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Conflict, Economic Activities and the Internet: Disentangling the (World Wide) Web

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Conflict, Economic Activities and the Internet: Disentangling the (World Wide) Web*

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Abstract

Information shapes people's narratives and, thus, collective action. The latter bears implications for both inter-group economic cooperation and conflict literature. In this paper, we examine the economic effects of ethnic conflicts under varying information levels as proxied by mobile Internet speeds. Our analysis of India from 2019 to 2023 yields that religious riots reduce night-time lights by 19.61% in the following year and mobile Internet speed *amplifies* the negative effects by approximately 1.2 - 5.1 percentage points. We posit that the mechanism is through spiteful narratives that are amplified by the faster Internet. The findings are robust to a battery of alternative specifications and tests. *JEL Codes:* D74, L86.

Keywords: Riots, Internet Speed, Hateful Narratives, Economic Activities.

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1 Introduction

Beyond the loss of innumerable lives, ethnic riots have a perverse effect on the economy (Blattman & Miguel 2010, Ray & Esteban 2017). As one of the most prevalent forms of civil disorders, they contribute to poverty, corruption, and a decline in the quality of institutions. For example, a study by Hess (2003) indicate that ethnic conflicts cost 8% of the world's GDP. In similar contexts, Mueller (2016) finds that for every 50 or more fatalities in civil wars, growth falls by 4.4 percentage points in that year.

A natural question which arises is the following: What is the role of information in this conflict-growth inter-relation? Information determines people's behaviour in uncertain, high-stakes, conflict-prone environments. The media, being the main source of information, play a crucial role in this context. It shapes the intensity of conflicts through the dissemination of information via newspapers, television and radio (e.g., see DellaVigna et al. (2014), Yanagizawa-Drott (2014), Blouin & Mukand (2019), Armand et al. (2020)).

In recent years, information communication technologies (ICTs) have proliferated tremendously, and the Internet has eclipsed traditional media as the primary channel through which individuals learn about unfolding events (Petrova & Tapsoba 2025). Thus, the Internet serves to primarily amplify the reach and speed of conflict-related narratives, influencing incentives, perceptions, and coordination among groups, shaping a range of economic, political and social outcomes such as voting, protest participation, hate crimes, terrorism, among others (Bauer & Latzer 2016, Zhuravskaya et al. 2020, Campante et al. 2022, Sabatini 2024, Petrova & Tapsoba 2025). To give an example, Amorim et al. (2022) found that an increase in broadband penetration by 0.5 percentage points accounted for the probability of Occupy protests breaking out by between 1 - 3 percentage points.

Emphasising the concerns of Petrova & Tapsoba (2025), what is lacking in the literature is quantitative evidence on how information communication through digital domains influences the relationship between economic growth and conflict. Such evidence is crucial for anticipating violence, moderating public responses, and designing policies that mitigate its economic, political and social consequences.

"The Internet may be part of the solution to our civic problem, or it may exacerbate it"

— Putnam (2000) (p. 170)

In this paper, we focus on the role of mobile Internet in *modulating* the relationship between riots and economic activity. Following the above quote, existing literature verifies that the Internet poses a *dual* nature. On one hand, it reduces people's costs of obtaining information and collective action (for example, see Acemoglu et al. (2018), Manacorda & Tesei (2020), Donati (2022)). On the other hand, it amplifies fake news, polarisation, and xenophobia, among others (for example, see Tufekci (2018), Allcott et al. (2020))[1].

Consider the communal Hindu-Muslim Riots in India: these riots are the most prevalent and persistent forms of ethnic conflicts in India, measured in terms of intensity and historical significance (Wilkinson 2009, Brass 2011, Amaral et al. 2014, Mitra & Ray 2014, Iyer & Shrivastava 2018, Mitra & Ray 2019). There are several instances of such riots eroding Hindu-Muslim relations. To cite one, The Print (24/02/2021) documents the Northeast Delhi riots in February 2020 that killed 53 people — 38 Muslims and 15 Hindus and drove a sharp wedge between the two communities. The article includes a Hindu victim's statement: "All Muslims are the same", which might lead the Hindu audience community to develop anti-Muslim sentiments (Shayo & Zussman 2017, Mjelva et al. 2025), leading to fewer inter-communal interactions. Likewise, Fisman et al. (2020) showed that riot-exposed Hindu bank branch managers lend less to Muslim borrowers.

The availability of the Internet in this context has *ambiguous* implications. Since people are more connected, the propagation of positive messaging might deter the disruption (Blouin & Mukand 2019, Armand et al. 2020). Equivalently, communal hatred might *also* spiral beyond the towns and villages of its origin, disincentivising inter-communal economic activities on a larger spatial extent. The ambiguity requires a careful empirical investigation, motivating us to examine whether improved digital connectivity *exacerbates* the economic effects of riots.

We draw upon another instance of Hindu-Muslim violence from Haryana's Nuh district. On July 31, 2023, communal violence erupted during a religious procession, and news quickly spread across social media, resulting in the unrest extending to nearby districts, including Mewat, Badshahpur, and Gurugram. Firstpost (03/08/2023) documents that related X (Twitter) hashtags reached a wide audience, with more than 67% of the content carrying a negative sentiment. Some (anonymised) examples of such tweets with hashtags like #NuhViolence, #MewatTerrorAttack, and #Haryanaviolence are given in Appendix A.1. A subset of tweets (Exhibit 2 and 5 of Figure A1) also shows clear evidence of Hindu groups attempting to boycott Muslim businesses and products.

