POLITICAL ECONOMY RESEARCH INSTITUTE
PERI
University of Massachusetts Amherst

POLITICAL ECONOMY RESEARCH INSTITUTE

Dominance of Majoritarian Politics and Hate Crimes Against Religious Minorities in India, 2009-2018

Deepankar Basu

August 2019

Updated December 2019

WORKINGPAPER SERIES

Number 493

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

Deepankar Basu*

December 2, 2019

Abstract

Using a novel state-level panel data set for the period 2009-18 on the incidence of hate crimes in India, and a difference in difference (DD) approach, this paper investigates the causal impact of the right-wing, Hindu nationalist BJP's win in the 2014 national elections on hate crimes against religious minorities. Using 2009-13 (pre-election) and 2014-18 (post-election) as the before and after periods, I estimate a standard DD model, where the treatment group consists of states where BJP won the largest share of popular votes in 2014, to get an initial estimate of the causal impact. I strengthen this result with a treatment intensity approach where BJP's vote share in 2014 functions as the treatment intensity. I instrument it with BJP's vote share in the previous national elections in 2009 to estimate the causal impact. I supplement the linear models with quasi-Poisson regressions to take account of the count data nature of the incidence of hate crimes. All approaches show that BJP's electoral victory in 2014 caused an increase in the incidence of hate crimes against religious minorities. I investigate three plausible mechanisms that might generate the result: laxity of state-level law enforcement; economic competition between religious groups; role of social media. I find evidence that weakening of state-level law enforcement is the key mechanism driving the rise in anti-minority hate crimes. This paper contributes to contemporary studies of the adverse impact of rising ethno-nationalist populism on marginalized social

*Department of Economics, University of Massachusetts Amherst, 310 Crotty Hall, 412 N. Pleasant Street, Amherst MA 01002. Email: dbasu@econs.umass.edu. Phone: (413)545-6359. Fax: (413)545-2921. This is a substantially revised version of, and supersedes, my earlier paper entitled, "Majoritarian Politics and Hate Crimes Against Religious Minorities in India, 2009–2018", (Working Paper 493, Political Economy Research Institute, University of Massachusetts Amherst). I would like to thank Michael Ash, Mary Ann Clawson, Debarshi Das, Ina Ganguli, Leila Gautham, Daniele Girardi, Kartik Misra, Karsten Müller, Soham Sahoo, Priyanka Srivastava, Sebastian Vollmer, and participants at the colloquim in the Center for Modern Indian Studies, University of Göttingen for very helpful comments on an earlier version of this paper. The usual disclaimers apply.

groups by investigating the case of India.
JEL Codes: D72; D74
Keywords: minorities, hate crimes, electoral outcomes, difference in difference.

1 Introduction

A small but growing body of scholarly work studies the connections between the recent growth of right-wing, ethno-nationalist populism and violence against marginalized social groups, like immigrants, and racial and religious minorities (Dancygier and Laitin, 2014; Muis and Immerzeel, 2017; Bonikowski, 2017; Cederman, 2019). The possibility of such connections have been commented on widely in the media in reference to the United States after the election of Donald Trump in 2016, the 2017 Brexit vote in the United Kingdom, and the recent growth of right-wing populist parties across Europe.[1] But the scholarly literature on this issue, especially within the discipline of economics, is still in its infancy: various aspects of the US case have been studied by Bursztyn et al. (2017); Edwards and Rushin (2018); Schaffner et al. (2018); Hobbs and Lajevardi (2019); Müller and Schwarz (2019); and the UK case has been studied by Cuerden and Rogers (2018); Devine (2018); Schilter (2019); and the case of Germany has been studied by Müller and Schwarz (2018); Entorf and Lange (2019).[2] This paper contributes to this literature by investigating the possible causal connection between the rise of a right-wing majoritarian party in India and hate crimes against religious minorities.

The national parliamentary elections of 2014 is seen widely as a watershed moment in India's post-independence history. The unprecedented and massive victory of the right-wing, Hindu nationalist Bharatiya Janata Party (BJP) marks the unmistakable rise to dominance of a majoritarian, exclusivist politics in India (Basu, 2015; Vanaik, 2017; Bose, 2018). Com-

[1]See, for instance, Williams (2018); Weaver (2018); Booth (2019); Knobbe and Weidmann-Schmidt (2019).
[2]There is a larger literature that has studied various aspects of violence against marginalised sections of the population upon the German unification. For instance, see Alber (1993); Krueger and Pischke (1997); Karapin (2002); Braun and Koopmans (2010).

mentators 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). In this paper, I wish to study the question: is there a 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 a majority of the constituencies (282 of the 543 parliamentary constituencies). 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.[3]

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 nationalism. 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.

The political scientist, Sumantra Bose, succinctly summarises the ideology of Hindutva as consisting 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, 2019). Founding ideologues of Hindu nationalsim, like V.

[3]For more details of BJP's ideology and electoral performance see section 2.

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. It is with this understanding of BJP's foundational principles that I approach the question of the possible link between its rise to dominance in 2014 and the increase in *hate crimes* against religious minorities, especially Muslims.

To empirically analyse the possible causal connection between the outcome of the 2014 Lok Sabha elections - which I interpret as the rise to dominance of majoritarian politics in India - and hate crimes against religious minorities, I use a state-level panel data set, covering the period 2009–2018. 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.[4]

I start the empirical analysis by estimating a simple difference model with state fixed effects and dummy variables for each year in my sample. The results of this exercise shows that average hate crimes against religious minorities did not change much between 2009 and 2013, but increased significantly in 2014 and remained high thereafter. To investigate whether the increase in anti-minority hate crimes in 2014 can be causally linked to BJP's

[4] For more details about the data, see section 3, and Appendix A and Appendix B.

electoral victory in that year, I use a difference in difference (DD) empirical strategy.[5]

For the DD approach, I divide states into two groups. The treatment group - which I call BJP States - consists of states where BJP won the largest share of popular votes in the 2014 Lok Sabha elections. The control group - which I call the non-BJP States - consists of all other states in my sample. I compare the *change* in anti-minority hate crimes in the two groups for 5 year periods before and after the 2014 Lok Sabha elections by estimating a DD model. 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 might even find greater support among the functionaries of the state. And I use BJP's performance in the 2014 Lok Sabha elections - captured by the share of popular votes it won - as a measure of this support.

I start the DD analysis with a specification with only state and year fixed effects, and then incrementally add time varying controls, pre-2014 controls interacted with the after-2014 dummy and finally state-level linear time trends. All specifications show a large, positive and statistically significant effect. For the specification with all controls and state-level linear time trends, I find that anti-minority hate crimes increased by 544% more in the treatment than in the control group of states (column 5, Table 7). This provides my initial estimate of the causal impact of BJP's electoral victory on the incidence of anti-minority hate crimes in the period, 2009–2018.

The key identifying assumption in a DD strategy is the parallel trends assumption. In the context of my study, this means that the incidence of anti-minority hate crimes would move in a similar manner in both treatment and control groups of states if BJP had not

[5] Standard DID research designs have been widely used in economics; for instance, see Card and Krueger (1994); Gruber (1994); Autor (2003); Muralidharan and Prakash (2017); Cengiz et al. (2019). Textbook treatments are available in Angrist and Pischke (2009, pp. 227–242), and Greene (2012, chapter 6).

won the 2014 Lok Sabha elections in the way it did. I test this key assumption both visually (in Figure 4) and by estimating the model with the full set of controls in the pre-election sample years, 2009–2013 (reported in Table 8). I find that average anti-minority hate crimes in treatment (BJP States) and control (non-BJP States) groups were growing at the same rate in the period 2009–2013. Thus, both visual and regression evidence suggests that the parallel trends assumption is valid for my DD research strategy.

I subject my findings to further critical scrutiny by running two sets of placebo tests. In the first placebo test, I re-estimate the DD model with full set of controls and vary the cut-off year for defining the 'after' dummy variable. Since the relevant election took place in 2014, after dummy variables defined for all other years give me placebos. I find that there is no effect before 2014, that the effect emerges in 2014 and persists after 2014 (though weaker in magnitude and significance; see Figure 5). This suggest that the election victory of BJP in 2014 was the turning point as far as the incidence of anti-minority hate crimes is concerned. For the second placebo test, I use the hate crimes against Hindus (the majority religious community in India) as the dependent variable - with everything else remaining the same in my DD model. Since BJP's electoral victory signals the rise to dominance of majoritarianism, it should not have any effect on hate crimes against member of the *majority* religious community. The results of this placebo test show that there is no discernible effect of BJP's victory on the incidence of hate crimes against Hindus (see Table 9).

Taken together, the results from the DD estimation, the test of the parallel trends assumption and the results of the two sets of placebo tests provide strong evidence of a causal impact of BJP's 2014 electoral victory on the incidence of anti-minority hate crimes. Strong as this evidence is, it is still not possible to identify this as a causal impact. After all, my empirical analysis is open to the following criticisms: (a) there is reverse causality running from hate crimes to BJP's vote share, as has been found in the case of religious riots (Wilkinson, 2004; Iyer and Shrivastava, 2018); (b) there is an unobserved factor that has caused both high BJP vote shares in 2014 and high anti-minority hate crimes thereafter. Since I have not been able to rule this out, my estimates might be an overestimate of the true causal impact. I address this concern with an instrumental variables strategy.

To implement the instrumental variables strategy, I estimate a treatment intensity model.[6] In this 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 itself as a measure of the 'treatment intensity'. Since BJP's vote share in the 2014 Lok Sabha elections might be correlated with unobserved factors that also increase anti-minority hate crimes in and after 2014, I am likely to get (upward) biased estimates of the treatment effect if I estimate the model with OLS. Hence, I use BJP's vote share in the previous Lok Sabha elections in 2009 as the instrumental variable for its vote share in 2014. The instrumental variable estimate with the full set of controls is positive and statistically significant and shows that every percentage point of vote share won by BJP in 2014 caused an increase in anti-minority hate crimes by about 2.43% (column 5, Table 11). I also conduct the same two sets of placebo tests, as I did for the DD model (see Table 12 and 13). The results from the placebo tests show no treatment effect and increase the confidence in my IV results.

I complement the above results from linear models with results from count data models. The dependent variable - the number of hate crimes faced by religious minorities - is a count variable, which has a large probability mass concentrated at zero. Hence, I estimate the model with a quasi-Poisson regression, which explicitly takes account of overdispersion of the count variable. To address possible concerns of endogeneity, I estimate both a standard quasi-Poisson regression and a quasi-Poisson model with a control function approach (to deal with possible problems of endogeneity). Both sets of results confirm the previous results from the linear models: there is a large and statistically significant effect of BJP's performance

[6] For an example of the treatment intensity approach see Card (1992), and Angrist and Pischke (2009, pp. 227–242).

in the 2014 Lok Sabha elections on the incidence of hate crimes against religious minorities (see Table 14 and 15).

After establishing the causal impact, I turn to investigating possible mechanisms that might be responsible for the effect we observe. A survey of the existing literature on this and similar issues suggests three possible mechanisms. First, research in political science has identified state-level political dynamics and state-level law enforcement as important factors that contribute to both the occurrence and prevention of religious riots in India (Brass, 2003; Wilkinson, 2004; Basu, 2015). Since law & order is a state subject in India, this makes intuitive sense and suggests the first mechanism for me to investigate: BJP's electoral victory in 2014 might have weakened law enforcement at the state-level with regard to crimes against social and religious minorities; this might have caused the spike in anti-minority hate crimes after 2014.

An equally large body of research in history and political science, many of these based on case studies, have highlighted the economic dimension of religious conflict in India (Engineer, 1984; Banu, 1989; Bagchi, 1990; Khan, 1992; Upadhyaya, 1992; Wilkinson, 2004). After surveying some of this literature, Mitra and Ray (2014) have taken the argument a step further by constructing a theoretical model to explain the role of economic competition in religious conflicts like riots. Their empirical analysis shows that relative prosperity of Muslims lead to an increase in inter-religious conflict. This suggest the second mechanism that I investigate: BJP's electoral victory in 2014 led to the increase in hate crimes against religious minorities, especially Muslims, by working through the channel of economic competition between the two groups.

The third mechanism I study comes from an engagement with a very recent literature that has studied the role of social media in the incidence of hate crimes against minorities, immigrants and other marginalized communities in the previous few years (Müller and Schwarz, 2018, 2019; Williams et al., 2019). Using novel data sets and credible identification strategies, this literature has shown that social media can be the conduit for the spread of hate-filled messaging about marginalized communities, which can then encourage or even trigger acts of verbal or physical violence against the targeted groups. This suggests that I study the possible role of the same mechanism in the case of anti-minority hate crimes in India: the role of social media.

I capture the possible role of social media in generating anti-minority hate crimes by the interaction of total wireless telecom subscriptions with the share of the Hindu population of a state in 2011 (the latest Census year); I capture the possible role of economic competition between Hindus and Muslims by the poverty rates of the two groups in 2009–10 and the share of each group with higher secondary education and above, all these variables interacted with the 'after' dummy variable; finally, I capture the role of state-level politics and law enforcement with three dummy variable: a dummy that indicates whether BJP is part of a state government in any year, a variable that measures the charge sheeting rates of all crimes covered by the Indian Penal Code (IPC), and a third variable which measures the charge sheeting rates of crimes committed against scheduled castes (SCs) that are covered by the SC/ST (Prevention of Atrocities) Act. To test the three mechanisms, I estimate the treatment intensity model using both OLS and IV estimators - with the full set of controls - and include the set of variables that, in turn, capture state-level law enforcement, group-level economic competition, and the reach of social media. My results suggest that the state-level law enforcement mechanism is the most important one in causing the increase in anti-minority hate crimes after 2014.

