach, where the variance is specified as a multiple of the mean, and the multiple (called the overdispersion parameter) is estimated along with other parameters in the model (McCullagh and Nelder, 1989). I use this approach in this paper and report the results in Table 5 in the same format in which I reported results from the basic DD regression. The exact magnitude of the estimated effect is different from the linear model, but the qualitative result remains the same: in all specifications in Table 5, the treatment effect is positive and significant. This means that even when we account for the count data nature of hate crimes, we see an increase in hate crimes against religious minorities due to BJP’s victory in the 2014 national elections.
6 Bias-Adjusted Treatment Effect

In the previous section, I have presented evidence from a DD research design that demonstrates that the unprecedented electoral victory of the BJP in the national parliamentary elections in 2014 resulted in a significant increase in hate crimes against religious minorities, especially Muslims. My results are open to serious criticism from two angles. The first line of criticism that I have to deal with is the possibility of variable reporting rate of hate crimes across time and states. It might be argued that what I have called BJP states had higher hate crimes even before 2014 but they were being under-reported. If the degree of under-reporting has declined after the 2014 elections in the BJP states, then this becomes an omitted variable in my model that will impart an upward bias in my results. The second line of criticism is similar but relies on a different mechanism. It might be argued that BJP stepped up anti-minority, especially anti-Muslim, propaganda in the BJP states prior to the 2014 elections. It is this stepped up campaigning, it might be surmised, that caused an increase both in BJP’s vote share and hate crimes against Muslims after 2014. If this is correct, then this, once again, brings in an omitted variable in my empirical model and biases my results away from zero (and towards a positive effect). Both of these are serious concerns and I wish to address them in this section. In a recent contribution to the omitted variables literature, Oster (2019) has proposed a method to assess the impact of possible omitted variables on treatment
effects. I will use a modified version of the methodology proposed in Oster (2019) to compute bias-adjusted treatment effects.

6.1 The Methodology

Consider a hypothetical ‘long’ regression,

\[ Y = \beta X + \Psi \omega^0 + W_2 + \varepsilon, \]  

(5)

where \( Y \) is the outcome variable, \( X \) is the treatment variable of interest, \( \omega^0 \) is a \( J \times 1 \) vector of observed controls, and \( W_2 \) is an index of unobserved confounders, and denote by \( R_{\text{max}} \), the R-squared from the long regression. Consider the corresponding ‘short’ regression,

\[ Y = \bar{\beta}X + \bar{\varepsilon}, \]  

(6)

in which both the observable and unobservable controls, i.e. \( \omega^0 \) and \( W_2 \), are missing from the model, and denote as \( \bar{R} \), the R-squared from the short regression. In a similar manner, consider the corresponding intermediate regression,

\[ Y = \tilde{\beta}X + \tilde{\Psi} \omega^0 + \tilde{\varepsilon}, \]  

(7)

in which only the unobservable control, \( W_2 \), is missing from the model, and denote by \( \tilde{R} \), the R-squared from the intermediate regression. Finally, con-
Consider an auxiliary regression,

\[ X = \alpha \omega^0 + u, \]  

(8)

and denote by \( \tilde{X} \), the residual from this auxiliary regression. Let \( \hat{\tau}_X \) denote the variance of \( \tilde{X} \), \( \sigma_X^2 \) denote the variance of \( X \) and \( \sigma_Y^2 \) denote the variance of \( Y \). Following Oster (2019), let us define the measure of proportional selection as,

\[ \delta = \frac{\sigma_{2X}/\sigma_Y^2}{\sigma_{1X}/\sigma_1^2} \]  

(9)

where \( \sigma_1X = \text{cov}(W_1, X) \), \( \sigma_{2X} = \text{cov}(W_2, X) \), \( \sigma_1^2 = \text{var}(W_1) \), and \( \sigma_2^2 = \text{var}(W_2) \), and \( W_1 = \Psi \omega^0 \) (an index of the observable controls). The measure of proportional selection, \( \delta \), captures the relative importance of unobservables compared to the observed controls in explaining the variation in the treatment variable. When \( \delta \) is larger than unity, unobservable are more important than the observed controls; when \( \delta \) is less then unity, the opposite holds.