Given this context, one may justifiably ask: Does faster mobile Internet worsen the economy following a riot? By proxying ethnic conflicts with the Hindu-Muslim Riots in India (Mitra & Ray 2014, 2019) and economic activities with night-time lights (Henderson et al. 2011, Asher et al. 2021), we find that riot exposure reduces economic activities by 19.61% and mobile Internet speed *amplifies* the negative effect. More specifically, a 1 millisecond (ms) *decrease* in average annual mobile network latency[2] amplifies the

[1]Interestingly, controlled field experiments show these threats can be countered, see Levy (2021), Beknazar-Yuzbashev et al. (2025).

[2]Mobile network latency is the time it takes for data to travel from a user device to the server network and back, reflecting the delay between sending a request and receiving a response.

marginal (negative) effect of riot exposure on nightlights by approximately 1.2 - 5.1 percentage points.

To get a sense of the economic significance of the estimates, consider two Indian cities — Surat (in Gujarat) and Lucknow (in Uttar Pradesh). According to the 2011 SECC[3], Lucknow has a higher estimated urban annual per capita consumption (in 2012 INR) than Surat. Our results indicate that for a 0.1 unit increase in riot exposure in the previous year in both cities, a 10 ms *increase* in average annual mobile latency in Surat (holding Lucknow's mobile latency constant) reduces the consumption gap between the cities by approximately 2.06% on average, thus bringing Surat closer to Lucknow in terms of per capita consumption.

A concern regarding causal inference of our results stems from the fact that both riots and Internet infrastructure might be endogenous in affecting night-time lights. For example, areas with higher economic activity might facilitate riot outbreaks or receive better Internet infrastructure. Again, there might be omitted confounders affecting the interplay. To overcome potential endogeneity, we employ an instrumental variable (IV) two-stage least-squares (2SLS) strategy to identify the exogenous variations in *both* riots and mobile Internet speed.

First, we instrument riots with the coincidence of a Hindu festival falling on a Friday — known to be a flashpoint for riots over contest for public spaces (Iyer & Shrivastava 2018). Second, we instrument mobile Internet speed with "lightning stroke density". While existing literature has used lightning as an instrument for mobile connectivity because lightning strikes are often associated with damage to infrastructure (for example, see Manacorda & Tesei (2020), Guriev et al. (2021)), we put forward a *novel* intuition. Beyond damaging cell towers, lightning is *also* known to influence mobile Internet speed through electromagnetic interference[4]. So, in principle, lightning phenomena might reduce the quality of mobile Internet speed even if they do not damage the infrastructure itself. Instrumenting the exploratory variables eliminates potential endogeneity concerns arising from omitted variables and/or reverse causation.

But through which channel does faster mobile Internet amplify the disruptive effects of riots? We attribute faster Internet to "enhanced coordination" and "enhanced information" among agents following Jackson & Yariv (2007). Enhanced coordination implies agents coordinate their actions with their neighbours and become more responsive to their actions. Enhanced information implies agents are more responsive to changes in economic conditions. Faster mobile Internet, which we attribute to better connected-

[3]Socio Economic and Caste Census (SECC) 2011; The Urban Consumption module of the 2011 SECC is taken from The SHRUG (Asher et al. 2021).

[4]Latest mobile network bandwidths, e.g., 4G, 5G, rely on electromagnetic propagation of signals, and lightning causes interference over the signals, see Crabtree & Kern (2018), Sumardi et al. (2024).

ness, enhances both effects (Manacorda & Tesei 2020). In synchronization with the The Print (24/02/2021) and Firstpost (03/08/2023) reports, we posit that riots worsen *communal dynamics* by promoting hateful narratives and faster mobile Internet, through its enabling properties of enhanced information and enhanced coordination, amplifies the negative economic impact of riots.

Episodes of Hindu-Muslim Riots increase the exposure to "bitter instances" of communal interactions. That is, events of communal interactions with a negative *tonality*[5], and faster mobile Internet amplifies this exposure. Mistrust sows within the community as both groups start to encounter amplified instances of bitter events concerning the current narrative of Hindu-Muslim relations. As a result, each group reduces interactions with the other even more, driving down the overall level of economic activity further.

Evidence from relevant settings shows that mobile coverage can increase mass mobilisation (violent conflicts), with episodes of economic downturns (growth) facilitating (moderating) these effects (Manacorda & Tesei 2020, Ackermann et al. 2021). Similarly, Ahmed et al. (2025) found that higher exposure to the televised adaptation of the Hindu epic "Ramayan" increased communal violence as cohesion among Hindu identity groups increased. From a different yet relevant perspective, Fisman et al. (2020) examined how riot exposure reduces inter-communal lending behaviour. In relation to the above, we extend the literature by examining how riots, in the presence of better mobile Internet quality, exacerbate the damage to economic growth.