Before turning to a discussion of methods and results, I would like to highlight the two contributions of this paper. First, I add to the recently started, and rapidly developing, literature on the rise of right-wing populism and its impact on marginalized communities (Bursztyn et al., 2017; Cuerden and Rogers, 2018; Devine, 2018; Edwards and Rushin, 2018; Schaffner et al., 2018; Entorf and Lange, 2019; Hobbs and Lajevardi, 2019; Müller and

Schwarz, 2019; Schilter, 2019). Existing studies have mostly studied developed economy contexts, like Germany and the US, and my paper adds to this literature by offering a similar analysis for a large developing economy, India. To the best of my knowledge, this paper is the first academic study of the relationship of majoritarian politics and anti-minority hate crimes in India.

Second, this paper speaks to a large literature that has studied various aspects of Hindu-Muslim violence in India (Varshney, 2002; Brass, 2003; Wilkinson, 2004; Corbridge et al., 2012; Mitra and Ray, 2014; Basu, 2015; Iyer and Shrivastava, 2018). These studies have investigated Hindu-Muslim violence in colonial and post-colonial India that has taken the form of *riots*. I extend this literature in two ways. First, I study a form of violence against religious minorities that is different from riots, i.e. hate crimes. Second, I investigate the causal impact of the rise of BJP on this form of violence against religious minorities.

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.[7]

Religion-motivated hate crimes, on the other hand, are instances of targeted mob violence directed against an individual or family. The direct loss of life and property is far smaller than in the case of riots. But the psychological impact on the whole community of the victim(s) is probably equally damaging. The following list gives some prominent examples of religion-motivated hate crimes that occurred during the period of my study.

- 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

[7]For detailed studies of riots, see Brass (2003); Wilkinson (2004); Basu (2015).

humiliated and forced to chant “Jai Shri Ram”. He died in hospital a few days later.[8]

- On 22 June, 2017, a 16 year old Muslim boy, Junaid Khan, was stabbed on a Delhi-Mathura train. He bled to death on platform in Asoti railway station, Faridabad.[9]

- 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.[10]

- 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.[11]

An updated version of the widely used Varshney-Wilkinson data set on religious riots 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. But, large scale riots are 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).

The rest of the paper is organised as follows: in section 2, I provide a brief history of Hindu nationalism to provide context for the analysis of this paper; in section 3, I discuss my data sources and key variables; in the following section, I provide a descriptive analysis of all-India and state-wise trends in hate crimes against religious minorities; in section 5, I present the main empirical analysis relating to the causal impact under investigation; in section 6, I analyse three possible mechanisms; and in section 7, I conclude the paper. Appendix A

[8]See the reports in Scroll and The Indian Express (accessed 24 November, 2019).
[9]See the report in NDTV
[10]See report in The Hindustan Times
[11]See report in Al Jazeera.

gives details of data sources and variable definitions; and Appendix B provides discussion of the source for my data on religion-motivated hate crimes.

2 A 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 - 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 political arena; and (c) electoral outcomes in 2014 as marking a qualitative break in the political history of Hindu nationalism in post-independence India.[12]

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.

[12] For the material in this section, I primarily use Sarkar (1984) and 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. In addition, I have also drawn on Andersen and Damle (1987), Jaffrelot (1996), Varshney (2002), Brass (2003), Wilkinson (2004), McGuire and Copland (2007), Bose (2013), Basu (2015), Vanaik (2017), Bose (2018), and Chatterjee et al. (2019).

Contact with the British, and with Christian missionaries in particular, in the context of colonial rule, led to an ambiguous response from local (mostly 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. This ambiguous reaction first took concrete shape in the early 19-th century 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.[13] 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 its 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

[13] Sumit Sarkar writes: "'Revivalism' thus obviously contributed to the assertion of an aggressive Hindu identity. But one has to add that the difference here with the 'reform' movements was of degree rather than kind. Not only 'moderninstic' trends like the Brahmos or Prarthana Samajas or the more secular movements of Young Bengal or Vidyasagar been entirely Hindu in composition; with few exceptions, they too had operated with a conception of 'Muslim tyranny' or a 'medieval' dark age ... from which British rule with its accompanying alleged 'renaissance' or 'awakening' had been a deliverance." (Sarkar, 1984, pp.75–76).

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. 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 - 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 an *Sanatan Dharmis*. 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.[14] 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 of 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).

[14]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.

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*?).[15]

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

[15] Cited in Jaffrelot (2007, pp. 95).

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 formed 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 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.

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.[16] From the figure, we can see that the rise to political dominance of Hindutva displays

[16] All figures in this paper have been created with the package `ggplot2` in R (Wickham, 2016).

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. BJP's political 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 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.

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 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

For the analysis reported in this paper, I have constructed a state-level panel data set which has 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.[17] The two key variables in my data set are the incidence of religion-motivated hate crimes and the electoral performance of the BJP. The former is the outcome variable of interest and the latter is used to construct the treatment group (of states) and treatment intensity (across states). The panel data set

[17]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.

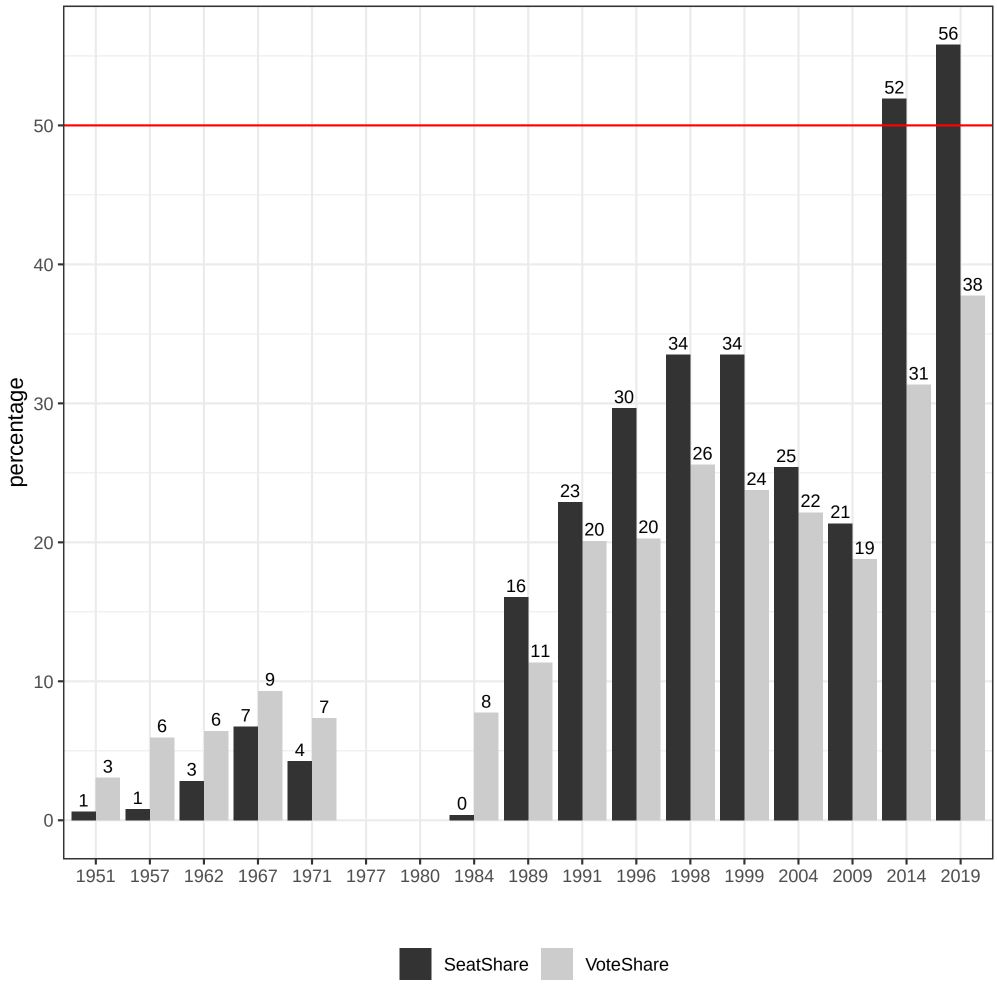

Figure 1: *Performance of the Hindutva strand of politics in elections to the Lok Sabha (lower house of parliament) in post-Independence India. Before 1980, the Bharatiya Jan Sangh was the political representative of Hindutva in the electoral arena; after 1980, it was the Bharatiya Janata Party. SeatShare 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. Source: Author's calculation from data accessed from the website of the Election Commission of India:* https://eci.gov.in/.

also includes other covariates that are either used as controls in the main regressions or for testing mechanisms.

3.1 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).[18] 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 religion-motivated hate crime in the way that is standard in the extant sociological literature. In particular, a religion-motivated hate crime is an incident with two characteristics - first, that it is a *prima facie* criminal act, under the provisions of the Indian legal system, and second, that it is partly or wholly motivated by prejudice towards the religious identity of the victim.[19] The main source of data on religion-motivated hate crimes recorded by the CRHCW are news reports in the national media.[20] Starting from reports about such incidents in English language online and print media, the CRHCW

[18] 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). For further details, see Appendix A.

[19] The FBI defines a hate crime as any "criminal offense against a person or property motivated in whole or in part by an offender's bias against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity." See the FBI website here.

[20] There is a long tradition in the social sciences of using data on violence against marginalized communities collected from news reports. For an example of the use of this methodology in economics, and references to other disciplines which have used this method of data collection and analysis, see Krueger and Pischke (1997). In studies of religious riots in India, the primary data set is the Varshney-Wilkinson data set, which was constructed from reports in the Bombay (Mumbai) edition of the leading English language daily, *The Times of India*. Among many other studies, Mitra and Ray (2014) has used the Varshney-Wilkinson data set.

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. Using this methodology, the CRHCW collected data on religion-motivated hate crimes in India going back to the year 2009.[21]

For the analysis reported in this paper, I 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.[22] 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 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

[21]For further details about the methodology used, see Appendix B and https://datajournalismawards.org/projects/hate-crime-watch/

[22]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. 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.

2014 - to isolate the impact of the electoral outcome on subsequent hate crimes.

3.2 Electoral Outcome and Treatment

I use state-level outcomes of the 2014 Lok Sabha elections to construct treatment groups (of states) and to measure treatment intensity (across states). The key electoral outcome variable that I have used is the share of popular vote won by BJP, and other political parties, for the 2014 Lok Sabha elections in India. I have downloaded this data from the website of the Election Commission of India.[23]

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 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 for very different magnitudes of vote share won by the BJP across states. What matters is whether it was largest among all political parties. For instance, we can see in Table 4 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. I will complement the standard DID analysis with a treatment intensity approach. For this latter approach, I use the share of

[23]An alternative measure that recommends itself is the share of seats won by the BJP. In India's electoral system, winners are decided by the 'first past the post' rule. Hence, the outcome in terms of which party wins a seat depends not only its vote share but on many other factors, including the number of key contestants, pre-poll alliances, etc. The vote share gives a direct measure of support for a party, which is not mapped in a straightforward fashion onto seat share. Hence, I prefer to use the vote share for my study to capture the level of support of the BJP in a state. The electoral data in available here: https://eci.gov.in/statistical-report/statistical-reports/

popular votes won by the BJP in the 2014 Lok Sabha elections as the treatment intensity variable - which captures the strength of BJP's support. For arriving at reliable causal estimates, I will use BJP's vote share in the previous Lok Sabha elections in 2009 as an instrumental variable for its vote share in the 2014 Lok Sabha elections (the treatment intensity variable). I will discuss the plausibility of this instrument below.

3.3 Other Covariates

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: incidence of IPC crimes, mid-year population, real per capita net state domestic product, share of population that is literate, share of population residing in urban areas, and the share of Muslims in a state's population. Among these covariates, data on the incidence of crimes, state-level population and per capita real net domestic product is available for every year. On the other hand, data on the share of population that is literate, share of population residing in urban areas, and the share of Muslims in a state's population is only available for 2011 (the census year). Hence, when I include these three covariates, I interact them with the after-2014 dummy variable (that identifies years after the 2014 Lok Sabha elections).

In addition, I use the following variables for testing three mechanisms (which I discuss in greater detail below): poverty rate (HCR) of Muslims; poverty rate of Hindus; proportion of Muslims with higher secondary education and above; proportion of Hindus with higher secondary education and above; the charge sheeting rate of IPC crimes; the charge sheeting rate of crimes against SCs that are covered by the SC/ST (Prevention of Atrocities) Act, 1989; the total number of wireless telecom subscribers; and a dummy variable indicating whether BJP is part of the State government in any year (Yes=1;No=0). Summary statistics of all variables used for the analysis in this paper are presented in Table 1.[24]

4 A Descriptive Analysis of Hate Crimes

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 minorities between 2009 and 2018.

4.1 All India Pattern

Table 2, 3 and Figure 2 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 2 and 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 (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 3, 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 3 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, 2009–2018, there was a total of 275

[24]Details about all the variables can be found in Appendix A.

Table 1: Summary Statistics for Covariates[a]

	N	Min	Mean	Max	St. Dev.
Key Variables					
Hate crimes ag rel minorities	280	0	0	19	1.95
BJP's vote share in 2014 (%)	28	0.00	31.26	60.11	20.39
BJP's vote share in 2009 (%)	28	0.00	16.55	49.58	16.89
Control Variables					
Log-Crime Incidence (number)	224	6.27	10.98	12.55	1.80
Log-PCNSDP (2012-13 rupess)	269	9.27	11.02	12.82	0.65
Log Mid-year Population (lakhs)	252	1.80	5.70	7.71	1.57
Share of Urban Population in 2011 (%)	28	10.05	29.48	97.71	17.75
Literacy Rate in 2011	28	61.80 (%)	76.05	94.00	8.21
Share of Muslim Population in 2011 (%)	28	1.00	9.00	68.00	13.72
Covariates for Testing Mechanisms					
Chargesheeting rate for All crimes (%)	252	3.40	76.95	97.80	18.06
Chargesheeting rate Crimes against SCs (%)	164	0.00	91.35	100.00	17.41
Wireless telecom subscribers (million)	170	1.71	7.55	18.16	2.87
BJP in State Govt (Yes=1;No=0)	280	0	0	1	0.47
Hghr Scndry and Above for Hindus in 2011-12 (%)	28	9.50	18.25	46.30	8.11
Hghr Scndry and Above for Muslims in 2011-12 (%)	28	4.30	10.70	22.30	5.60
Poverty among Hindus in 2009–10 (%)	17	12.10	24.50	54.00	11.80
Poverty among Muslims in 2009–10 (%)	17	11.60	31.60	53.60	13.75

[a] Summary statistics for variables used for the analysis in this paper. For definitions of variables and sources, see Appendix A.