The omitted variable bias in the intermediate regression can be expressed in terms of coefficients in the short and intermediate regressions, the R-squared in the short, intermediate and long regressions, the measure of proportional selection and some parameters related to the auxiliary regression, and reduced into a cubic equation in \( \nu \) - asymptotic bias of the treatment
effect in the intermediate regression - given by,

\[ a\nu^3 + b\nu^2 + c\nu + d = 0, \] (10)

where,

\[ a = (\delta - 1) (\tau_x \sigma_X^2 - \tau_X^2), \] (11)
\[ b = \tau_x \left( \bar{\beta} - \hat{\beta} \right) \sigma_X^2 (\delta - 2), \] (12)
\[ c = \delta \left( R_{\text{max}} - \tilde{R} \right) \sigma_Y^2 \left( \sigma_X^2 - \tau_X \right) - \left( \tilde{R} - \bar{R} \right) \sigma_Y^2 \tau_X - \sigma_X^2 \tau_X \left( \bar{\beta} - \hat{\beta} \right)^2, \] (13)
\[ d = \delta \left( R_{\text{max}} - \tilde{R} \right) \sigma_Y^2 \left( \bar{\beta} - \hat{\beta} \right) \sigma_X^2. \] (14)

In general, the cubic equation will have either one real root or three real roots. In the case when there is only one real root, it gives us the unique estimate of the omitted variable bias. Hence, we can use it to compute the bias-adjusted treatment effect. To be more precise, let \( \nu_1 \) denote the unique real root of (10), and let \( \beta^* = \bar{\beta} - \nu_1 \). Proposition 2 in Oster (2019) shows that \( \beta^* \xrightarrow{p} \beta \), so that \( \nu_1 \) is the asymptotic bias in the treatment effect estimated by the intermediate regression. Hence, \( \bar{\beta} - \nu_1 \) is the bias-adjusted treatment effect (which will converge in probability to the true treatment effect).

In the case when the cubic equation has three real roots, then only one of these will give us the correct asymptotic bias in the treatment effect. The method proposed by Oster (2019) for computing the unique bias-adjusted treatment effect relies on the assumption of equal selection, i.e. \( \delta = 1 \).
Basu (2021b) shows that such a method suffers from several problems: it requires additional assumption that cannot be justified; the method does not work when the estimate of the treatment effect declines with the addition of controls (which is the case for this paper); conclusions can change drastically when we relax the assumption of equal selection by a small magnitude. Hence, I follow Basu (2021b) and compute all the roots of (10) for a plausible range of values of $R_{max}$ and $\delta$, and work with all these cases.

The computation of the bias-adjusted treatment effect (BATE) rests crucially on the choice of $R_{max}$ and $\delta$. We know that $R_{max}$ is bounded below by $\tilde{R}$. Hence, I will use a range of values of $R_{max}$ running over the interval defined by $\tilde{R}$ and 1 (the maximum possible value of R-squared in any regression). To choose a plausible range of values of $\delta$, let us recall that it is a measure of proportional selection on unobservables. My reported estimates of the treatment effect will be robust when it holds up for values of $\delta$ that are larger than unity. In such cases, the analysis allows unobservables, which have been left out of the model, to have more importance than observed, included, controls. If the reported estimate holds up even when the unobservables are more important than the included controls, then that should increase confidence in the reliability of my results.

6.2 Results

In Table 6, I report the three roots of the cubic equation in (10) and the associated BATE for a range of values of $R_{max}$ and $\delta$. For carrying out
these computations, the ‘short regression’ is one where I regress hate crimes against religious minorities on the interaction of $After_t$ and $BJP_s$ without any controls. The treatment effect (coefficient on the interaction term) is estimated as 1.907 and the R-squared for this regression is 0.196. The ‘intermediate regression’ is the regression with the full set of controls included (reported in column 4 in Table 2). The estimated treatment effect is 0.964 and the R-squared for this regression is 0.497. Using the notation of the previous section, we therefore have, $\tilde{\beta} = 1.907$, $\bar{\beta} = 0.964$, $\bar{R} = 0.196$, and $\tilde{R} = 0.497$. From the auxiliary regression of the treatment variable on all the observables, we get $\hat{\sigma}_X = 0.453$, and $\hat{r}_X = 0.040$. Using these parameter values, I then calculate the roots of the cubic equation in (10) for $R_{max} \in \{0.55, 0.65, 0.75, 0.85, 1.00\}$ and $\delta \in \{1.25, 1.50, 1.75, 2.00, 5.00\}$.

Note that my choice of $\delta$ are all larger than unity, so that I am deliberately choosing to assign larger explanatory power to the unobservable confounders than the observed controls. If my reported estimates of the treatment effect survives in this combination of $R_{max}$ and $\delta$, then it will provide robustness to my results.