Our approach is innovative on several fronts. First, using mobile Internet *speed* instead of coverage in proxying mobile Internet/connectivity quality provides us with a substantial advantage over earlier works that relied on (binary) mobile coverage indicators — typically population-weighted and susceptible to measurement error (Manacorda & Tesei 2020, Sabatini 2024). This allows us to identify the *intensive* margin of riots in the presence of varying Internet speeds, rather than the extensive margin. Second, we utilise the exogenous role of lightning stroke density in affecting cellular Internet speed through electromagnetic interference, which, to the best of our knowledge, has not been done before. Third, we *introduce* a novel, high-resolution dataset on Internet speed metrics from a publicly available source. This improves on standard proxies for information-diffusion technologies, such as mobile signal strength and coverage, radio and television transmissions, or social network structure, which are often erroneous, unavailable, or costly.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 details the data, and Section 4 outlines the empirical strategy. Section 5 presents the main results. Section 6 explains the mechanism channel, and

[5]We use the Global Database on Events, Location and Tone (GDELT) Project (Leetaru & Schrodt 2013) to extract information on communal events with a negative tonality (detailed in Section 6).

Section 7 provides the robustness checks. Section 8 concludes.

2 Related Literature

Our study builds on two separate strands of literature. The first one examines the independent effects of Information Communication Technologies (ICTs) on a cache of economic, political and social outcomes. The second strand looks at the impact of conflicts. To the best of our knowledge, no study explores the intensive margin of mobile Internet speed in modulating the economic effects of ethnic conflicts.

The relationship between traditional ICTs (e.g., media formats such as television, newspapers and radio) and various economic, social, and political outcomes provides mixed evidence - emphasising its duality. DellaVigna & La Ferrara (2015) provide a detailed review of recent literature and outlines their empirical strategies. On the one hand, the media is found to have a positive impact on various outcomes. We find evidence of the traditional ICTs' fundamental enabling features of facilitating information and coordination in increasing inter-ethnic trust (Blouin & Mukand 2019), and counterinsurgency (Armand et al. 2020) through positive messaging. On the other hand, there are negative impacts too through the same enabling features. For example, inciting violence (DellaVigna et al. 2014, Yanagizawa-Drott 2014), and substituting social activities (DellaVigna & La Ferrara 2015).

Similar to traditional ICTs, the Internet (broadband or mobile) has mixed effects on a range of outcomes. More importantly, the recent forms of ICTs (e.g., the Internet, mobile phones and social media) are shown to crowd out traditional media even more (Campante et al. 2022). In this context, Bauer & Latzer (2016), Zhuravskaya et al. (2020), Campante et al. (2022) and Sabatini (2024) provide a detailed literature review. Existing evidence finds positive effects of mobile phones, social media, and/or the Internet on outcomes such as social capital, property prices, fertility, firm performance, and education[6]. However, some studies find negative effects on a different set of outcomes, such as social participation, voter turnout, sleep duration, and mental health[7].

On outcomes of social disorders, like violence, enhanced information and enhanced coordination enable mobile Internet (or coverage) to increase violence (Pierskalla & Hollenbach 2013, Ackermann et al. 2021), protest participation (Steinert-Threlkeld 2017, Acemoglu et al. 2018), mass mobilisations (Manacorda & Tesei 2020), and hate crimes (Müller & Schwarz 2023). Equivalently, they can also help reduce violence and hatred by facilitating

[6]See Bauernschuster et al. (2014), Ahlfeldt et al. (2017), Billari et al. (2019), DeStefano et al. (2023), Sanchis-Guarner et al. (2025).

[7]See Olken (2009), Falck et al. (2014), Billari et al. (2018), Gavazza et al. (2019), Arenas-Arroyo et al. (2025).

counterinsurgency measures (Shapiro & Weidmann 2015) and by substituting physical collective actions with digital ones (Absher & Grier 2019), respectively.

Without the influence of ICTs, ethnic conflicts alone are established to have a perverse effect on the economy, especially on lives, institutions, and per capita income[8]. For a detailed review of the literature, see Blattman & Miguel (2010), Ray & Esteban (2017). Other examples include how conflict increases production of narcotics in war-torn Afghanistan (Lind et al. 2014) due to weak institutions, and how exogenous shocks to conflicts (such as the sudden death of a rebel leader) reduced returns to firms holding concessions in the Angolan conflict zones (Guidolin & La Ferrara 2007).

For India, the implications of the Hindu-Muslim Riots primarily depend on inter-ethnic complementarities. During the 2002 Gujarat Riots, localities with high ethnic diversity and animosity were affected more (Field et al. 2008), whereas ethnically diverse localities with historic inter-ethnic complementarities were less damaged economically (Jha 2014). On political outcomes, Iyer & Shrivastava (2018) found that communal violence increases the vote share of the Hindu nationalist Bharatiya Janata Party (BJP) primarily through a decrease in the registration ratio of Muslim voters. Similarly, Ahmed et al. (2025) shows that areas with higher exposure to the televised adaptation of the Hindu epic, "Ramayan", between 1987-1988 displayed stronger religious cohesion among Hindus, resulting in increased episodes of Hindu-Muslim violence through 1992.

While existing literature primarily explores the role of ICTs in instigating violence, our study contributes by examining their interaction in the recent context, specifically, whether mobile Internet infrastructure facilitates the perverse effects of riots. By bridging these two strands of research, our study sheds light on the broader implications of the Internet in conflict settings.

3 Data

In this section, we outline the variables of interest that we use for analysis, along with their corresponding data sources. The analysis period spans from 2019 to 2023, and is at the level of *shrids*. A *shrid* is the lowest level of administrative boundary (a town, or a village) defined by The SHRUG (The Socioeconomic High-resolution Rural-Urban Geographic Platform for India) (Asher et al. 2021).