Table 2: Total Number of Religion-motivated Hate Crimes by Community of Victims in India, 2009–18[a]

	Community of Victims					All	All Minorities
	Muslim	Christian	Sikh	Hindu	Unknown	Minorities	Less Hindus
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

[a] 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/

religious hate crimes, of which 217, or 80 percent, were hate crimes committed against religious minorities (Muslims, Christians and Sikhs).[25] 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 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 magni-

[25]To get a sense of magnitudes, it is useful to compare the incidence of religion-motivated hate crimes with the incidence of Hindu-Muslim riots using the Varshney-Wilkinson data set. Between 1950 and 1995, there were a toal 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. But as I have pointed out earlier, the casualties in riots are much higher, even though the psychological impacts of both might be comparable.

Table 3: Total Number of Religion-motivated Hate Crimes in India, 2009–18[a]

	2009–2013	2014–2018
Religious Community of Victims		
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

[a] 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 occured 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/

tude 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

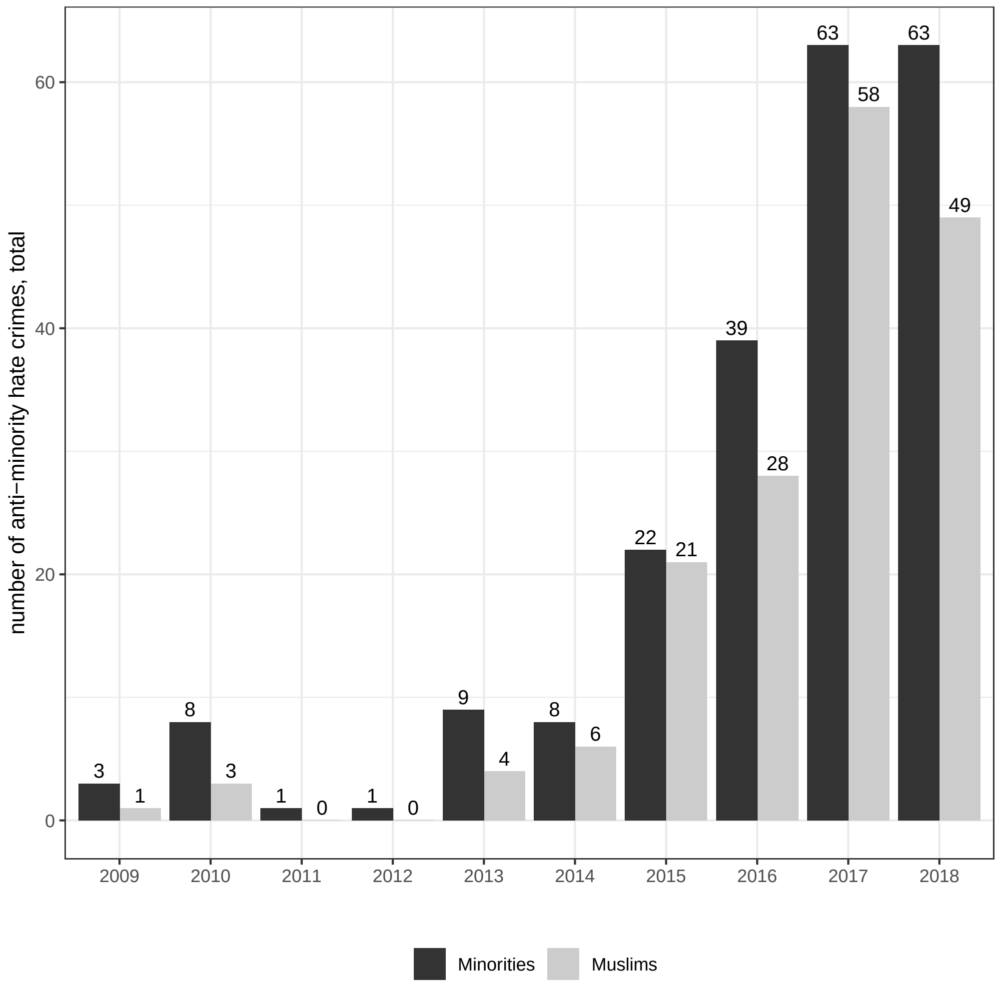

Figure 2: *Total number of hate crimes against religious minorities (Muslims, Christians, and Sikhs) and against Muslims in India,* 2009–2018*. Source: Author's calculation from data accessed from the CRHCW website:* `https://p.factchecker.in/`.

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 2 and 3 and Figure 2, 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.

4.2 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 4 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.

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

Table 4: Hate Crimes Against Religious Minorities across Indian States, 2009–18[a]

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

[a] 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 occured 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 column, I report the share of popular votes won by BJP in the 2014 Lok Sabha elections. Source: Author's calculation using data from the CRHCW website: https://p.factchecker.in/

ranking of Bihar and Maharashtra). 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. Hence, 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.

5 Empirical Analysis

5.1 Simple Difference Model

I begin my empirical analysis by estimating a simple difference model:

$$\log(0.1 + hc_{st}) = \mu_s + \sum_{k=2010}^{k=2018} \delta_t D_t + \varepsilon_{st} \tag{1}$$

where s, t are indexes for states and year, hc_{st} is number of anti-minority hate crimes in state s in year t, D_t is dummy variable for year t, where $t = 2010, 2011, \ldots, 2018$, μ_s is an unobserved time-constant state-level effect. My primary interest is in the coefficients associated with the year dummy variables (the reference dummy variable is for the year 2009), which show if there is a difference in the average incidence of anti-minority hate crimes in comparison to its incidence in 2009 even after accounting for time-constant state-level unobserved factors.[26]

In Figure 3, I plot the coefficient estimates, along with 95% confidence intervals, of $\delta_{2010}, \delta_{2011}, \ldots, \delta_{2018}$. From Figure 3 we see that the coefficient on the year dummy variable for 2014 onwards is positive and significant. The coefficients on the dummy variables for the years before 2014 are either negative (and insignificant) or positive (but insignificant). We can conclude that average anti-minority hate crimes did not vary much between 2009

[26]In defining the dependent variable in my regression models, I follow Mitra and Ray (2014) and add a small number, 0.1, to the number of hate crimes to avoid losing observations because many state-year observations have 0 hate crimes.

and 2013, and that there is a sustained increase in hate crimes since 2014. To investigate the possibility that this increase is caused by BJP's electoral performance in 2014, I will use variation across states, summarised in Table 4, in a DD research design.

5.2 Difference in Difference

5.2.1 Motivation and Set-Up

As a first approach to the question of causation, I will compare the difference in the average incidence of hate crimes in treatment and control groups before and after 2014. The treatment group consists of all states where BJP emerged as the largest party in terms of popular votes in the 2014 Lok Sabha elections; I call these the "BJP States". The control group consists of all other states in my sample; I call these the "Non-BJP States". Table 5 provides sample means and differences in means of the incidence of hate crimes against religious minorities for the two groups. In the control group, the average incidence of anti-minority hate crimes increased from 0.183 before the elections (2009–13), to 0.4 after the elections (2014–18). In the treatment groups, the corresponding increase was from 0.138 before the elections to 2.14 after the elections. The increase in the treatment group over and above the increase in the control group was 1.785. Compared to the average incidence in either group before the election, this difference-in-difference, of 1.785, seems to be significantly large.

To get a firmer estimate, along with confidence intervals, of the simple difference-in-difference of anti-minority hate crimes I will estimate a DD model:

$$\log\left(0.1 + h_{st}\right) = \beta_1 \left(BJP_s \times After_t\right) + X_{st}'\lambda + \mu_{0s} + \mu_{1s}t + \delta_t + \varepsilon_{st} \tag{2}$$

where $s = 1, 2, \ldots, 28$ and $t = 2009, 2010, \ldots, 2018$ index states and years, respectively, h_{st} denotes the number of hate crimes against religious minorities in state s in year t, $BJP_s = 1$

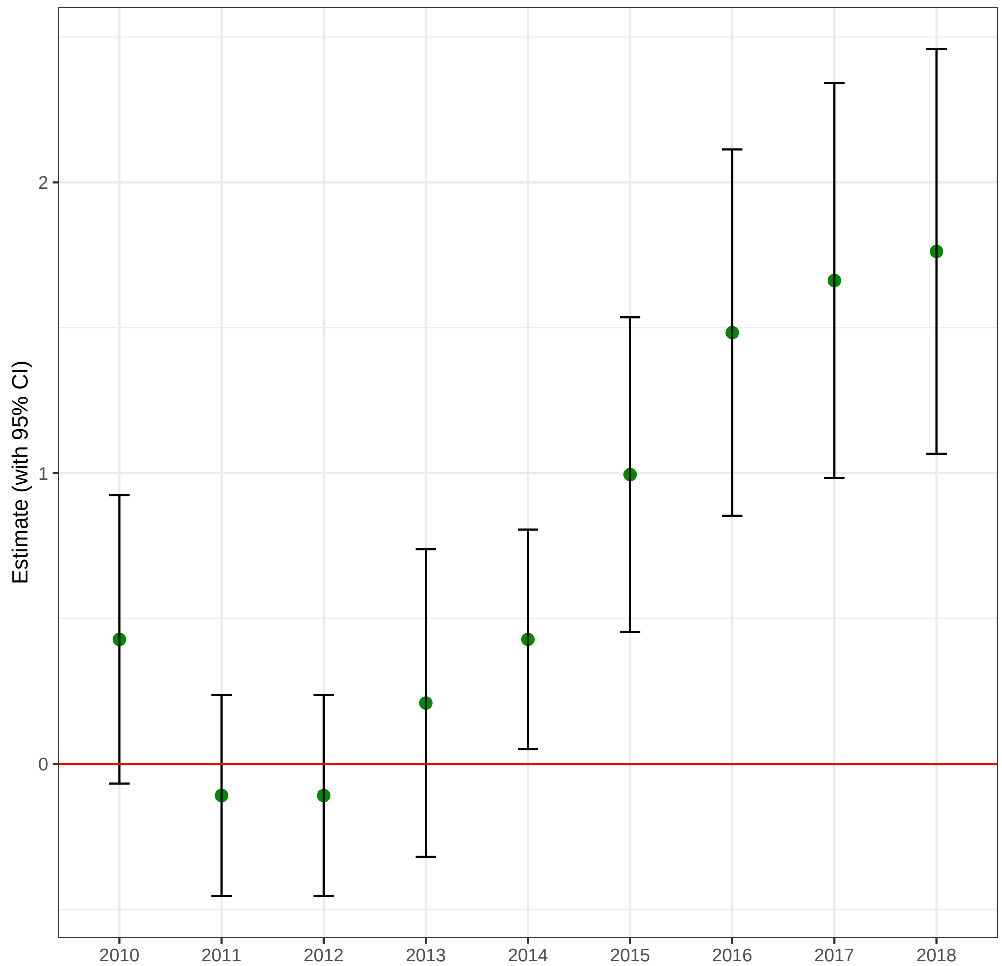

Figure 3: *Parameter estimates on year dummy variables in a simple difference model in (1) with 95% confidence intervals. The dependent variable is* $\log(0.1 + hc_{st})$*, where* hc_{st} *is the number of hate crimes against religious minorities in state* s *and year* t*. The model includes state fixed effects (but no controls) and is estimated on the state-level panel data set described in section 3.*

Table 5: Average Religion-motivated Hate Crimes Against Religious Minorities in BJP and non-BJP States[a]

	2009–2013	2014–2018	Difference
BJP States	0.138	2.140	2.002
Non-BJP States	0.183	0.400	0.217
Difference in Difference			1.785

[a] Average anti-minority hate crimes in India between 2009 and 2018. The number for 2014 only counts incidents that occurred after May, 2014; incidents that occured between January and May 2014 are included in the number for 2013. Source: Author's calculation using data from the CRHCW website: https://p.factchecker.in/

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 2014 and after, i.e. for $t \geq 2014$, and 0 otherwise, X_{st} is a vector of controls, μ_{0s} is a state fixed effect, $\mu_{1s}t$ denote state-specific linear time trends, δ_t is a year fixed effect and ε_{st} is an idiosyncratic error. The coefficient of interest is β_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, β_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.

5.2.2 How Similar are the Two Groups Before 2014?

Before I present regression results, I wish to probe an initial question that makes the DD approach plausible: how similar are the two groups - treatment and control - before 2014? In Table 6, I present sample means of all variables used for the analysis in this paper for the period before 2014. The first column gives the sample mean of variables for the control group (Non-BJP States), the second column gives the corresponding sample mean for the treatment group (BJP States) and the last column reports the p-value for testing the null hypothesis that the sample means are the same for both groups. At this point, I would like

Table 6: Difference in Mean in BJP and non-BJP States Before 2014[a]

	Non-BJP	BJP	p-value
Hate crimes against rel minorities	0.18	0.14	0.69
BJP's vote share in 2014	8.46	44.95	0
BJP's vote share in 2009	5.01	31.29	0
Log-Crime Incidence (number)	9.61	10.98	0
Log-PCNSDP (2012-13 rupess)	10.89	10.89	0.98
Log Mid-year Population (lakhs)	4.58	5.73	0
Share of Urban Population in 2011	33.25	33.52	0.97
Literacy Rate in 2011	79.75	74.30	0.08
Share of Muslim Population in 2011	8.33	15.62	0.14
Chargesheeting rate for All crimes	73.04	72.75	0.93
Chargesheeting rate Crimes against SCs	87.57	87.85	0.92
Wireless telecom subscribers (million)	6.59	5.76	0.16
BJP in State Govt (Yes=1;No=0)	0.08	0.35	0
Hghr Scndry and Above for Hindus in 2011-12	20.43	21.48	0.73
Hghr Scndry and Above for Muslims in 2011-12	13.73	11.04	0.24
Poverty among Hindus in 2009–10	21.67	32.95	0.04
Poverty among Muslims in 2009–10	22.43	36.05	0.04

[a] This table reports the sample mean of covariates for the control (non-BJP) and treatment (BJP) groups of states. The treatment group consists of 16 states where BJP emerged as the largest political party (by share of popular votes) in the 2014 Lok Sabha elections. The other 12 states in my sample form the control group. For definitions of variables and sources, see Appendix A.

to comment on the variables in the top two panels - I will return to the bottom panel when I study mechanisms (section 6).