The roots of the cubic equation (10) are reported in Table 6, and we see that in each case, there is a unique real root. For instance, when I choose $R_{max} = 0.55$ and $\delta = 1.25$, the unique real root is $-2.81$ (first row of the table). This can be interpreted to mean the following: if the unobservable confounders are 1.25 times more important than the observable controls, and the hypothetical long regression has a R-squared of 0.55, then the BATE is
3.78 (= 0.964 − (−2.81)). Hence the interval formed by treatment effect reported in column 4, Table 2, and the BATE is given by [0.964, 3.78]. Note that this interval does not contain zero. To take another case, when I choose $R_{\text{max}} = 0.85$ and $\delta = 2.00$, the unique real root is $−1.30$. Thus, when the unobservable confounders are 2 times as important as the observable controls and the hypothetical long regression explains 85% of the variation of hate crimes against religious minorities, the BATE is 2.26. In this case, the interval formed by treatment effect reported in column 4, Table 2, and the BATE is given by [0.964, 2.26], which, once again, does not contain zero.

Finally, let us use the maximum possible value of $R_{\text{max}}$, i.e. $R_{\text{max}} = 1$, and a very large value of $\delta$, i.e. $\delta = 5.00$. In this case, the unique real root is $−1.21$ (last row of the table) and the corresponding BATE is 2.17. In this case, the interval formed by treatment effect reported in column 4, Table 2, and the BATE is given by [0.964, 2.17]. This interval, once again, does not contain zero. The important thing to note is that in all cases reported in Table 6, the unique real root is negative. This means that the bias-adjusted treatment effect is larger than the estimate of the treatment effect in the intermediate regression: 0.964. Hence, the interval formed by treatment effect reported in column 4, Table 2, and the BATE does not contain zero. Not only does the reported estimate holds up, it becomes stronger. This suggests that even after accounting for unobserved confounders, there will be a statistically significant treatment effect. Hence we can conclude with lot of confidence that BJP’s electoral victory in the 2014 elections has increased
the incidence of hate crimes against religious minorities.

7 Conclusion

In this paper I have demonstrated that BJP’s unprecedented victory in the 2014 Lok Sabha (lower house of parliament) elections in India caused an increase in hate crimes against religious minorities. While many commentators in national and international media have conjectured about the existence of such a link, to the best of my knowledge, this paper is the first scholarly work to provide reliable causal estimates of the effect.

I arrived at consistent causal estimates with a difference-in-difference research design. To implement my research design, I used data on BJP’s performance in the 2014 Lok Sabha elections to define treatment and control groups. The former group consists of all states where BJP won the largest share of popular votes; the latter consists of states where BJP did not emerge as the largest political party in 2014. By comparing the change in the number of anti-minority hate crimes between treatment and control groups over a five year pre-election period, 2009–13, with a five year post-election period, 2014–18, I arrive at the causal impact of BJP’s electoral victory on anti-minority hate crimes. My preferred estimates show that hate crimes against religious minorities increased by 514% compared to the pre-2014 mean. I solidify these results with a battery of robustness tests. I also compute bias-adjusted treatment effects and find that the effect becomes stronger when we
account for the possible effect of unobservable confounders.

For lack of data on relevant variables, I have not investigated possible mechanisms that might be driving my results. I hope to take up a study of mechanisms in future research and offer some ideas that could be explored. One fruitful approach would be to bring together insights from two strands of literature. From a political science literature that studies the causes of hate crimes, one can borrow the class of explanations that is known as the ‘political theory of hate crimes’ (Hamm, 1994; Koopmans, 1996; Green et al., 2001). This theory explains hate crimes as the result of the mobilization of grievances, real or imagined, by political actors and the ‘political opportunity structure’ confronting hate criminals.

One way in which the political opportunity structure can change is through a rapid change in societal norms. To understand why societal norms might have changed in 2014, one can borrow insights from a second strand of literature in economics that investigates conditions for rapid changes in social norms through information aggregation (Bursztyn et al., 2017; Schilter, 2019). This literature has demonstrated, both theoretically and through experimental evidence, that elections can be understood as information aggregation mechanisms that can, in turn, lead to rapid unraveling of societal norms. This suggests that we could see the massive electoral victory of the BJP in 2014 as leading to a rapid change in societal norms about behaviour towards religious minorities, and especially Muslims.