Most of the variables used in our analysis are extracted from The SHRUG. The database contains open, high-resolution data that integrates information from multiple satellite-derived, administrative, and survey sources, such as Population and Economic censuses,

[8]For example, see Fearon & Laitin (2003), Collier & Hoeffler (2004), Collins & Margo (2004).

Elections, Nighttime Lights, and Vegetation Continuous Fields. It has been used extensively in development research in the context of India[9].

3.1 Internet Speed

The Internet is one of the main sources of information. As per the World Bank, the mobile cellular subscription in India was approximately 83% in 2019. To capture Internet speed, we exploit the rich high-resolution Internet performance data from Speedtest® by Ookla® Global Fixed and Mobile Network Performance Maps[10].

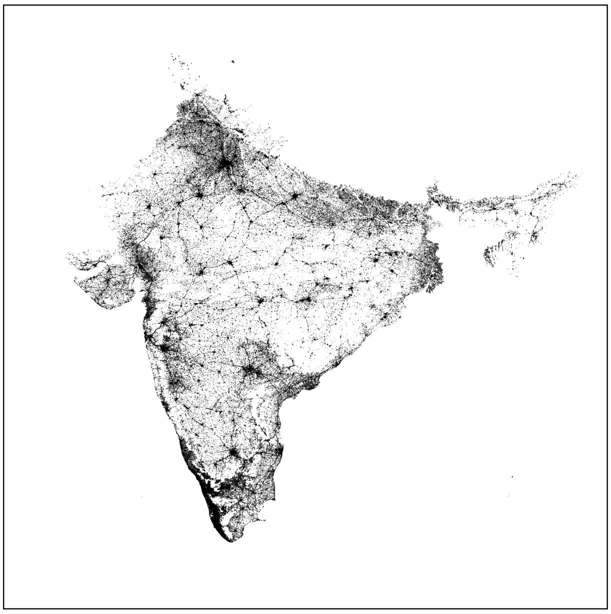

Figure 1: Mobile Network Performance Map, 2019-2023

This global dataset records cellular (e.g., 4G LTE, 5G NR) mobile Internet download speed in kilobytes per second (kbps), upload speed in kbps and latency in milliseconds (ms). The Speedtest metrics are recorded by test devices throughout the year, which are represented as "tiles" in a map marking the precise location of the device. Ookla aggregates and averages these metrics based on the number of test devices used quarterly.

Figure 1 presents a map of mobile network performance in India from 2019 to 2023. Each dot on the map represents a specific "tile" where internet speed metrics were recorded, meaning we have precise data on the location of the test devices and the results. The data was collected and cleaned using Geographic Information Systems (GIS) software, ArcGIS Pro, and the performance metrics were averaged and attributed to *shrid*-year units. Figure 2 shows the distribution of the mobile Internet speed metrics at a logarithmic scale over the estimation sample.

[9]For example, to examine the effects of infrastructure/polity size on economic outcomes, such as rural development (Burlig & Preonas 2024) or access to public goods (Narasimhan & Weaver 2024).

[10]Speedtest by Ookla Global Fixed and Mobile Network Performance Maps was accessed on 13-01-2025 from `https://registry.opendata.aws/speedtest-global-performance` (2025)

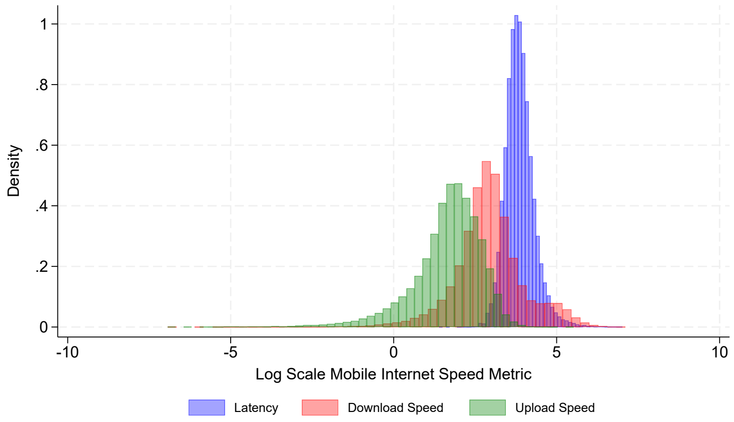

Figure 2: Mobile Internet Speed Distribution

3.2 Economic Activity

We proxy economic activity with night-time lights because it captures economic activity and growth at a high-resolution level (Henderson et al. 2011, Asher et al. 2021). Figure 3 shows a reference satellite imagery of India at night as of 01/01/2022.

Source: NASA Worldview

Figure 3: Nightlight Emission of India as of 01/01/2022

We use nightlight data from The SHRUG. The data contains consistently processed *shrid*-wise time series of annual global NASA/NOAA[11] Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime lights produced from monthly cloud-free average radi-

[11]NASA: National Aeronautics and Space Administration, NOAA: National Oceanic and Atmospheric Administration.

ance grids. This data is aggregated and calibrated for consistent time series estimation by The SHRUG developers.

The nightlight data consists annual sum of nightlight detected in each shrid polygon and the total pixels in those polygons. Each polygon in a given year is consistently attributed to the shrid-years. For simplified interpretation, we divided the annual sum of nightlight detected in a polygon by the total number of pixels present in that polygon and then applied a natural logarithmic transformation. Since in some polygons (shrids), the annual sum of nightlight is recorded as zero, we added a small magnitude of 0.001 to avoid missing values.