From the top panel, we see that the average number of anti-minority hate crimes is not significantly different in the treatment group (0.14) compared to the control group (0.18). The p-value of the test of equality of means is 0.69. This is important because it means that the DD estimates will not be overly responsive to functional forms used. We also see that the share of popular votes won by BJP, in both the 2009 and the 2014 Lok Sabha elections, is significantly higher in the treatment, as compared to, the control group. For the 2014 elections, the average of the vote share won by BJP in the treatment group was 44.95% and in the control group was 8.46%. The difference of more than 36% is highly significant.

The middle panel in Table 6 contains the variables I use as controls in my regression - drawing on existing literature on religious conflicts in India (Jha, 2013; Mitra and Ray, 2014; Iyer and Shrivastava, 2018). From this panel, we see that the two groups are significantly different in terms of crime incidence (with the treatment group having higher incidence) and population (with the treatment group being larger), but are similar in terms of per capita net state domestic product (in constant prices). We also see that the two groups differ in terms of the literacy rate - with the control group being more literate than the control group. But the two groups are not significantly different in terms of either the urbanization rate or the share of Muslims in the state's population.

The picture that emerges from the data in Table 6 is that the two groups are significantly different in several variables that are relevant for explaining the incidence of hate crimes against religious minorities. Hence, it is important to control these variables: crime incidence, literacy rate. While sample means of the other variables in the middle panel of Table 6 are not significantly different among the two groups, I will follow the existing literature in including them as controls. But data availability forces me to treat some of these variables differently.

While data on per capita net state domestic product (PCNSDP) and population are available for all years, I have data on the other three variables listed in the middle panel - urbanization, literacy and share of Muslims - only for Census years. I use their values for 2011, which is the latest Census year for which data is available. I include the log of PCNSDP and population as controls by themselves, but when I include urbanization, literacy and 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. Hence I estimate some specifications with this important variable included - but with a smaller sample size - and also use state-specific linear time trends - with a larger sample size - as an alternative strategy to control for possibly confounding trends. Hence, all models are estimated, among other specifications, with two important alternatives, the first with log of crime incidence (but without state-specific trends) and the other with state-specific trends (but without log crime incidence).

5.2.3 DD Results

Table 7 presents results of estimating the DD model in (2) with OLS.[27] 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 variables for four specifications. In the first specification (column 1), the model includes state and year fixed effects. State fixed effects control for unobserved state-specific factors, like history of Hindu-Muslim violence (see Mitra and Ray (2014, Table I).), and year fixed effects control for common shocks to all states. In the second specification (column 2), I add time two varying controls (log PCNSDP, log population) because existing studies have shown the importance of economic factors like income in determining religious conflict and violence (Jha, 2013; Mitra and Ray, 2014; Iyer and Shrivastava, 2018); in the third specification (column 3), I add three pre-2014 controls (share of urban 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; and in the final specification (column 5), I add state-specific linear time trends (but exclude log incidence of crime). Standard errors are always clustered by state to address possible problems of

[27] I use the LSDV estimator, i.e., I use the full set of state and year dummy variables and estimate the model with OLS.

Table 7: Estimates of Treatment Effect from DD Model with Hate Crimes Against Religious Minorities[a]

	(1)	(2)	(3)	(4)	(5)
$After_t X BJP_s$	1.455***	1.411***	1.183***	1.116***	1.862**
	(0.308)	(0.291)	(0.379)	(0.388)	(0.732)
Observations	280	252	252	224	252
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Time-Varying Controls		Y	Y	Y	Y
Pre-Treatment Controls			Y	Y	Y
Log-Crime Incidence				Y	
State Specific Trends					Y

[a] OLS estimates of the treatment effect from the DD model in (2). The dependent variable is $\log(0.1 + hc_{st})$, where hc_{st} is the number of hate crimes against religious minorities in state s and year t. BJP_s is a dummy variable that takes the value 1 for states where BJP won the largest share of popular votes in the 2014 Lok Sabha elections, and 0 otherwise; $After_t$ is a dummy variable that takes the value 1 for $t \geq 2014$, and 0 otherwise. Time varying controls: log population, log per capita real net state domestic product. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `lm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019).

inference arising from within-state serial correlations of the error term (Bertrand et al., 2004).

In Table 7 we see that the estimates of the treatment effect are positive and significant in all specifications. The magnitude of the estimate declines as we add controls, but then increases sharply in column 5, when I add state-specific linear time trends. The magnitude of the coefficient in column 5 suggests that the causal impact of BJP's political dominance on the incidence of hate crimes against religious minorities is very large, at about 544% $(= 100 * (\exp(1.862) - 1))$. This means that, on average, BJP's victory increased anti-minority hate crimes by 544% in the treatment group over and above the change in the control group. If we instead use the estimate from the model with log crime incidence (but without state-specific trends) in column 4, we get an effect of 206% ($= 100 * (\exp(1.116) - 1)$). In either case, the effect is large and statistically significant at standard levels of significance. This provides initial estimates of the causal impact of BJP's electoral victory in 2014 on the incidence of anti-minority hate crimes. To asses the validity of the DD estimates of the causal impact under investigation, I would like to investigate if the parallel trends assumption, the key identifying assumption in the DD approach, is valid?

5.2.4 Parallel Trends Before 2014?

The key identification assumption in the DD research design is 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 move in a similar manner. In effect the Non-BJP states 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.

The first piece of evidence of parallel trends is visual and is summarized in Figure 4. In this figure, we have time series plots of the average of $\log(0.1 + hc_{st})$, where hc_{st} is the number of anti-minority hate crimes in state s in year t, for the treatment and control groups. A vertical line at year 2013 separates out the pre-election and post-election 5 year periods. From the figure we see that the average of $\log(0.1 + hc_{st})$ moved similarly in both groups before 2014. While there in 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 seems to be valid before 2014, and that there is a divergence since then (which is what the DD approach wishes to estimate).

I complement the visual evidence with regression results, along the lines of Muralidharan

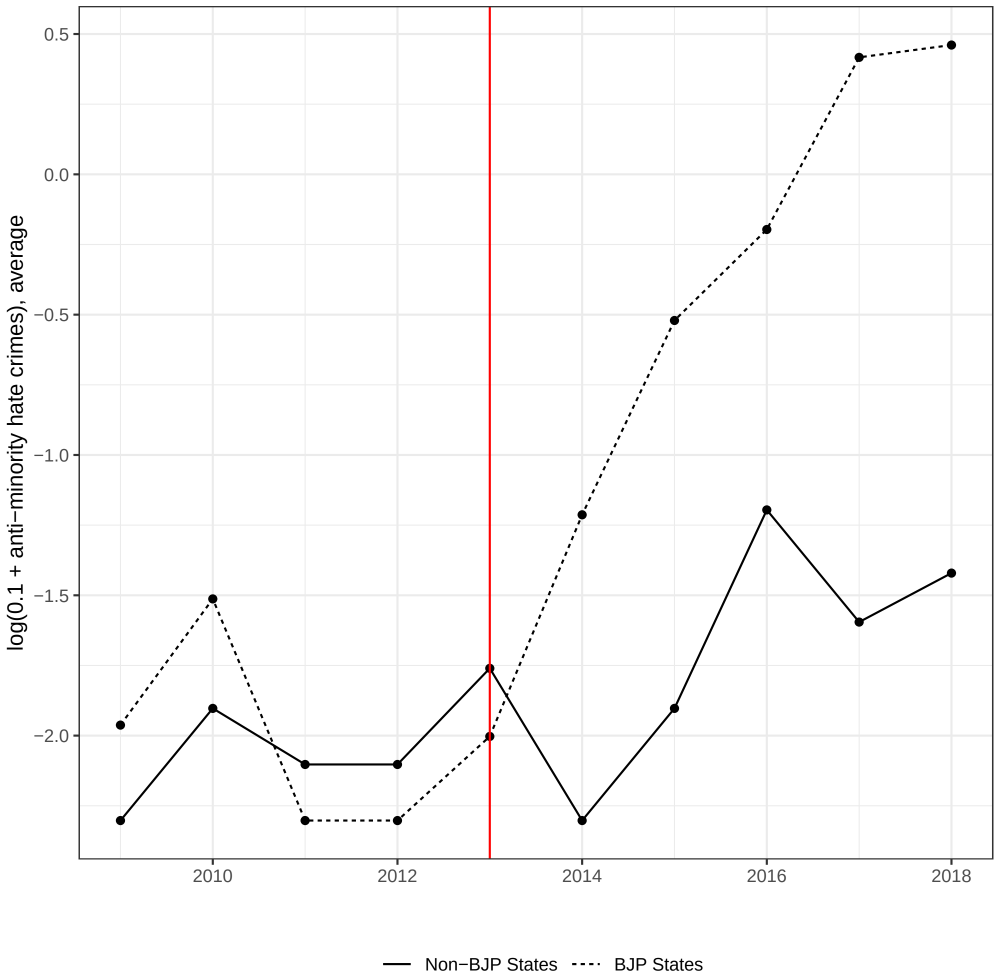

Figure 4: *The figure plots the average of* $log(0.1 + hc_{st})$ *per year in the treatment group (BJP states; dotted line) and the control group (non-BJP states; solid line) between* 2009 *and* 2018, *where* hc_{st} *is the number of anti-minority hate crimes. The treatment group consists of states 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.*

and Prakash (2017), by estimating the following model on the sample for 2009–13:

$$\log(0.1 + hc_{st}) = \alpha + \beta_0(YEAR_t * BJP_s) + \mu_s + \delta_t + CONTROLS + \varepsilon_{st} \tag{3}$$

where $YEAR_t$ is a linear time trend, BJP_s is 1 for BJP states (largest party in 2014), and the model includes unobserved year and state fixed effects and control variables. My interest is in the coefficient, α, which will allows 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 8 presents estimates of α, with standard errors clustered by state appearing in parentheses below the estimate, for three specification of the model in (3). In column 1 of Table 8, the model includes state and year fixed effects; in column 2, I add time-varying controls, including the log of crime incidence; in column 3, I add state-specific time trends. The parameter estimates in all the columns are negative, suggesting that the incidence of anti-minority hate crimes was growing at a slower rate in the treatment group.

If we take the last column's result, then we conclude that average anti-minority hate crimes in BJP states is growing at a slower rate than in non-BJP states in the period 2009–2013. This suggests that the parallel trends assumption is over-satisfied. Hence, if these trends continued, we should have seen lower anti-minority hate crimes in BJP states (than in non-BJP states) after 2014. In fact, we see significantly higher anti-minority hate crimes in BJP states (than in non-BJP states) after 2014 (see Figure 4). This suggest that the increase in anti-minority hate crimes *might* have been caused by BJP's victory in 2014. I will now report on two sets of placebo tests to increase confidence in my results - one where different years are used to define the $After_t$ dummy variable and another where hate crimes against the majority religious group members are used as the dependent variable.

Table 8: Testing Parallel Trends in the DD Model before 2014[a]

	(1)	(2)	(3)
$BJP_s \times TIME$	-0.176^{*}	-0.167	-0.329^{**}
	(0.103)	(0.111)	(0.167)
Observations	140	140	140
State FE	Y	Y	Y
Year FE	Y	Y	Y
Time-Varying Controls		Y	Y
State Specific Trends			Y

[a] OLS estimates of the model in (3) when the sample is restricted to the years 2009–2013. BJP_s is a dummy variable that takes the value 1 for states where BJP won the largest share of popular votes in the 2014 Lok Sabha elections, and 0 otherwise; $TIME$ is a linear time treand that takes the value $0, 1, 2, \ldots$ for $t = 2009, 2010, \ldots$. Time varying controls: log population, log per capita real net state domestic product, log crime incidence. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `lm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019).

5.2.5 Placebo Tests with Different Years

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 *other than* 2014, and especially before 2014, should not give me any effect. I test this by running placebo tests, i.e. I estimate the DD model with full set of controls and vary the $AFTER_t$ dummy variable

$$\log(0.1 + hc_{st}) = \beta(BJP_s \times AFTER_t) + \mu_s + \delta_t + CONTROLS + \varepsilon_{st}. \tag{4}$$

I estimate this model for 7 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. All models include the following controls: state and year fixed effects; time varying controls (log PCNSDP, log population); pre-2014 controls interacted with the $After_t$ dummy (urbanization, literacy rate, share of Muslim population); and state-specific linear time trends.

In Figure 5, I plot the estimate of β for each model in (4) (indexed by the year), along with the 95% confidence interval. In this figure, each model, other than for 2014, is a placebo - because the crucial elections took place in 2014. Hence, we expect the effect to be positive and strongest in 2014, and to be weak or non-existent in other years. From Figure 5, we see that for 2011 and 2012, the effect is negative and statistically significant. For 2013, 2015, 2016, 2017, the effect is positive or close to zero but statistically insignificant. It is only for the year 2014 that we have a positive effect that is statistically significant at the 5% level. Thus, the placebo tests with different years increase confidence in my results.