The change in norms can lead to an increased acceptability of attacks on
marginalized groups - like Muslims in India. It can also seep into the law enforcement machinery, making law enforcement officials timid, incompetent or complicit in crimes against marginalised groups (Green et al., 2001). Since law enforcement is a state subject under the Indian constitution, it is possible for the political success of BJP in the national elections to differentially impact the law enforcement machinery across states. The differential slack in law enforcement, especially for crimes against marginalized groups, could then lead to an increase in verbal and physical attacks against such groups.

My study raises several important and interesting questions that calls for future research. While researchers have pointed out that the number of religious riots have declined, my study shows that there has been a rise in religion-motivated hate crimes against minorities since 2014. Thus, my study points out that the form of violence against religious minorities might have changed in recent years. On the other hand, religious riots engulfed Delhi in the third week of February, 2020. It was widely reported in the Indian and international media. News reports from across the world highlighted the timidity and complicity of the Delhi police and the disproportionately larger violence against Muslims.\textsuperscript{20} This suggests caution in drawing conclusions even about the decline in the incidence of religious riots. Both these facts show that it is important to study the similarities and differences between religion-motivated hate crimes and religious riots, and to understand the causes and consequences of both (Ray, 2007).

In the study of both religion-motivated hate crimes and religious riots in India, it will be important to investigate the mechanisms that perpetuate anti-Muslim attitudes, the role of the police and political parties, the role of social media, and the different causal weight that can be assigned to on-the-ground attitudes versus encouragement from sections of the political elite. In studying these issues in India, social scientists can draw on a rich literature on similar issues from other countries and periods (Krueger and Pischke, 1997; Green et al., 2001).

It seems obvious that the phenomenon studied in this paper is a worldwide one - marginalized minorities have been under attack in many countries across the world (for instance, see the March/April 2019 issue of *Foreign Affairs* on ‘The New Nationalism’). Hence, a comparative analysis across countries might throw light on some of the important dimensions of the problem. Moreover, 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 earlier periods as well. Finally, 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?
References


Williams, M. L., Burnap, P., Javed, A., Liu, H., and Ozlap, S. (2020). Hate in the machine: Anti-Black and anti-Muslim social media posts as predic-
Table 1: Total Number of Religion-motivated Hate Crimes in India, 2009–18

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

*Notes:* This table reports the count of religion-motivated 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.
Table 2: OLS Estimates of Treatment Effect from Binary Treatment Model of Hate Crimes Against Religious Minorities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>After X TREAT</td>
<td>1.783***</td>
<td>1.623***</td>
<td>1.251***</td>
<td>0.964***</td>
<td>0.890**</td>
<td>1.007***</td>
</tr>
<tr>
<td></td>
<td>(0.553)</td>
<td>(0.405)</td>
<td>(0.455)</td>
<td>(0.358)</td>
<td>(0.346)</td>
<td>(0.389)</td>
</tr>
<tr>
<td>Observations</td>
<td>280</td>
<td>252</td>
<td>252</td>
<td>224</td>
<td>216</td>
<td>184</td>
</tr>
<tr>
<td>R2</td>
<td>0.48</td>
<td>0.481</td>
<td>0.496</td>
<td>0.497</td>
<td>0.462</td>
<td>0.499</td>
</tr>
<tr>
<td>State FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time Varying Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Pre-Treatment Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Log Crime Incidence</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drop Uttar Pradesh</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drop NE States</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>WCB p-values</td>
<td>0.000</td>
<td>0.000</td>
<td>0.010</td>
<td>0.016</td>
<td>0.012</td>
<td>0.021</td>
</tr>
</tbody>
</table>

Notes: OLS estimates of the treatment effect from the Binary Treatment model in (1). The dependent variable is the number of hate crimes against religious minorities. $BJP_s = 1$ 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 $t \geq 2014$, and 0 otherwise. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: ***1 percent; **5 percent; *10 percent. Since the number of clusters is relatively small, I also report wild cluster bootstrapped (WCB) p-values for robustness. North Eastern (NE) states: Manipur, Meghalaya, Mizoram, Nagaland, Sikkim.
Table 3: Testing Parallel Trends Before 2014