3.3 Conflicts

We use Hindu-Muslim riots as conflicts in our analysis since this particular form of ethnic riot is still prevalent and significant in India (Mitra & Ray 2019). It is also one of the most important forms of conflict measured by intensity at the sub-national level (Amaral et al. 2014). The source of data on Hindu-Muslim riots in India is ACLED[12] (Raleigh et al. 2023).

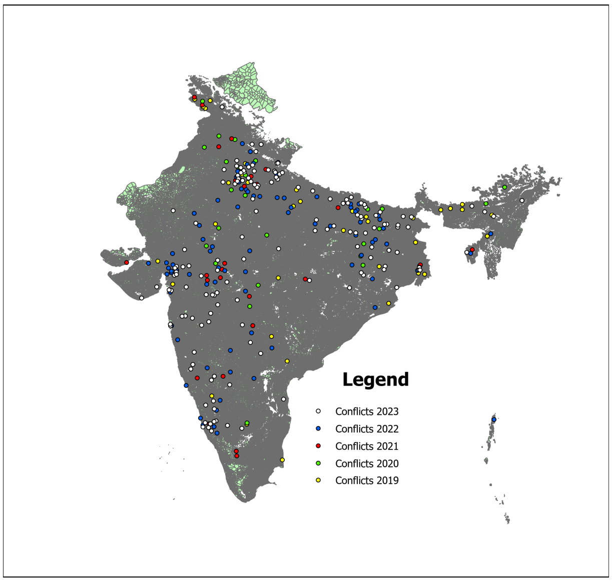

Figure 4: Hindu-Muslim Riots Location, 2019-2023

The ACLED data contains information on all forms of conflicts and disorders, from armed military combat to peaceful protests. The data contains information on the actors engaged in the conflict events. We extracted Hindu-Muslim riots from the dataset using a string function on Stata that only filtered out events classified as "Riots" by ACLED and had variants of the words "Hindu" and "Muslim" as the associated actors. We exploited the riot count, their timing, and coordinates to develop our exploratory variable.

[12]Armed Conflict Location & Event Data (ACLED) was accessed on 10/11/2024 from `www.acleddata.com`.

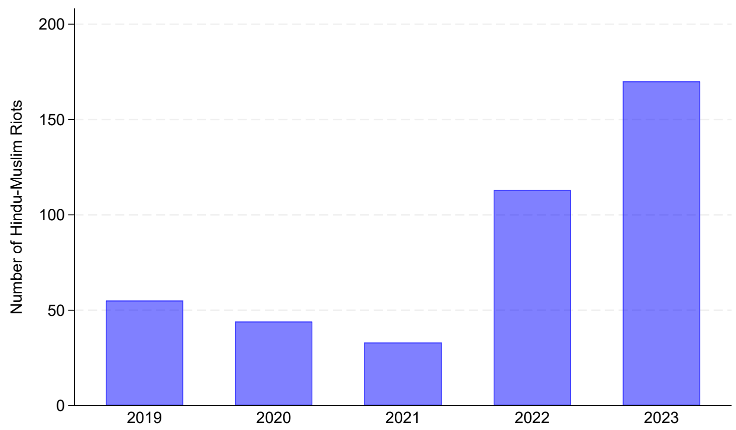

Figure 5: Hindu-Muslim Riots Count

Figure 4 shows the precise location of each Hindu-Muslim riot that occurred in India between 2019 and 2023. We attributed each riot that falls within a shrid to a riot in that shrid using spatial join in ArcGIS Pro. Then, we calculated the distance of the nearest riots from each shrid centroid and used them in our analysis. Figure 5 shows the total number of riots over the years.

3.4 Controls

We control for time-varying measures that might affect nightlights, riots, and Internet speed. The controls we use are population, forest cover, literacy rate, religious composition, political affiliation, crime rate, and bank deposits. Some of the controls are at the district level due to data availability constraints; however, this is not a big concern for us since the unobserved district-specific characteristics will be absorbed by shrid fixed effects since shrids are nested within districts.

Shrids and districts are made consistent with the latest (2011) Indian census. We exponentially extrapolated the total population, the literate population and the population by religious communities (Hindu and Muslim) using the growth rates observed from the Indian Census (2001, 2011) (Office of the Registrar General and Census Commissioner, India 2011, Asher et al. 2021).

Forest cover data is used as a proxy for urbanicity. Urbanicity can influence nightlights, riots, and mobile Internet speed. Urbanised areas, like cities, are more likely to have better infrastructure, such as high-capacity power grids and faster Internet. Communal riots are also more likely to break out in cities as a contest for these resources. The forest cover data comes from Vegetation Continuous Fields (VCF) in The SHRUG (Dimiceli et al. 2015, Asher et al. 2021), which provides annual tree cover in the form of the percentage of each pixel under forest cover, generated from a machine learning model based on a combination of images from Moderate Resolution Imaging Spectroradiometer (MODIS) and samples from higher resolution satellites.

Electoral data comes from The SHRUG (Jensenius & Verniers 2017, Prakash et al. 2019, Asher et al. 2021) and the TCPD[13]. The data contains assembly constituency (AC) wise information on state assembly elections. We attributed each assembly constituency to the shrid it falls into. For simplification, we did not include any data points where an assembly constituency overlaps multiple shrids. From this dataset, we extracted the political party the winner represents, and approximated the election results for all the years where an election did not take place. We created a variable, "BJP Rule", that records 1 if the main identity party - the Bharatiya Janata Party - is the assembly constituency seat holder and 0 otherwise. The intuition behind using BJP's rule as control is that the literature suggests it plays a crucial role in the interplay of Hindu-Muslim violence and elections (Iyer & Shrivastava 2018).