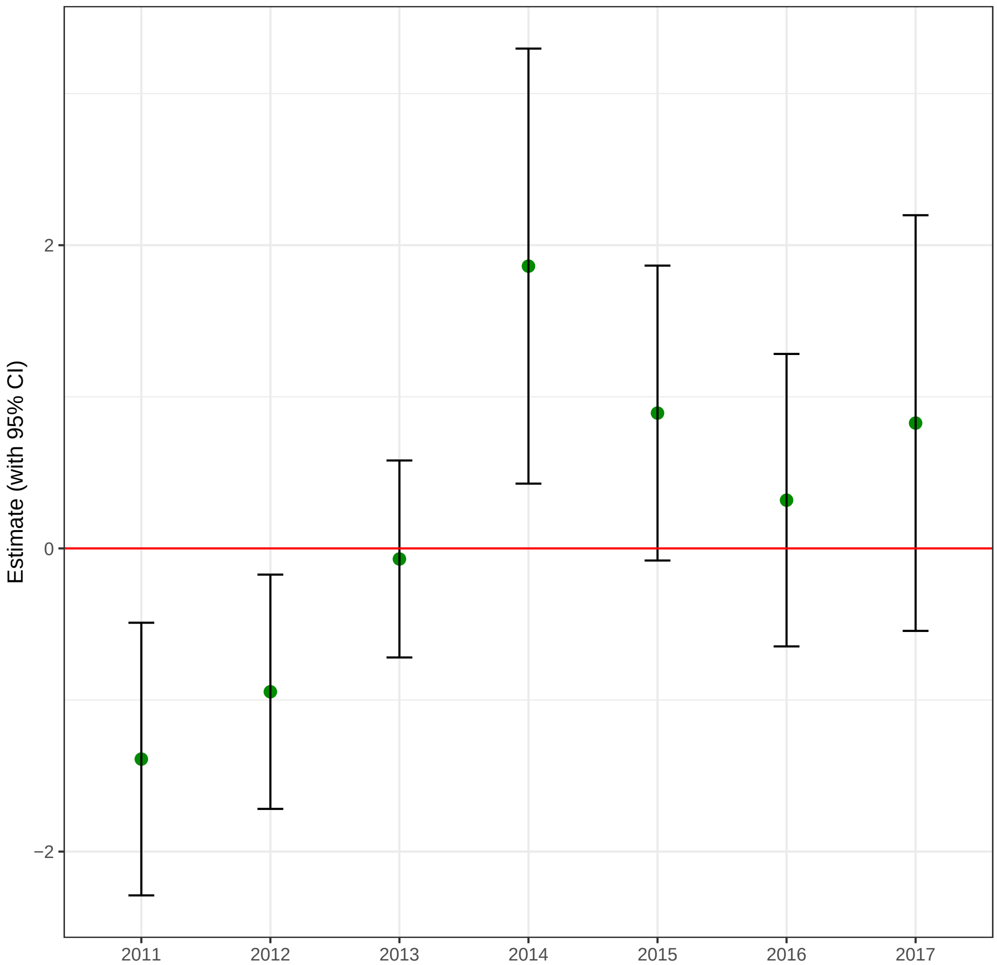

Figure 5: *Placebo tests for the treatment effect from the model in (4), where different years are used to define the $After_t$ dummy variable. The dependent variable is $log(0.1+hc_{st})$, where hc_{st} is the number of anti-minority hate crimes. The treatment group consists of states where BJP won the largest share of popular votes in the* 2014 *Lok Sabha elections. The y-axis gives the year that was used to define the $After_t$ dummy. Thus, the year corresponding to* 2014 *is the correct definition of the $After_t$ dummy, and the other years serve as placebos.*

5.2.6 Placebo Tests with a Different Religious Group

The hypothesis I have been investigating in this paper is that BJP's electoral victory in 2014 lead to an increase in hate crimes against *religious minorities*. This comes from the understanding that BJP's politics targets and demonizes religious minorities, especially Muslims. This means that 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 DD model. To test this I run a placebo test again, i.e. I estimate the following DD model:

$$\log(0.1 + hch_{st}) = \beta(BJP_s \times AFTER_t) + \mu_s + \delta_t + CONTROLS + \varepsilon_{st} \tag{5}$$

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 DD model in (2). Table 9 presents estimates of β in the model in (5) for four different specifications. We see that the coefficient is not statistically significantly different from 0 in any of the specifications. Thus, the placebo test with hate crimes against the majority religious community further increases confidence in my results.

5.3 Treatment Intensity Model

5.3.1 Motivation and Set-Up

Can we accept the results presented in the previous sub-sections as causal? Probably not. That is because of at least two reasons. First, there might be reverse causality running from hate crimes against minorities to the electoral fortunes of BJP. In the study of religious riots, scholars have emphasized this causal link (Wilkinson, 2004; Iyer and Shrivastava, 2018). Second, we cannot yet rule out the following scenario: some unobserved factors might have caused both high BJP vote share in a state in 2014 and increase in anti-minority hate

Table 9: Estimates of Treatment Effect from DD Model with Hate Crimes Against Hindus (Majority Religious Community)[a]

	(1)	(2)	(3)	(4)	(5)
$After_t \times BJP_s$	0.222	0.058	0.082	0.096	-0.067
	(0.137)	(0.127)	(0.152)	(0.188)	(0.128)
Observations	280	252	252	224	224
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Time-Varying Controls		Y	Y	Y	Y
Pre-Treatment Controls			Y	Y	Y
Log-Crime Incidence				Y	
State Specific Trends					Y

[a] OLS estimates of the treatment effect from the DD model in (5). The dependent variable is $\log(0.1 + hch_{st})$, where hch_{st} is the number of hate crimes against Hindus (religious majority community) in state s and year t. BJP_s is a dummy variable that takes the value 1 for states where BJP won the largest share of popular votes in the 2014 Lok Sabha elections, and 0 otherwise; $After_t$ is a dummy variable that takes the value 1 for $t \geq 2014$, and 0 otherwise. Time varying controls: log population, log per capita real net state domestic product. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `lm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019).

crimes thereafter in that state. To address these concerns, I will now present estimates of a treatment intensity model using an *instrumental variable.*

To estimate the relevant causal effect with an instrumental variables estimator, I will estimate the following *treatment intensity* model:

$$\log(0.1 + hc_{st}) = \beta(BJP14VS_s \times AFTER_t) + \mu_s + \delta_t + CONTROLS + \varepsilon_{st} \qquad (6)$$

where all variables are the same as in the DD model in (2) other than the fact that we have replaced the BJP_s dummy variable (which defined the treatment group of states) with $BJP14VS_s$, BJP's vote share in state s in the 2014 Lok Sabha elections, which now functions as a continuous measure of treatment *intensity*. In the DD model in (2), we compared two groups (BJP and non-BJP states) before and after 2014. In the treatment intensity model in (6), every state becomes it own comparison group because we use the full variation in BJP's vote share across states.[28] While I will estimate the treatment intensity model with OLS, my preferred strategy will be to estimate it with an IV estimator where I will use BJP's vote share in the 2009 Lok Sabha elections as an instrumental variable for $BJP14VS_s$ (BJP's vote share in 2014).

5.3.2 OLS and IV Estimates

Table 10 and 11 present OLS and IV estimates of the treatment effect in (6). In general the OLS estimates are larger in magnitude than the IV estimates - suggesting the presence of upward bias of OLS. To save on space, I will only comment on the IV estimates (from Table 11). The first column presents the model with state and year fixed effects only; in column 2, I add time-varying controls; in column 3, I add pre-2014 controls interacted with the $After_t$ dummy; in column 4, I add the log of crime incidence; and in column 5, I add

[28]This method has been used in Card (1992).

Table 10: OLS Estimates from Treatment Intensity Model for Hate Crimes Against Religious Minorities[a]

	(1)	(2)	(3)	(4)	(5)
$After_t \times BJP14VS_s$	0.029***	0.028***	0.021**	0.020**	0.029*
	(0.009)	(0.009)	(0.010)	(0.009)	(0.017)
Observations	280	252	252	224	252
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Time-Varying Controls		Y	Y	Y	Y
Pre-Treatment Controls			Y	Y	Y
Log-Crime Incidence				Y	
State Specific Trends					Y

[a] OLS estimates of the treatment effect from the treatment intensity model in (6). $BJP14VS_s$ is the vote share won by BJP in the 2014 Lok Sabha elections and is a measure of treatment intensity; and $After_t$ is a dummy variable that takes the value 1 for $t \geq 2014$, and 0 otherwise. Time varying controls: log population, log per capita real net state domestic product. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `lm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019).

state-specific linear time trends but exclude log crime incidence. My preferred estimate lies between the results for column 4 and 5. Using the lower value in column 4, the IV estimation shows that the causal effect is statistically significant and its magnitude is 2.02% $(= 100 * (\exp(0.02) - 1))$. Thus, if a state saw BJP winning 1 percentage point more vote share in 2014, that would have caused an increase in average anti-minority hate crimes by about 2.02%.

5.3.3 Is the Instrument Valid?

BJP's vote share in the 2009 Lok Sabha elections is likely to be a good instrument for BJP's vote share in the 2014 Lok Sabha elections because it satisfies both the relevance and exogeneity conditions. In terms of relevance, BJP's state-level vote share in Lok Sabha elections is quite persistent. That is why the vote share won by BJP in 2009 is a strong predictor of the vote share it won on 2014.[29] In Table 11, I have reported results of some diagnostics for the IV estimator, where we can see that the F-statistic for the first stage regression are all larger than 150, with corresponding p-values significantly smaller than 0.001. Hence, these results and the intuition about persistence of BJP's vote share across Lok Sabha elections suggests that there are no weak instrument problems. The instrument strongly satisfies the relevance condition.

The exogeneity condition is of course more difficult to establish but equally crucial for the validity of the IV estimates. To begin with, let us look at the diagnostics for the IV estimator in Table 11 again. We see that the Wu-Hausman test is not able to reject the null of no endogeneity in specifications 3,4 and 5. This suggests that including time-varying controls and either log crime incidence or state specific linear trends substantially reduces endogeneity problems. Of course, the Wu-Hausman test is only as good as the instrument. In

[29]The Pearson correlation coefficient between BJP's state-level vote share in the two elections is 0.93.

Table 11: IV Estimates from Treatment Intensity Model for Hate Crimes Against Religious Minorities[a]

	(1)	(2)	(3)	(4)	(5)
$After_t \times BJP14VS_s$	0.022**	0.023**	0.017*	0.020**	0.024*
	(0.011)	(0.010)	(0.010)	(0.010)	(0.014)
Observations	280	252	252	224	252
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Time-Varying Controls		Y	Y	Y	Y
Pre-Treatment Controls			Y	Y	Y
Log-Crime Incidence				Y	
State Specific Trends					Y
First Stage (F-stat)	200.05	166.54	233.2	209.1	464.35
First Stage (p-value)	0	0	0	0	0
Wu-Hausman (p-value)	0.002	0.062	0.177	0.997	0.296

[a] IV estimates of the treatment effect from the treatment intensity model in (6). $BJP14VS_s$ is the vote share won by BJP in the 2014 Lok Sabha elections and is a measure of treatment intensity; and $After_t$ is a dummy variable that takes the value 1 for $t \geq 2014$, and 0 otherwise. $BJP14VS_s$ is instrumented with $BJP09VS_s$, BJP's vote share in 2009 (the previous Lok Sabha elections). Time varying controls: log population, log per capita real net state domestic product. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. Standard errors are clustered by state and appear in parentheses below parameter estimates. The null hypothesis of the Wu-Hausmann test is that the model suffers from the problem of endogeneity. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `ivreg` function from the `AER` package (Kleiber and Zeileis, 2008). Clustered standard errors were computed with the `vcovCR()` function from the `clubSandwich` package (Pustejovsky, 2019).

the final analysis, the exogeneity of the instrument can only be argued on intuitive grounds - not on statistical grounds.

It is probably a valid concern that BJP's vote share in 2009 might be correlated with unobserved factors that are determinants of hate crimes against religious minorities. After all it is not inconceivable that states where BJP won relatively high shares of the popular vote in 2009 then saw the growth of right-wing Hindu nationalist organizations, which then caused higher incidence of anti-minority hate crimes. While this narrative sounds apparently plausible, it cannot stand scrutiny. If states with high BJP vote share in 2009 also saw growth of factors that cause higher incidence of hate crimes against religious minorities, this should have been manifested in the years between 2009 and 2013. It is difficult to see why such forces, assuming they had been encouraged by the 2009 Lok Sabha election results, would be dormant for four years and then suddenly come to the fore in and after 2014.

A counter argument might be that such forces would be dormant for the four years, 2009–13, because of instrumental reasons. Their utility is mainly to polarize the electorate and garner votes for the BJP. Hence, it might be argued, that these forces might very well lie dormant for four years and then make their appearance only during the Lok Sabha elections in 2014. There are two problems in this argument. If such forces were to be instrumental for winning votes for BJP by carrying out hate crimes against religious minorities - for which there is much evidence when we consider religious riots (Wilkinson, 2004; Iyer and Shrivastava, 2018) - then their actions should have occurred before, and not after, the 2014 elections. Since we do not see any effect in 2013, this argument cannot be valid.

But there is another problem with the instrumentality argument. Between two Lok Sabha elections, elections to the state legislatures take place. If the 2009 elections had encouraged forces that would ultimately increase anti-minority hate crimes, and that too for instrumental reasons of the kind that is valid for religious riots, then incidents should have increased in the years 2009–13 when many important state-level elections were held. Since we do not see any discernible increase in anti-minority hate crimes before 2014, this narrative is difficult to sustain. Thus, on intuitive ground, the exogeneity assumption seems to be valid.

5.3.4 Placebo Tests

While intuition suggests validity of the instrument, as far as exogeneity goes, I also present placebo tests of two kinds to further allay concerns. In Table 12, I present results of estimating the treatment intensity model with IV for the sample before 2014. In this regression, I try to measure the average difference in the incidence of anti-minority hate crimes for the period, 2009–2013, that correlates with BJP's 2014 vote share. I find no positive treatment effect. In fact I find a negative effect, which provides support for my basic results.