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$After_t XTREND$</td>
<td>-0.158</td>
<td>-0.157</td>
<td>-0.159</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.117)</td>
<td>(0.119)</td>
</tr>
<tr>
<td>Observations</td>
<td>140</td>
<td>140</td>
<td>140</td>
</tr>
<tr>
<td>State Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time Varying Controls</td>
<td>Y</td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>Log Crime Incidence</td>
<td></td>
<td>Y</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Estimates of the treatment effect from the binary treatment model in (2). The dependent variable is the number of hate crimes against religious minorities in state $s$ and year $t$, and $TREND$ is a linear trend. Sample: 2009–13. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: ***1 percent; **5 percent; *10 percent.
Table 4: Estimates of Treatment Effect from Binary Treatment Model with Hate Crimes Against Hindus

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>After_tXBJS_s</td>
<td>0.196*</td>
<td>0.024</td>
<td>0.034</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.053)</td>
<td>(0.063)</td>
<td>(0.078)</td>
</tr>
<tr>
<td>Observations</td>
<td>280</td>
<td>252</td>
<td>252</td>
<td>224</td>
</tr>
<tr>
<td>State Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time Varying Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Pre-Treatment Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Log Crime Incidence</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Estimates of the treatment effect from the binary treatment model in (1) where the dependent variable is the number of hate crimes against Hindus (majority religious community in India) in state s and year t. All other details remain the same as in Table 2.
Table 5: Estimates of Treatment Effect from Binary Treatment Quasi-Poisson Regression Model with Hate Crimes Against Religious Minorities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>After X TREAT</td>
<td>1.964***</td>
<td>2.121***</td>
<td>2.395***</td>
<td>2.240***</td>
<td>1.946***</td>
<td>2.605***</td>
</tr>
<tr>
<td></td>
<td>(0.637)</td>
<td>(0.365)</td>
<td>(0.481)</td>
<td>(0.726)</td>
<td>(0.645)</td>
<td>(0.821)</td>
</tr>
<tr>
<td>Observations</td>
<td>280</td>
<td>252</td>
<td>252</td>
<td>224</td>
<td>216</td>
<td>184</td>
</tr>
<tr>
<td>State FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time Varying Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Pre-Treatment Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Log Crime Incidence</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drop Uttar Pradesh</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Drop NE States</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
</tr>
</tbody>
</table>

Notes: Estimates of the treatment effect from the Binary Treatment Quasi-Poisson regression model in (4). Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: ***1 percent; **5 percent; *10 percent.
Table 6: Bias-Adjusted Treatment Effect (BATE) for a Range of Values of $R_{max}$ and $\delta$