Additionally, we also control for crime rate per 10,000 inhabitants to capture the propensity of violence of each shrid. We used district-wise data on total crimes registered under the Indian Penal Code (IPC) for each district from the National Crime Records Bureau (NCRB). We also control for income because it can also influence economic activities, riots and Internet speed. Nightlight is related to income - more per capita income implies more economic activity, as observed in cities and towns rather than villages in general. Again, riots are influenced by income as well (Mitra & Ray 2014). Moreover, places with higher income may demand better Internet infrastructure. Since shrid-level income data is unavailable, we proxy income by the total value of bank deposits (in Rupees) in scheduled commercial banks for each district from the Reserve Bank of India (RBI).

4 Empirical Strategy

We examine the role of riots on economic activity under variations in Internet speed by estimating the following specification:

$$\begin{aligned} \text{Log Avg NL}_{st} = \beta_0 + \beta_1 \text{Riot}'_{st-1} + \beta_2 \text{Latency}_{st-1} \\ + \beta_3 (\text{Riot}'_{st-1} \times \text{Latency}_{st-1}) \\ + \text{X}_{1st} + \text{X}_{2dt} + \lambda_s + \delta_t + \epsilon_{st} \end{aligned} \tag{1}$$

where s indexes the *shrids*, d the districts, and t the year. X_{1st} is the set of time-varying shrid-level controls, X_{2dt} is the set of time-varying district-level controls. λ_s indexes shrid fixed effects (FE), which subsumes all time-invariant shrid and district characteristics. δ_t is year FE, which absorbs all unobserved, time-invariant year characteristics. Standard

[13] Trivedi Centre for Political Data, Ashoka University (2024)

errors are clustered at the shrid level.

Our main dependent variable is Log Avg NL_{st}, the natural logarithmic transformed average nightlight in shrid s at year t. The main exploratory variables are lagged riot exposure, average latency in milliseconds, and their interaction. Latency_{st-1} captures the average latency in shrid s in year $t-1$. Latency is defined as the time it takes for data to travel from one point on a network (such as the user's device) to another point (like an online server) and back again (Virgin Media). Hence, higher latency implies *slower* Internet speed. Riot'_{st-1} represents the riot exposure of shrid s in year $t-1$. We use riot exposure, i.e., the extent to which a shrid is exposed to the nearest riot, instead of riot counts, following the recommendations of Iyer & Shrivastava (2018).

The intuition behind using riot exposure instead of riot counts is that riots in a shrid might have spillover effects on adjoining shrids. We construct riot exposure by making the same assumption as Iyer & Shrivastava (2018) that when there is no riot in the shrid s itself, the nightlight is influenced by the nearest occurring riot, and the effect is lower as the distance of the riot increases (details on the construction of riot exposure are provided in the next section).

Variable	Type	Definition	Obs	Mean (SD)
Nightlight	Log	Average nightlight emission	2,929,555	-1.49 (2.98)
Riots	Count	Number of riots in a given *shrid*	2,929,555	0.00 (0.01)
Latency	Average	Mobile network latency (ms)	424,787	56.66 (44.7)
Download Speed	Average	Mobile Internet download speed (Mbps)	424,787	28.19 (50.77)
Upload Speed	Average	Mobile Internet upload speed (Mbps)	424,787	6.98 (6.82)
Forest Cover	Log	Average vegetation continuous fields	2,925,462	-1.91 (1.51)
Crime Rate	Fraction	Number of crimes per 10,000 inhabitants	2,890,614	0.60 (0.63)
BJP Rule	Binary	If BJP is the AC seat holder	1,403,149	0.31 (0.46)
Literacy Rate	Fraction	Literacy rate	2,929,555	0.64 (0.26)
Hindu Majority	Binary	If Hinduism is the dominant religion	2,929,555	0.96 (0.19)
Total Population	Log	Population abstract	2,929,555	6.84 (1.35)
Bank Deposits	Log	Value of total bank deposits in Rupees	2,926,849	25.34 (1.06)

Table 1: Variables Summary

Table 1 contains the descriptions of the variables used and descriptive statistics. We have a total of 2,929,555 strongly balanced observations over 2019-2023. Our estimation sample exploits 5.38% of the total observations due to the presence of singleton observations and missing values for the internet speed metrics. We justify the sampling using the standardised mean difference of the covariates across the estimated and non-estimated samples (< 0.1), indicating a weak-to-no imbalance between the samples. The final estimation sample includes a total of 1,57,674 towns or villages (shrids) nested within 448 districts, among 29 states.

We use specification (1) to understand how variations in internet speed affect the role of riot exposure on nightlights in the following year. However, there are endogeneity concerns arising from confounding variables that might be omitted (omitted variable bias), or there might be reverse causation. Endogeneity might also arise from the fact that riots might be caused in expectation of higher nightlights, or that Internet infrastructure is developed expecting higher economic activities.