In Table 13, I present results from re-estimating the treatment intensity model with IV on the incidence of hate crimes against Hindus (members of the majority religious community). I estimate this model for the full sample period, 2009–18, and find that there is no statistically discernible positive impact of BJP's 2014 vote share on the difference in hate crimes faced by Hindus before and after 2014. If anything, the effect is negative. This is reassuring: the rise of majoritarian politics is not expected to have any adverse impacts on members of the majority community. And that is what I find. Taken together, therefore, the placebo tests increase the confidence in my IV results of a causal impact of BJP's electoral performance in 2014 on the increase in anti-minority hate crimes.

5.4 Quasi-Poisson Regressions

The analysis presented so far has treated the incidence of hate crimes as a continuous random variable and estimated models with OLS and IV. An alternative empirical strategy takes into account an important characteristic of the incidence of hate crimes: that it is a non-negative

Table 12: Testing Treatment Effect in the Treatment Intensity Model of Hate Crimes Against Religious Minorities Before 2014[a]

	(1)	(2)	(3)	(4)	
$BJP14VS_s \times TIME$	-0.001	-0.0004	-0.0004	-0.0004	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	140	140	140	140	140
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Time-Varying Controls		Y	Y	Y	Y
Pre-Treatment Controls			Y	Y	Y
Log-Crime Incidence				Y	
State Specific Trends					Y

[a] IV estimates of the treatment effect from the treatment intensity model with the sample limited to years, 2009–2013. $BJP14VS_s$ is the vote share won by BJP in the 2014 Lok Sabha elections and is a measure of treatment intensity; and $TIME$ is a linear time treand that takes the value $0, 1, 2, \ldots$ for $t = 2009, 2010, \ldots$. $BJP14VS_s$, is instrumented with, $BJP09VS_s$, BJP's vote share in 2009 (the previous Lok Sabha elections). Time varying controls: log population, log per capita real net state domestic product. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `ivreg` function from the `AER` package (Kleiber and Zeileis, 2008). Clustered standard errors were computed with the `vcovCR()` function from the `clubSandwich` package (Pustejovsky, 2019).

Table 13: Placebo Test of Treatment Intensity Model on Hate Crimes Against Hindus (Majority Religious Community)[a]

	(1)	(2)	(3)	(4)	(5)
$After_t \times BJP14VS$	0.004	-0.00002	0.0003	-0.003	-0.007^{*}
	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)
Observations	280	252	252	224	252
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Time-Varying Controls		Y	Y	Y	Y
Pre-Treatment Controls			Y	Y	Y
Log-Crime Incidence				Y	
State Specific Trends					Y

[a] Results of estimating the treatment intensity model with IV where the dependent variable is $\log(0.1 + hch_{st})$, where hch is hate crimes against Hindus (the majority religious community). The model includes all controls reported in the final column of Table 10. Treatment intensity is captured by $BJP14VS_s$, BJP's vote share in the 2014 Lok Sabha elections and is instrumented with $BJP09VS_s$, its vote share in the previous Lok Sabha elections in 2009. Time varying controls: log population, log per capita real net state domestic product. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `ivreg` function from the `AER` package (Kleiber and Zeileis, 2008). Clustered standard errors were computed with the `vcovCR()` function from the `clubSandwich` package (Pustejovsky, 2019).

integer and not a real number. Taking this characteristic explicitly into account means treating the dependent variable as a discrete random variable that only takes non-negative integer values and using count data model. A popular version of count data models is the Poisson regression model.(Greene, 2012, chapter 18) 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'. For the number of hate crimes against religious minorities, we see from Table 1 that the variance (3.8) is close to five times the mean (0.78). A common way to deal with overdispersion is a quasi-Poisson approach, and I use this approach in this paper (McCullagh and Nelder, 1989).[30]

In Table 14 and 15, I present results of estimating two versions of a quasi-Poisson regression model, without and with taking account of potential endogeneity, where the dependent variable is the level of anti-minority hate crimes.[31] For a standard quasi-Poisson regression model, the dependent variable, hc_{st}, is assumed to follow a Poisson distribution:

$$hc_{st} \sim Poisson(\mu_{st}, \theta),$$

where the mean $\mu_{st} > 0$ is a function of covariates,

$$\mu_{st} = \exp\left[\beta(BJPVS_s \times AFTER_t) + \mu_s + \delta_t + CONTROLS\right], \tag{7}$$

and variance of the dependent variable is related to its mean as

$$Var\left(hc_{st}\right) = \mu_{st}\theta. \tag{8}$$

[30] Another popular approach to dealing with overdispersion is to use a Negative Binomial regression. I do not use this approach as, in my case, the negative binomial regression models could not be consistently estimated. The iterative procedure to estimate parameters did not converge.

[31] In these models, I do not lose observations when the incidence of hate crime for any state-year observation is 0. Hence, I do not need to add 0.1, as I did for my previous models.

Table 14: Quasi Poisson Regression Model for Hate Crimes Against Religious Minorities[a]

	(1)	(2)	(3)	(4)
$After_t \times BJP14VS_s$	0.054**	0.055***	0.060***	0.055***
	(0.022)	(0.015)	(0.015)	(0.016)
Observations	280	252	252	224
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Time Varying Controls		Y	Y	Y
Pre-Treatment Controls			Y	Y
Log Crime Incidence				Y
<u>Memo</u>:				
Avg Marginal Effect	0.042	0.034	0.037	0.022
Std Error	(0.011)	(0.009)	(0.009)	(0.007)

[a] This table reports estimates of the treatment effect from a quasi Poisson regression model in (7) and (8). The dependent variable is hc_{st}, with hc being the number of hate crimes against religious minorities. Treatment intensity is captured by $BJP14VS_s$, BJP's vote share in the 2014 Lok Sabha elections; $After_t$ is a dummy variable that takes the value of 1 for $t \geq 2014$, and 0 otherwise. Time varying controls: log population, log per capita real net state domestic product. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. The model parameters are estimated by iterated reweighted least squares. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `glm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019).

All the parameters of the model in (7) and (8), including the overdispersion parameter, $\theta > 1$, are estimated by the use of the iterated re-weighted least squares (IWLS) algorithm, which has been shown to be equivalent to Fisher scoring and leads to maximum likelihood estimates (McCullagh and Nelder, 1989). In Table 14, I present results for the quasi-Poisson treatment intensity model - which, in effect, ignores the possible problem of endogeneity of BJP's vote share.

Table 15: Control Function Approach Estimates of Quasi Poisson Regression Model for Hate Crimes Against Religious Minorities[a]

	(1)	(2)	(3)	(4)
$After_t XBJP14VS_s$	0.042**	0.053***	0.059***	0.055***
	(0.020)	(0.015)	(0.015)	(0.017)
$FSResid_{st}$	0.208***	0.055	0.101	0.059
	(0.070)	(0.080)	(0.075)	(0.097)
Observations	280	252	252	224
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Time Varying Controls		Y	Y	Y
Pre-Treatment Controls			Y	Y
Log Crime Incidence				Y

[a] This table reports estimates of the treatment effect from a quasi Poisson regression model in (7) and (8) that has been estimated with a control function approach. The dependent variable is hc_{st}, with hc the number of hate crimes against religious minorities. Treatment intensity is captured by BJP's vote share in the 2014 Lok Sabha elections and is instrumented with its vote share in the previous Lok Sabha elections in 2009. $FSResid_{st}$ refers to the residual from the first stage regression, estimated by OLS, of $After_t \times BJP14VS_s$ on $After_t \times BJP09VS_s$ with the full set of controls. In the second stage, the residual is included as an additional regressor and the Poisson model estimated by iterated reweighted least squares. Time varying controls: log population, log per capita real net state domestic product, log crime incidence. Pre-treatment controls (interacted with $After_t$): urban population share, literacy rate, share of Muslim population, all measured in 2011. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. The model was estimated with the `glm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019).

To address the problem of endogeneity, I use a control function approach (Wooldridge, 2015). In the first stage of the control function approach, I regress $After_t \times BJP14VS_s$ on $After_t \times BJP09VS_s$, where $BJP14VS_s$ and $BJP09VS_s$ are BJP's vote share in the 2014 and 2009 Lok Sabha elections, respectively, and the full set of controls. I then include the residual from the first stage as an additional regressor in the second stage model, which is the quasi-Poisson regression model (7) and (8). In Table 15, I present results for the treatment treatment intensity model where I address the possible problems of endogeneity of BJP's vote share with a control function approach.

The estimates in Table 14 are all positive and significant, much along the lines of the linear model discussed thus far. When we turn to Table 15, we see that the first stage residual is not significant once we include controls - which is what we also saw for the Wu-Hausman test in Table 11. Once that is the case, the estimates from the basic quasi-Poisson and the control function quasi-Poisson model give very similar estimates. Thus these estimates confirm the results of the linear specification used earlier in this paper: there is an increase in hate crimes against religious minorities due to BJP's electoral performance in 2014.

To interpret the results, I have computed average marginal effects (AMEs) of $After_t \times BJP14VS_s$ and reported them in the bottom panel in Table 14. All the AMEs are positive and statistically significant. If we use the last column in the table, which is the model with the full set of controls, we see that the AME is 0.022. This means that for every percentage point increase in BJP's popular vote share in 2014, hate crimes against religious minorities increase by the multiple $1.022 (= \exp(0.022))$, i.e. hate crimes against religious minorities increase by about 2.2% for every percentage point of BJP's 2014 vote share (which is close to the IV estimate in column 5, Table 11). However, I prefer to use the linear models for the discussion because parameters are easier to interpret in such models.

6 Three Mechanisms

Having established the causal impact of BJP's electoral victory in the 2014 Lok Sabha elections on the incidence of anti-minority hate crimes, I would now like to investigate three possible mechanisms that might be driving the result.

6.1 Mechanism 1: State-level Law Enforcement

In India, law & order is a state subject under the seventh schedule of the Constitution. This means that state governments are primarily responsible for preventing, detecting, investigating and prosecuting crimes. Since hate crimes are incidents that are *prima facie* recognized as crimes under the Indian Penal Code, law & order relating to such incidents are also the responsibility of state governments. One way in which BJP's electoral victory in the 2014 Lok Sabha elections might have increased anti-minority hate crimes is by adversely impacting law enforcement efforts related to hate crimes against religious minorities.[32] To investigate this possible mechanism, I use three variables.

The first variable is a dummy variable that takes the value 1 if BJP is part of the government at the *state level* in any year, and 0 otherwise. The idea behind using this variable is that BJP's presence in a state government would have a larger adverse impact of BJP's electoral victory in the 2014 Lok Sabha elections on law enforcement related to hate crimes against religious minorities than if BJP was not part of the state government. Key state-level ministers of BJP might be able to, directly and indirectly, influence law enforcement officials - which they would not be able to do without being part of the state government.

The second variable is the charge sheeting rate for all crimes covered by the Indian Penal Code (IPC). This measures the proportion of true reports of IPC crimes submitted to the

[32] This mechanism has been highlighted in the political science literature on religious riots in India (Wilkinson, 2004; Basu, 2015).

police that are converted into charge sheets submitted by the police. Hence, this captures the efficacy of the policing administration as far as it relates to filing charge sheets about crimes. If BJP's electoral victory in 2014 negatively impacted law enforcement, then this variable would capture some of that effect. But this variable is less than perfect for my purpose. This is because BJP's electoral victory is likely to differentially impact law enforcement related to crimes committed against persons that BJP's ideology demonises. Hence, the charge sheeting rate for all crimes might not capture the effect of interest. To address this concern, I use the third variable: the charge sheeting rate by the police for all crimes against schedule caste (SC) persons covered by the SC/ST (Prevention of Atrocities) Act, 1989.

Scheduled Castes (SCs), and Scheduled Tribes (STs), are among the most socio-economically disadvantaged groups in India. Traditional Hindu society has considered SCs as 'untouchables' and consigned them to the margins of society. Centuries of discrimination and marginalization has accumulated into significant socio-economic disadvantages for the SCs. BJP's ideology has a dual approach to SCs. On the political front, it tries to include SCs in the construction of a unified Hindu bloc against the Muslim other; on the social front, it has seldom challenged the discrimination and violence faced by SCs from Hindu society. Hence, if BJP's electoral victory in 2014 adversely impact law enforcement at the state level, that impact can be expected to have a differential impact on crimes committed against SCs. The charge sheeting rate by the police for crimes committed against SCs by non-SC/STs, which are explicitly covered by the SC/ST (Prevention of Atrocities) Act, 1989, is meant to capture this differential impact.

6.2 Mechanism 2: Economic Competition

In an influential study of communal riots in India, Mitra and Ray (2014) show that relative economic prosperity of Muslims leads to violence against them by Hindus. In section II of the paper, Mitra and Ray (2014) review a large literature in history and political science, many of these case studies, that had highlighted the role of economic competition in religious, i.e. Hindu-Muslim, riots in India. The paper takes "the economic argument a step further" by constructing a formal model of religious conflict and testing the implications of the model with a region panel data set. Their key empirical finding is that "an increase in Muslim prosperity is positively associated with greater religious fatalities in the near future, while the opposite is true of a change in Hindu prosperity." (pp. 742).

The implication of the historical and contemporary evidence summarised in Mitra and Ray (2014) for my study is that one possible mechanism behind the rise in anti-minority hate crimes could be the relative prosperity of religious minorities, especially Muslims. I capture this possible mechanism underlying the causal impact identified in the previous sections of the paper using four variables. The first two variables are the poverty rates (head count ratio) of Hindus and Muslims in 2009–10 (Panagariya and Mukim, 2014). The next two variables are the proportion of Hindus and Muslims who attained a level of formal education that was higher secondary or above in 2011–12. By including the poverty rate and higher education attainment of both Muslims and Hindus, I hope to capture the effect of relative prosperity of Muslims - as compared to Hindus - and thereby to test for the economic competition mechanism studied in Mitra and Ray (2014).