<table>
<thead>
<tr>
<th>$R_{max}$</th>
<th>$\delta$</th>
<th>$Root_1$</th>
<th>$Root_2$</th>
<th>$Root_3$</th>
<th>BATE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.55</td>
<td>-2.81</td>
<td>3.17-0.62i</td>
<td>3.17+0.62i</td>
<td>3.78</td>
</tr>
<tr>
<td>2</td>
<td>0.55</td>
<td>-2.39</td>
<td>1.78-2.04i</td>
<td>1.78+2.04i</td>
<td>3.36</td>
</tr>
<tr>
<td>3</td>
<td>0.55</td>
<td>-2.15</td>
<td>1.27-2.17i</td>
<td>1.27+2.17i</td>
<td>3.12</td>
</tr>
<tr>
<td>4</td>
<td>0.55</td>
<td>-1.99</td>
<td>1.00-2.21i</td>
<td>1.00+2.21i</td>
<td>2.96</td>
</tr>
<tr>
<td>5</td>
<td>0.55</td>
<td>-1.45</td>
<td>0.29-2.23i</td>
<td>0.29+2.23i</td>
<td>2.41</td>
</tr>
<tr>
<td>6</td>
<td>0.65</td>
<td>-1.73</td>
<td>2.62-6.50i</td>
<td>2.62+6.50i</td>
<td>2.69</td>
</tr>
<tr>
<td>7</td>
<td>0.65</td>
<td>-1.61</td>
<td>1.39-5.46i</td>
<td>1.39+5.46i</td>
<td>2.57</td>
</tr>
<tr>
<td>8</td>
<td>0.65</td>
<td>-1.53</td>
<td>0.96-5.00i</td>
<td>0.96+5.00i</td>
<td>2.49</td>
</tr>
<tr>
<td>9</td>
<td>0.65</td>
<td>-1.47</td>
<td>0.74-4.75i</td>
<td>0.74+4.75i</td>
<td>2.44</td>
</tr>
<tr>
<td>10</td>
<td>0.65</td>
<td>-1.28</td>
<td>0.20-4.07i</td>
<td>0.20+4.07i</td>
<td>2.24</td>
</tr>
<tr>
<td>11</td>
<td>0.75</td>
<td>-1.48</td>
<td>2.50-9.42i</td>
<td>2.50+9.42i</td>
<td>2.45</td>
</tr>
<tr>
<td>12</td>
<td>0.75</td>
<td>-1.42</td>
<td>1.30-7.60i</td>
<td>1.30+7.60i</td>
<td>2.38</td>
</tr>
<tr>
<td>13</td>
<td>0.75</td>
<td>-1.38</td>
<td>0.88-6.84i</td>
<td>0.88+6.84i</td>
<td>2.34</td>
</tr>
<tr>
<td>14</td>
<td>0.75</td>
<td>-1.35</td>
<td>0.67-6.42i</td>
<td>0.67+6.42i</td>
<td>2.31</td>
</tr>
<tr>
<td>15</td>
<td>0.75</td>
<td>-1.24</td>
<td>0.18-5.33i</td>
<td>0.18+5.33i</td>
<td>2.20</td>
</tr>
<tr>
<td>16</td>
<td>0.85</td>
<td>-1.38</td>
<td>2.45-11.65i</td>
<td>2.45+11.65i</td>
<td>2.35</td>
</tr>
<tr>
<td>17</td>
<td>0.85</td>
<td>-1.34</td>
<td>1.26-9.28i</td>
<td>1.26+9.28i</td>
<td>2.31</td>
</tr>
<tr>
<td>18</td>
<td>0.85</td>
<td>-1.32</td>
<td>0.85-8.30i</td>
<td>0.85+8.30i</td>
<td>2.28</td>
</tr>
<tr>
<td>19</td>
<td>0.85</td>
<td>-1.30</td>
<td>0.65-7.75i</td>
<td>0.65+7.75i</td>
<td>2.26</td>
</tr>
<tr>
<td>20</td>
<td>0.85</td>
<td>-1.22</td>
<td>0.17-6.34i</td>
<td>0.17+6.34i</td>
<td>2.18</td>
</tr>
<tr>
<td>21</td>
<td>1.00</td>
<td>-1.32</td>
<td>2.42-14.38i</td>
<td>2.42+14.38i</td>
<td>2.28</td>
</tr>
<tr>
<td>22</td>
<td>1.00</td>
<td>-1.29</td>
<td>1.23-11.34i</td>
<td>1.23+11.34i</td>
<td>2.25</td>
</tr>
<tr>
<td>23</td>
<td>1.00</td>
<td>-1.27</td>
<td>0.83-10.10i</td>
<td>0.83+10.10i</td>
<td>2.24</td>
</tr>
<tr>
<td>24</td>
<td>1.00</td>
<td>-1.26</td>
<td>0.63-9.41i</td>
<td>0.63+9.41i</td>
<td>2.22</td>
</tr>
<tr>
<td>25</td>
<td>1.00</td>
<td>-1.21</td>
<td>0.16-7.62i</td>
<td>0.16+7.62i</td>
<td>2.17</td>
</tr>
</tbody>
</table>

Notes: This table reports the three roots - $Root_1$, $Root_2$, $Root_3$ - of the cubic polynomial in (10), and the bias-adjusted treatment effect (BATE) for a range of values of $R_{max}$ and $\delta$, where $R_{max}$ denotes the R-squared of the hypothetical model that includes all observed and unobservable controls, and $\delta$ is the proportional selection on unobservables defined in (9). The bias-adjusted treatment effect is given by the estimate reported in column 4, Table 2, less the unique real root reported in this table. Note that for all cases reported in this table, there is a unique real root: $Root_1$. 

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Figure 1: Performance of the Hindutva strand of politics in elections to the Lok Sabha (lower house of parliament) in post-Independence India. Before 1980, the Bharatiya Jan Sangh was the political representative of Hindutva in the electoral arena; after 1980, it was the Bharatiya Janata Party. SeatShare refers to the share of seats won in the Lok Sabha; and VoteShare denotes the share of popular votes won in the Lok Sabha elections. The horizontal axis gives the years in which the Lok Sabha elections took place.
Figure 2: Total number of hate crimes against religious minorities (Muslims, Christians, and Sikhs) and against Muslims in India, 2009–2018.
Figure 3: Scatter plot of BJP’s 2014 vote share and change in the count of hate crimes against religious minorities (Muslims, Christians, and Sikhs) across Indian states between 2009-13 (pre-election) and 2014-18 (post-election).
Figure 4: The figure plots the average of anti-minority hate crimes per year in the treatment group (BJP states) and the control group (non-BJP states). The vertical line represents the year 2014 and demarcates the pre-election and post-election periods.
Figure 5: Placebo tests for the treatment effect from the model in (1), where different years are used to define the $After_t$ dummy variable. The x-axis gives the year that was used to define the $After_t$ dummy. The year 2014 is the election year.
A The CRHCW Website and Data