4.1 Causal Identification

The first step in our causal identification strategy involves instrumenting riot exposure with the Iyer & Shrivastava (2018) instrument - the coincidence of a Hindu festival falling on a Friday, the Holy Day for Muslims. The study documents that communal tensions in India predominantly arise when events of religious significance for Hindus and Muslims coincide, often leading to riots due to contests over public spaces, satisfying the relevance criterion. We find similar evidence from studying the context of the riots occurring between 2019 and 2023 from the event descriptions column present in the ACLED dataset. An example of such an instance leading to a riot is given below in Figure 6.


Tensions in Bihar after violence during Ram Navami processions

Aurangabad police superintendent Kantesh Mishra said two groups clashed when one of them on motorcycles was trying to use a lane for a procession

Updated on: Apr 12, 2022 1:05 PM IST

By Avinash Kumar

Devotees take part in a 'Ram Navami' procession in Bihar's Bodh Gaya on Monday. (PTI PHOTO)

Source: Hindustan Times, dated 12/04/2022

Figure 6: Illustration of Instrument Relevance

We construct the instrument "Festival", which takes a value of 1 if any important Hindu festival in a given state fell on a Friday in year t, and 0 otherwise. Our instrument also meets the exclusion restriction. Further, since Hindu festivals follow the Hindu lunar calendar, the coincidence of an important festival falling on a Friday is entirely exogenous.

We restrict five key festivals specific to each state, following Iyer & Shrivastava (2018). The list of festivals is given in Appendix A.2. There is a limitation to using the instrument. Important Hindu festivals vary by state. So, there is little cross-sectional variation in it.

Analysis of variance of the instrument on variables indexing the shrid and year over the estimation sample shows the two variables explain 75% of the variation, and from that 77% is explained by the year variable. The explained variation is less than what Iyer & Shrivastava (2018) found in their study, where the year variable explained 98% of the variation from the two variables. They addressed it by including a quadratic time trend instead of using year FE. We, instead, continue using the year FE and still retain enough variation. Although it risks weak identification, we use weak-instrument-robust inference to overcome the bias.

The second step involves instrumenting mobile Internet speed. We exploit the exogenous variations in the standard deviation (SD) of lightning stroke density to causally identify mobile Internet speed. Stroke density is defined as the number of strokes per square Km of surface area per day ($km^{-2}d^{-1}$) detected at a particular location during a time period - that is, how much lightning is occurring.

Our intuition behind using lightning as an instrument contrasts with the intuition provided by Manacorda & Tesei (2020) and Guriev et al. (2021). They used this natural phenomenon because it damages cellular infrastructure. We *instead* argue that lightning reduces mobile network quality through electromagnetic interference, because mobile signals rely on electromagnetic propagation (Crabtree & Kern 2018, Sumardi et al. 2024). Since lightning depends on atmospheric conditions, it is purely exogenous and satisfies the relevance criterion as it is correlated with mobile network quality. Figure 7 shows the distribution of mean and SD in lightning stroke density.

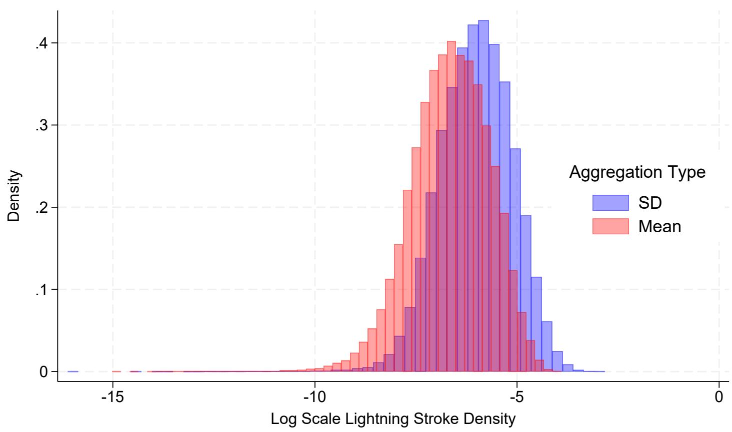

Figure 7: Lightning Stroke Density Distribution

However, it might be that lightning strikes over power plants, transmission lines or grids. Such an occurrence will affect nightlights, violating exclusion restrictions. We account for this possibility. We find that over the analysis period, only 4 thermal power plants (and power stations inclusive) were on forced outage due to a natural disaster, and all of the outages occurred during 2023-24. These 4 power plants only account for 0.5% of the total installed capacity of power plants in India as of 31/12/2023[14], so the effect of lightning on nightlights is trivial. Further, since all these outages were in a single year that falls into our analysis (i.e., 2023), any possibility of effects is absorbed by the year fixed effects.

We use lightning data from The World Wide Lightning Location Network (WWLLN) Global Lightning Climatology (WGLC) and time series (Kaplan & Lau 2021, 2022, Kaplan 2025). The data contains a subset that includes NetCDF multidimensional files consisting of lightning stroke density at 0.5-degree 5-arc-minute resolution at a monthly time dimension. We extracted the subset and approximated them to a shrid-year level mean and SD stroke densities. Images of the raster subsets are given in Appendix A.3.

5 Main Results

One of the main exploratory variables in specification (1) is riot exposure, $\text{Riot}'_{st-1} = \phi(d_{st-1})$. To derive riot exposure, we use a standard Gaussian decay function $\phi(d_{st-1}) = e^{(-d_{st-1}/\sigma)}$ where d_{st-1} is the distance between the centroid of a shrid s and the nearest riot in year $t-1$. The selection of the standard deviation, σ, for calculating the decay function is an issue.