6.3 Mechanism 3: Role of Social Media

A recent literature has highlighted the role of social media is spreading rumours and sustaining hate campaigns against marginzalized and vulnerable segments of the population. Müller and Schwarz (2018) study the relationship between anti-refugee sentiment on Facebook and hate crimes against refugees in Germany. The authors find "that anti-refugee hate crimes disproportionally increase in areas with higher Facebook usage" during periods of high anti-refugee sentiments on Facebook (which they measure by looking at posts on the Facebook page of the right-wing political party, AfD). Müller and Schwarz (2019) study the role of social media is generating and sustaining anti-Muslim sentiments in the US and the role of the latter in physical acts of violence against Muslims. Using county level variation in Twitter penetration over time, they find that "Trump's tweets about Muslims are highly correlated with the number of anti-Muslim hate crimes, but only for the time period after the start of his presidential campaign." This result obtains in an instrumental variable strategy too - leading them to conclude that social media might very well have a role to play in the recent rise of anti-minority violence in the US.[33]

This body of literature suggests another possible mechanism for the causal impact of BJP's electoral victory in 2014 on the subsequent increase in anti-minority hate crimes in India. It has been widely commented that the BJP is far ahead of all other political parties in India in terms of social media usage. For instance, *The Economic Times* reported on May 16, 2019 that BJP was the top spender on political ads on Google and Facebook.[34] Sam and Thakurta (2019) document the important ways in which BJP's electoral campaign in 2014 relied on social media. To test if social media plays an important role in the rise in anti-minority hate crimes that can be associated with BJP's electoral victory in 2014, I use information on the total number of subscriptions to telecom wireless. If social media has a role to play in sustaining anti-Muslim sentiments, then its salience will increase with the proportion of Hindus in a state. Hence, I interact the total number of telecom wireless subscribes in a state-year with the share of Hindus in the state in 2011.

6.4 Results on Mechanisms

In Table 16 and 17, I present results of testing the efficacy of each of the three mechanisms separately. Columns 1 and 2 test the state-level law & order mechanism; columns 3 and 4 test

[33] Edwards and Rushin (2018) also find evidence of an increase in hate crimes after Donald Trump's election in the US in 2016; and Williams et al. (2019) study the case of UK.

[34] See https://economictimes.indiatimes.com/news/elections/lok-sabha/india/bjp-top-spender-on-political-ads-on-digital-platforms/articleshow/69351792.cms?from=mdr

the economic competition mechanism; and columns 5 and 6 test the social media mechanism. For each of these mechanisms, I present both OLS and IV estimates from estimating the treatment intensity model in (6). The results in Table 16 control for state-specific linear time trends (but exclude the log incidence of crimes) and the results in Table 17 control for the log incidence of crime (but exclude state-specific linear time trends). The results are qualitatively and quantitatively similar. So, I will only comment on the results in Table 16.

In columns 1 and 2 of Table 16, I take the treatment intensity model in (6) with the full set of controls, including state-level linear time trends, and add three variables to capture state-level law enforcement: a dummy variable for whether BJP is part of the state government; the charge sheeting rate for all IPC crimes; the charge sheeting rate for crimes committed by non-SC/STs on SCs that are covered by the SC/ST (Prevention of Atrocities) Act, 1989. When I estimate the model by OLS, the coefficient capturing the continuous treatment effect is 0.035 and is significant at the 10% level. When I estimate the model by using BJP's vote share in 2009 as the instrument for BJP's vote share in 2014, the magnitude of the coefficient reduces to 0.030 and it is no longer statistically significant at even then 10% level. This suggests that the adverse effect of BJP's electoral victory in 2014 on state-level law enforcement is an important mechanism for increasing hate crimes against religious minorities.

In columns 3 and 4 of Table 16, I present results for testing the importance of the mechanism of economic competition. I take the treatment intensity model in (6) with the full set of controls, including state-level linear time trends, and add four variables, each of them interacted with the $After_t$ dummy variable, to capture economic competition between Hindus and Muslims (the largest religious minority group in India): poverty rate of Hindus in 2009-10; poverty rate of Muslims in 2009-10; proportion of Hindus with higher secondary education and above in 2011-12; proportion of Muslims with higher secondary education and

Table 16: OLS and IV Estimates of Treatment Intensity Model to Test Three Mechanisms Controlling for State-Specific Trends[a]

	(1)	(2)	(3)	(4)	(5)	(6)
	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
$After_t \times BJPVS_s$	0.035*	0.030	0.053***	0.047***	0.058**	0.049**
	(0.020)	(0.018)	(0.016)	(0.012)	(0.024)	(0.021)
Observations	215	215	153	153	153	153
State FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
IV		Y		Y		Y
State Specific Trends	Y	Y	Y	Y	Y	Y
Law and Order	Y	Y				
Econ Competition			Y	Y		
Social Media					Y	Y

[a] In all specifications, the dependent variable is $\log(0.1 + hc_{st})$, where hc_{st} is the number of hate crimes against religious minorities. $BJPVS_s$ is the vote share won by BJP in the 2014 Lok Sabha elections; and $After_t$ is a dummy variable that takes the value 1 for $t \geq 2014$, and 0 otherwise. Columns 1 and 2 test the state-level law enforcement mechanism; columns 3 and 4 test the relative prosperity mechanism; columns 5 and 6 test the social media mechanism. For IV estimates in columns 2, 4, and 6, BJP's vote share in the 2009 Lok Sabha elections is used as an instrumental variable for BJP's vote share in 2014. All models include time varying controls (log population, log per capita real net state domestic product), pre-treatment controls interacted with $After_t$ (urban population share, literacy rate, share of Muslim population, all measured in 2011), and state-specific linear time trends. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. for OLS, the model was estimated with the `lm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019). For the IV estimates, the model was estimated with the `ivreg` function from the `AER` package (Kleiber and Zeileis, 2008); and clustered standard errors were computed with the `vcovCR()` function from the `clubSandwich` package (Pustejovsky, 2019).

above in 2011-12. The OLS estimate of the treatment effect is 0.053 and the IV estimate is 0.047, and both are significant at the 5% level. Thus, while economic competition might very well play a role, it does not seem to be the main mechanism at work.

In columns 5 and 6 of Table 16, I present results for testing the social media mechanism. Again, I take the treatment intensity model in (6) with the full set of controls, including state-level linear time trends, and add a variable to capture the role of social media: total telecom wireless subscribers in a state-year interacted with the share of Hindus in a state in 2011. The OLS estimate of the treatment effect is 0.058 and the IV estimate is 0.049, and both are significant at the 5% level. I conclude that while social media might be important, it is unlikely to be the main mechanism at work with regard to anti-minority hate crimes.

7 Discussion, Caveats and Conclusions

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, with Muslims functioning as the prime 'other', it is natural to ask if the two - BJP's rise to dominance in 2014 and an increase in hate crimes against religious minorities, especially Muslims - 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

Table 17: OLS and IV Estimates of Treatment Intensity Model to Test Three Mechanisms Controlling for Crime Incidence[a]

	(1)	(2)	(3)	(4)	(5)	(6)
	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
$After_t \times BJPVS_s$	0.020*	0.019	0.046***	0.044***	0.043***	0.041***
	(0.011)	(0.012)	(0.013)	(0.015)	(0.010)	(0.012)
Observations	192	192	136	136	136	136
State FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
IV		Y		Y		Y
State Specific Trends	Y	Y	Y	Y	Y	Y
Law and Order	Y	Y				
Econ Competition			Y	Y		
Social Media					Y	Y

[a] In all specifications, the dependent variable is $\log(0.1 + hc_{st})$, where hc_{st} is the number of hate crimes against religious minorities. $BJPVS_s$ is the vote share won by BJP in the 2014 Lok Sabha elections; and $After_t$ is a dummy variable that takes the value 1 for $t \geq 2014$, and 0 otherwise. Columns 1 and 2 test the state-level law enforcement mechanism; columns 3 and 4 test the relative prosperity mechanism; columns 5 and 6 test the social media mechanism. For IV estimates in columns 2, 4, and 6, BJP's vote share in the 2009 Lok Sabha elections is used as an instrumental variable for BJP's vote share in 2014. All models include time varying controls (log population, log per capita real net state domestic product), pre-treatment controls interacted with $After_t$ (urban population share, literacy rate, share of Muslim population, all measured in 2011), and state-specific linear time trends. Standard errors are clustered by state and appear in parentheses below parameter estimates. Significance levels: *** 1 percent level; ** 5 percent; * 10 percent. for OLS, the model was estimated with the `lm.cluster()` function from the `miceadds` package (Robitzsch and Grund, 2019). For the IV estimates, the model was estimated with the `ivreg` function from the `AER` package (Kleiber and Zeileis, 2008); and clustered standard errors were computed with the `vcovCR()` function from the `clubSandwich` package (Pustejovsky, 2019).

empirical analysis, I compare 5-year periods before and after the 2014 election and find that in the treatment group of states (where BJP was the winner of the largest share of popular votes in 2014), hate crimes against religious minorities increased by 544% more than in the control group of states (where BJP was *not* the winner of the largest share of popular votes in 2014). I show that the parallel trends assumption is satisfied. Placebo tests with different years for defining the 'after' dummy variable and on hate crimes faced by the majority community members show no results.

When I use a treatment intensity approach, where BJP's vote share in 2014 is used a the treatment intensity variable and is instrumented by its vote share in the 2009 Lok Sabha elections, I find that every percentage point increase in BJP's vote share caused hate crimes against religious minorities to increase by 2.02%. An analogue of the parallel trends assumption is satisfied, and placebo tests - like in the previous model - show no effects. I also use a quasi Poisson regression - where the count data nature of hate crimes is explicitly taken into account - and get results that are qualitatively and quantitatively similar to those from the linear models. Taken together, this evidence allows me to conclude that BJP's electoral performance in 2014 caused an increase in hate crimes against religious minorities.

An election is a way in which information about attitudes, in this case anti-Muslim attitudes, can be thought to be aggregated (Bursztyn et al., 2017; Schilter, 2019). 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. I test three ways in which this general process might create mechanisms for the increase in anti-minority hate crimes: (a) slack in State-level law enforcement; (b) rising economic competition between Muslims and Hindus; and (c) the role of social media in facilitating such violence. I find strongest evidence for the 'State-level law enforcement' mechanism.

The most important limitation of the analysis presented in this paper relates to the quality of data on the incidence of religion-motivated hate crimes. The data that I have used in this research was collected from newspaper reports by a citizen's initiative (CRHCW). While there is a long tradition in the social sciences to use data collected from newspaper reports, especially related to violence against marginalized social groups, there is no doubt that such data come with many problems. Since the data only includes 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 across states and years. I hope that the different ways in which I have tried to control for confounding factors would at least partly deal with biases arising from these obvious data problems. 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.

This analysis points to several avenues for future research. 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 (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. 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 earlier periods as well. Third, 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?

The issues analyzed in this paper has important policy and political implications. 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".[35] 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.[36] Recently, the Congress government in the state of Madhya Pradesh has made some changes in existing laws to deal more firmly with cow vigilantism,[37] and the Congress government in Rajasthan has promised to enact fresh legislation to check mob lynching and hate crimes.[38] 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.[39] How best to deal with such a serious problem that is gravely undermining the democratic republic of India is a question all Indian citizens have to engage with seriously.

[35] Source: The Washington Post, 17 July, 2018 (internet edition). (link)
[36] Source: The Wire, 12 July, 2019. (link)
[37] Source: The Hindustan Times, 27 June, 2019 (internet edition). (link)
[38] Source: The Hindustan Times, 17 July, 2019 (internet edition). (link)
[39] Source: The Times of India, 24 July (internet edition). (link)

Appendix A

In this appendix, I provide details about all the variables used for the analysis in this paper.

- Incidence of religion-motivated hate crime (number): The data on this variable was manually collected from the CRHCW website.

- Vote share won by BJP in the 2014 and 2009 Lok Sabha (lower house of parliament) elections: The data for these variables are taken from the website of the Election Commission of India.

- Incidence of crime (number): This variables gives the incidence (number) of crimes covered by the Indian Penal Codel (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. It is one of the main sources for information on crime-related matters in India.

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

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

- 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 *Census of India, 2011*.

- Share of urban population in 2011 (%): The urbanization rate is the share of total population residing in urban areas. An urban unit can be of two types. It is defined as a statutory town if it has a municipality, corporation, cantonment board or notified town area. It is defined as a census town if it satisfies either of the following characteristics: (a) it has a minimum population of 5000; (b) At least 75 per cent of the male main workers are engaged in non-agricultural pursuits; (c) population density is at least 400 per square kilometers. Data on this variable is taken from the *Census of India, 2011*.

- Share of Muslim population in 2011 (%): The variable measures the share of Muslims in a state's population in 2011. Data on this variable is taken from the *Census of India, 2011*.

- Poverty rate (HCR) of Muslims in 2009-10 (%): The head count ratio of Muslims below the poverty line in 2009-10 using the Tendulkar poverty line. Data on this are taken from Table 16 in Panagariya and Mukim (2014).

- Poverty rate (HCR) of Hindus in 2009-10 (%): The head count ratio of Hindus below the poverty line in 2009-10 using the Tendulkar poverty line. Data on this are taken from Table 16 in Panagariya and Mukim (2014).

- Proportion of Muslims with higher secondary education and above in 2011-12 (%): This variable gives the proportion of Muslims in a state with higher secondary education and above, which includes: higher secondary; diploma/certificate course; graduate; and postgraduate and above. Data on this variable are taken from NSSO (2016, Table S3.10, pp. 99).

- Proportion of Hindus with higher secondary education and above in 2011-12 (%): This variable gives the proportion of Hindus in a state with higher secondary education and above, which includes: higher secondary; diploma/certificate course; graduate; and postgraduate and above. Data on this variable are taken from NSSO (2016, Table S3.10, pp. 99).