The data on the incidence of religion-motivated hate crimes used for the analysis in this paper was collected from the Citizen’s Religious Hate Crimes Watch (CRHCW) website in the second week of August 2019. On September 12, 2019, the Indian news forum, Scroll, reported that the CRHCW website had been taken down on 1 September 2019. The report in Scroll shows a screenshot of the CRHCW website, when it was operational. Figure 6 shows the screenshot of the webpage that was generated when I tried to access the CRHCW website on 1 February, 2020. The screenshot shows that the website can no longer be accessed.

The CRHCW website was awarded the data journalism awards in 2019 “for best data journalism team portfolio (small newsroom)”.

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21 Follow this link for the report and the screenshot.
22 See here.
reporting about this award to the CRHCW website can be still accessed.\footnote{23}{See here.}

This report provides vital information about the CRHCW website and the citizen’s project that created the website. For instance, it tells us why the website was created, the definition of a hate crime, the methods used to collect the data, and the impact it had on public discussions on the issue of religious-based crimes against minorities.

About the method used to collect data, this is what the website says:

...over a period of six months, we collated reports of hate violence from the English language online and print media. Each incident was then subjected to a test–to establish whether it fits the definition. These incidents were then cross-verified from other media sources to assimilate the full extent of facts, and to include information on any progress in the investigation and/or prosecution of the attacks.\footnote{24}{See here.}

A report generated on the WayBack Machine about the CRHCW website shows that the website was crawled by the WayBack Machine 7 times between 15 November, 2018 and 31 August, 2019. The CRHCW website has not seen any activity since 31 August, 2019.\footnote{25}{See here.} When the CRHCW website was active, the data it made available was used widely in the national and international media. Here are some prominent examples:

\footnotetext[23]{See here.} \footnotetext[24]{See here.} \footnotetext[25]{See here.}
B Data: Sources and Definitions

- Hate crimes (count): The count of religion-motivated hate crimes is taken from the website of the Citizen's Religious Hate Crime Watch (CRHCW). 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. The data is no longer available in the public domain. It was reported in the media that the website had been pulled down on September 1, 2019 (Scroll, 2019).

- Electoral outcomes: The data on electoral outcomes for the 2009 and 2014 Lok Sabha elections is taken from the website of the Election Commission of India. The electoral data is available here: https://eci.gov.in/statistical-report/statistical-reports/

- Incidence of crime (number): This variable gives the incidence (number) of crimes covered by the Indian Penal Code (IPC). These data are collected from: (1) Table 1.5, Crime in India 2013; and (2) Table 1A.1, Crime in India 2016. The publication, Crime in India, is an
annual publication of the National Crime Records Bureau (NCRB) of the Ministry of Home Affairs, Government of India.\textsuperscript{26}

- Estimated mid-year population (lakhs): The data on this variable come from various issues of \textit{Crime in India}. The NCRB, in turn, takes the data on population from the Registrar General of India.

- Per capita net state domestic product (PCNSDP) at 2011-12 prices (rupees): The data on this variable are taken from the \textit{Handbook of Statistics on Indian Economy, 2018-19}, an annual publication of the Reserve Bank of India.\textsuperscript{27}

- Literacy rate in 2011 (%): The literacy rate is defined as the ratio of the literate population aged 7 years and above divided by the total population aged 7 years and above. This definition has been used in the Censuses since 1991, and is known as the effective literacy rate. Data on this variable is taken from the \textit{Census of India, 2011}.\textsuperscript{28}

- Share of urban population in 2011 (%): The urbanization rate is the share of total population residing in urban areas, where an urban unit can be either a statutory town or a census town. Data on this variable is taken from the \textit{Census of India, 2011}.

- Share of Muslim population in 2011 (%): The variable measures the

\textsuperscript{26}See http://ncrb.gov.in/
\textsuperscript{27}See https://www.rbi.org.in/Scripts/publications.aspx
share of Muslims in a state’s population in 2011. Data on this variable is taken from the *Census of India, 2011*.

Table B.1 presents summary statistics for all the variables used in this study, and Table B.2 presents means for the pre-election (2009–13) and post-election (2014–18) periods. In the last column of Table B.2, I report p-values for testing the equality of means over the two periods.

**Table B.1: Summary Statistics for Key Covariates**

<table>
<thead>
<tr>
<th>Key Variables</th>
<th>N</th>
<th>Min</th>
<th>Mean</th>
<th>Max</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hate crimes against rel minorities</td>
<td>280</td>
<td>0</td>
<td>0.78</td>
<td>19</td>
<td>1.95</td>
</tr>
<tr>
<td>BJP’s vote share in 2014 (%)</td>
<td>28</td>
<td>0.00</td>
<td>29.31</td>
<td>60.11</td>
<td>20.39</td>
</tr>
<tr>
<td>BJP’s vote share in 2009 (%)</td>
<td>28</td>
<td>0.00</td>
<td>20.03</td>
<td>49.58</td>
<td>16.89</td>
</tr>
<tr>
<td>Log-Crime Incidence (number)</td>
<td>224</td>
<td>6.27</td>
<td>10.45</td>
<td>12.55</td>
<td>1.80</td>
</tr>
<tr>
<td>Log-PCNSDP (2012-13 rupees)</td>
<td>269</td>
<td>9.27</td>
<td>11.13</td>
<td>12.82</td>
<td>0.65</td>
</tr>
<tr>
<td>Log Mid-year Population (lakhs)</td>
<td>252</td>
<td>1.80</td>
<td>5.26</td>
<td>7.71</td>
<td>1.57</td>
</tr>
<tr>
<td>Share of Urban Population in 2011 (%)</td>
<td>280</td>
<td>10.05</td>
<td>33.41</td>
<td>97.71</td>
<td>17.46</td>
</tr>
<tr>
<td>Literacy Rate in 2011 (%)</td>
<td>280</td>
<td>61.80</td>
<td>76.63</td>
<td>94.00</td>
<td>8.08</td>
</tr>
<tr>
<td>Share of Muslim Population in 2011 (%)</td>
<td>280</td>
<td>1</td>
<td>12.50</td>
<td>68</td>
<td>13.49</td>
</tr>
</tbody>
</table>

*Notes: Summary statistics for variables used for the analysis in this paper.*
### Table B.2: Difference in Mean in BJP and non-BJP States Before 2014

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Non-BJP</th>
<th>BJP</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hate crimes against rel minorities</td>
<td>0.18</td>
<td>0.14</td>
<td>0.69</td>
</tr>
<tr>
<td>BJP’s vote share in 2014 (%)</td>
<td>8.46</td>
<td>44.95</td>
<td>0</td>
</tr>
<tr>
<td>BJP’s vote share in 2009 (%)</td>
<td>5.01</td>
<td>31.29</td>
<td>0</td>
</tr>
<tr>
<td>Log-Crime Incidence (number)</td>
<td>9.61</td>
<td>10.98</td>
<td>0</td>
</tr>
<tr>
<td>Log-PCNSDP (2012-13 rupees)</td>
<td>10.89</td>
<td>10.89</td>
<td>0.98</td>
</tr>
<tr>
<td>Log Mid-year Population (lakhs)</td>
<td>4.58</td>
<td>5.73</td>
<td>0</td>
</tr>
<tr>
<td>Share of Urban Population in 2011 (%)</td>
<td>33.25</td>
<td>33.52</td>
<td>0.92</td>
</tr>
<tr>
<td>Literacy Rate in 2011 (%)</td>
<td>79.75</td>
<td>74.30</td>
<td>0</td>
</tr>
<tr>
<td>Share of Muslim Population in 2011 (%)</td>
<td>8.33</td>
<td>15.62</td>
<td>0.001</td>
</tr>
<tr>
<td>Number of states</td>
<td>12</td>
<td>16</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table reports the sample mean of covariates for the control (non-BJP) and treatment (BJP) groups of states, and a test for the equality of the means (p-value reported in last column) before 2014. BJP states: Assam, Bihar, Chhattisgarh, NCT of Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra, Rajasthan, Uttar Pradesh, Uttarakhand. Non-BJP states: Andhra Pradesh, Kerala, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Punjab, Sikkim, Tamil Nadu, Tripura, West Bengal.