- Charge sheeting rate for all IPC crimes (%): This variable measures the charge sheeting rate in police disposal of IPC (Indian Penal Code) crimes committed against all persons. The variable is defined as charge sheets submitted by the police divided by true reports submitted to the police, expressed as a percentage. Data on this variable is available for all years in my sample, other than 2018, and is available in the following tables in the publication, *Crime in India*: Table 4.2. for 2009 to 2015, and in Table 17A.2 for 2016 and 2017. *Crime in India* is an annual publication of the National Crime Records Bureau (NCRB) of the Ministry of Home Affairs, Government of India.[40]

- Charge sheeting rate for all crimes against SCs covered by the SC/ST Prevention of Atrocities Act, 1989 (%): This variable measures the charge sheeting rate in police disposal of crimes committed against Scheduled Caste persons by non-Scheduled Caste persons. All such cases are covered by the SC/ST Prevention of Atrocities Act, 1989. The variable is defined as charge sheets submitted by the police with reference to such cases divided by true reports submitted to the police with reference to such cases, expressed as a percentage. Data on this variable is available for all years in my sample, other than 2018 and is taken from Table 7.4 in the publication *Crime in India*.

- Wireless telecom subscribers (million): This variable measures the total number of wireless telecom subscribers. Data on this variable is available for all years in my sample and is taken from *Telecom Statistics India 2018 (pp. 24–41)*, an annual publication of the Department of Telecommunications, Ministry of Communications, Government of India.

[40] See http://ncrb.gov.in/

- Whether BJP is part of the State Government (Yes=1;No=0): This is a dummy variable that takes the value 1 if the BJP is part of the state government, and 0 otherwise. Data on this variable is constructed for each year using information from the website of the Election Commission of India, and reports in the news media.

Appendix B

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.[41] Figure 6 shows the screenshot of the webpage that was generated when I tried to access the CRHCW website on 13 November, 2019. The screenshot shows that the website can no longer be accessed.

[FUGURE 6 about here]

The CRHCW website was awarded the data journalism awards in 2019 "for best data journalism team portfolio (small newsroom)".[42] The detailed reporting about this award to the CRHCW website can be still accessed.[43] 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:

[41]Follow this link for the report and the screenshot.
[42]See here.
[43]See here.

> ...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.[44]

At the bottom of the page, there is a video interview about the website with Mohsin Alam Bhatt, Assistant Professor, Jindal Global Law School, who seems to have been part of the CRHCW project.

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.[45] 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:

- The Washington Post, 31 October 2018
- The New York Times, 18 February 2019
- Human Rights Watch, 18 February 2019

[44] See here.
[45] See here.

References

Alber, J. (1993). Towards explaining anti-foreign violence in germany. Universität Konstanz, Working Paper Series 53. Available here: http://aei.pitt.edu/63691/1/PSGE_WP4_8.pdf (Accessed 20 November, 2019).

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.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labour Economics*, 21(1):1–42.

Bagchi, A. K. (1990). Predatory commercialization and communalism in india. In Gopal, S., editor, *Anatomy of a Confrontation*. Penguin, New Delhi.

Banu, Z. (1989). *Politics of Communalism*. Popular Prakashan, Bombay.

Basu, A. (2015). *Violent Conjunctures in Democratic India*. Cambridge University Press, New York, NY.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):249–275.

Bonikowski, B. (2017). Ethno-nationalist populism and the mobilization of collective resentment. *The British Journal of Sociology*, 68(S1):S181–S213.

Booth, R. (2019). Racism rising since brexit vote, nationwide study reveals. *The Guardian*. Published on 20 May. Available here: https://www.theguardian.com/world/2019/may/

20/racism-on-the-rise-since-brexit-vote-nationwide-study-reveals (accessed 20 November, 2019).

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).

Brass, P. R. (2003). *The Production of Hindu-Muslim Violence in Contemporary India*. University of Washington Press, Seattle, WA.

Braun, R. and Koopmans, R. (2010). The diffusion of ethnic violencein germany: The role of social similarity. *European Sociological Review*, 26(1):111–123.

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.

Cederman, L.-E. (2019). Blood for soil: The fatal temptations of ethnic politics. *Foreign Affairs*, pages 61–68.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *Quarterly Journal of Economics*, pages 1405–1454.

Chatterjee, A. P., Hansen, T. B., and Jaffrelot, C., editors (2019). *Majoritarian State: How Hindu Nationalism is Changing India*. Oxford University Press, New York, NY.

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.

Cuerden, G. and Rogers, C. (2018). Exploring race hate crime reporting in wales following brexit. *Review of European Studies*, 9(1):158–164.

Dancygier, R. M. and Laitin, D. D. (2014). Immigration into europe: Economic discrimination, violence, and public policy. *Annual Review of Political Science*, 17:43–64.

Devine, D. (2018). The uk referendum on membership of the european union as a trigger event for hate crimes. Available here: https://ssrn.com/abstract=3118190 (Accessed 20 November, 2019).

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).

Engineer, A. A. (1984). *Communalism in Post-Independence India*, chapter The Causes of Riots in the Post-Partition Period in India, pages 33–41. Sangam Books, Hyderabad.

Entorf, H. and Lange, M. (2019). Refugees welcome? understanding the regional heterogeneity of anti-foreigner hate crimes in germany. Available here: http://ftp.zew.de/pub/zew-docs/dp/dp19005.pdf (Accessed 20 November, 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 (accessed 23 July, 2019).

Greene, W. H. (2012). *Econometric Analysis*. Prentice Hall, seventh edition.

Gruber, J. (1994). The incidence of mandated maternity benefits. *The American Economic Review*, 84(3):622–641.

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.

Iyer, S. and Shrivastava, A. (2018). Religious riots and electoral politics in india. *Journal of Development Economics*, 131:104–122.

Jaffrelot, C. (1996). *The Hindu Nationalist Movement and Indian Politics: From 1925 to the 1990s*. Hurst & Co, London.

Jaffrelot, C., editor (2007). *Hindu Nationalism: A Reader*. Permanent Black, Ranikhet.

Jha, S. (2013). Trade, institutions, and ethnic tolerance: Evidence from south asia. *The American Political Science Review*, 107(4):806–832.

Karapin, R. (2002). Antiminority riots in unified germany: Cultural conflicts and mischanneled political participation. *Comparative Politics*, 34(2):147–167.

Khan, D. (1992). Meerut riots: An analysis. In Kumar, P., editor, *Towards Understanding Communalism*. Center for Research in Rural and Industrial Development.

Kleiber, C. and Zeileis, A. (2008). *Applied Econometrics with R*. Springer-Verlag, New York. ISBN 978-0-387-77316-2.

Knobbe, M. and Weidmann-Schmidt, W. (2019). 'we are doing what we can': German domestic intellience chief on the new wave of hate. *Spiegel Online*. Published on 23 October. Available here: https://www.spiegel.de/international/germany/german-domestic-intellience-chief-on-hate-crimes-like-halle-a-1292535.html (accessed 20 November, 2019).

Krueger, A. B. and Pischke, J.-S. (1997). A statistical analysis of crime against foreigners in unified germany. *The Journal of Human Resources*, 32(1):182–209.

McCullagh, P. and Nelder, J. A. (1989). *Generalized Linear Models*. Chapman Hall, New York, NY, second edition.

McGuire, J. and Copland, I., editors (2007). *Hindu Nationalism and Governance*. Oxford University Press, New Delhi.

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.

Muis, J. and Immerzeel, T. (2017). Causes and consequences of the rise of populist radical right parties and movements in europe. *Current Sociology*, 65(6):909–930.

Müller, K. and Schwarz, C. (2018). Fanning the flames of hate: Social media and hate crime. Available here: https://dx.doi.org/10.2139/ssrn.3082972 (Accessed 20 November, 2019).

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).

Muralidharan, K. and Prakash, N. (2017). Cycling to school: Increasing secondary school enrollment for girls in india. *American Economic Journal: Applied Economics*, 9(3):321–350.

NSSO (2016). *Employment and Unemployment Situation Among Major Religious Groups in India: NSS 68-th Round, July 2011 – June 2012*. National Sample Survey Office, Ministry of Statistics and Programme Implementation, Government of India, New Delhi.

Panagariya, A. and Mukim, M. (2014). A comprehensive analysis of poverty in india. *Asian Development Review*, 31(1):1–52.

Pustejovsky, J. (2019). *clubSandwich: Cluster-Robust (Sandwich) Variance Estimators with Small-Sample Corrections*. R package version 0.3.5.

Robitzsch, A. and Grund, S. (2019). *miceadds: Some Additional Multiple Imputation Functions, Especially for 'mice'*. R package version 3.5-14.

Sam, C. and Thakurta, P. G. (2019). *The Real Face of Facebook in India: How Social Media have Become a Propaganda Weapon and Disseminator of Disinformation and Falsehood*. AuthorsUpFront, New Delhi.

Sarkar, S. (1984). *Modern India: 1885-1947*. Macmillan India Limited, Delhi.

Schaffner, B. F., Macwillaims, M., and Nteta, T. (2018). Understanding white polarizationin the 2016 vote for president: The sobering role of racism and sexism. *Political Science Quarterly*, 133(1):9–34.

Schilter, C. (2019). Hate crime after the brexit vote: Heterogeneity analysis based on a universal treatment. Available here: http://www.lse.ac.uk/economics/Assets/Documents/job-market-candidates-2018-2019/JobMarketPaper-ClaudioSchilter.pdf (Accessed 20 November, 2019).

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).

Scroll (2019). Factchecker pulls down hate crime database, indiaspend editor samar halarnkar resigns. *Scroll*. Published on 12 September. Available here: https://scroll.in/latest/937076/factchecker-pulls-down-hate-crime-watch-database-sister-websites-editor-resigns (accessed 11 November, 2019).

Upadhyaya, A. (1992). Recent trends in communal violence: A case study of varanasi. In *Proceedings of the International Conference on Conflict and Change*. United Nations University, Portrush, Ulster.

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.

Weaver, M. (2018). Hate crime surge linked to brexit and 2017 terrorist attacks. *The Guardian*. Published on 20 May. Available here: https://www.theguardian.com/society/2018/oct/16/hate-crime-brexit-terrorist-attacks-england-wales (accessed 20 November, 2019).

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.

Williams, A. (2018). Hate crimes rose the day after trump was elected, fbi data show. *The Washington Post*. Published on 23 March. Available here: https://www.washingtonpost.com/news/post-nation/wp/2018/03/23/hate-crimes-rose-the-day-after-trump-was-elected-fbi-data-show/ (accessed 20 November, 2019).

Williams, M. L., Burnap, P., Javed, A., Liu, H., and Ozalp, S. (2019). Hate in the Machine: Anti-Black and Anti-Muslim Social Media Posts as Predictors of Offline Racially and Religiously Aggravated Crime. *The British Journal of Criminology*. azz049.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, 50(2):420–445.

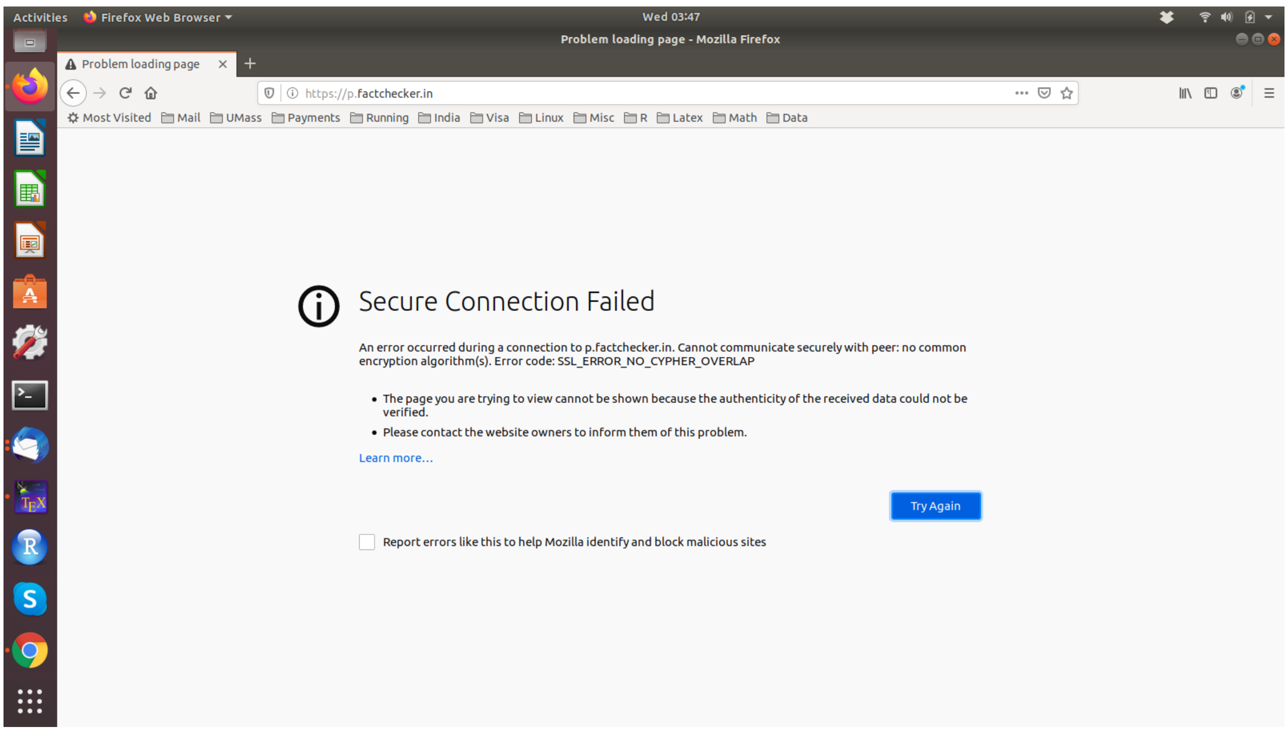

Figure 6: Screenshot of the CRHCW website on 13 November, 2019.