To overcome this, we follow the method of riot exposure calculation from Iyer & Shrivastava (2018). If we assume the average district corresponds to a circle, then the area of the circle is approximately 4230 Square Km as per the 2011 Indian census. That means the average district has a radius of 35 Km. Hence, we start with a standard deviation of 70 Km and increase in steps of 35 Km.

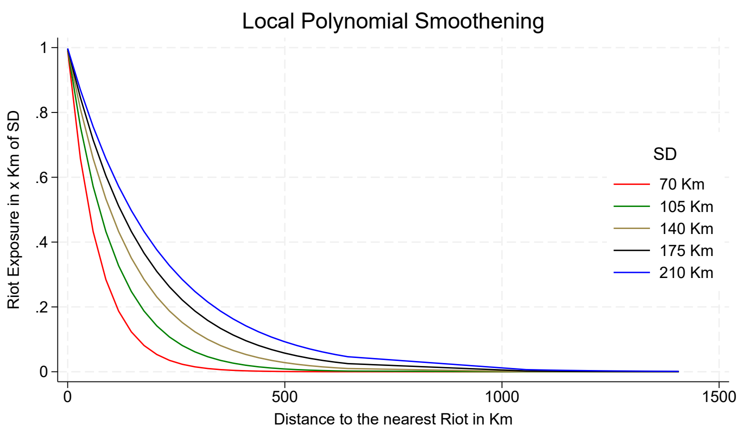

Figure 8: Riot Exposure in x Km of SD

Our choice of standard deviation implies that a riot in a town/village has spillovers not only in the adjoining towns and villages but also in the adjoining districts. Evidence of the

[14]Source: Press Information Bureau (2024), India Climate & Energy Dashboard.

same is already present in Iyer & Shrivastava (2018). Figure 8 shows the local polynomial smoothing plots of riot exposure under different SD in Km. As seen, $\text{Riot}'_{st-1} \to 1$ as $d_{st-1} \to 0$ and $\text{Riot}'_{st-1} \to 0$ as $d_{st-1} \to \infty$.

Table 2 tabulates the results of instrumental variable two-stage least square (IV 2SLS) regressions with controls for different values of the standard deviation, namely 70, 105, 140, 175 and 210 in Km. The coefficient estimates, $\hat{\beta}_1$ and $\hat{\beta}_3$, from specification (1) are shown in the second and third columns. The value of 70 Km as standard deviation provides the best fit as measured by the smallness of the root mean squared error (RMS), Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). Hence, we use this value of SD for all subsequent regressions.

SD in Km	Riot'_{st-1}	$\text{Riot}'_{st-1} \times \text{Latency}_{st-1}$	RMS	AIC	BIC
70	-2.183***	0.028***	0.446	192934.5	193034.2
	(0.454)	(0.010)			
105	-2.122***	0.027***	0.451	196270.5	196370.2
	(0.404)	(0.009)			
140	-2.159***	0.028***	0.453	198018	198117.7
	(0.402)	(0.009)			
175	-2.245***	0.029***	0.455	199276.2	199375.9
	(0.416)	(0.010)			
210	-2.359***	0.032***	0.457	200413.4	200513.1
	(0.439)	(0.011)			

Robust standard errors clustered at a shrid level in parentheses. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

The dependent variable is Log Avg NL_{st}. Coefficient estimates shown are for the explanatory variables Riot'_{st-1} and $\text{Riot}'_{st-1} \times \text{Latency}_{st-1}$ instrumented by Festival_{st-1} and $\text{Festival}_{st-1} \times \text{Lightning}_{st-1}$ respectively.

RMS: Root Mean Squared Error, AIC: Akaike's Information Criterion, BIC: Bayesian Information Criterion. Minimum AIC, BIC, and RMS indicate that the standard deviation of 70 Km gives the best fit and is used in all subsequent regressions.

Table 2: Regression results for different standard deviations for $\phi(.)$

Table 3 shows the Panel FE, and IV 2SLS regressions of nightlights on riot exposure, average latency and their interaction. Since we have panel data, we control for the shrid fixed effects and year fixed effects to absorb the unobserved shrid-specific and year-specific characteristics. We control for population, forest cover, literacy rate, religious composition, political affiliation, crime rate, and bank deposits, and use these variables alternatively in different models.

Columns (1) and (2) of Table 3 show the structural ordinary least squares (OLS) regressions without and with controls, respectively. The baseline results suggest a statistically insignificant correlation between riot exposure and nightlights in the following year. It further shows that the interaction effect is weakly correlated with a *decrease* in nightlights as average latency decreases (or, as Internet speed increases). However, since the correlations are low, the marginal effect of riots is statistically insignificant. This may be due to omitted confounding factors that affect nightlights, the likelihood of riots, and mobile Internet speed, thereby limiting causal interpretation.

Dep Var. Log Avg NL_{st}	(1)	(2)	(3)	(4)
$Riot'_{st-1}$	0.007	0.004	-2.531***	-2.183***
	(0.011)	(0.011)	(0.477)	(0.454)
			[-3.653, -1.783]	[-3.249, -1.471]
$Latency_{st-1}$	-0.000***	-0.000***	-0.003	-0.001
	(0.000)	(0.000)	(0.003)	(0.003)
			[-0.010, 0.001]	[-0.007, 0.003]
$Riot'_{st-1} \times Latency_{st-1}$	0.001***	0.001***	0.035***	0.028***
	(0.000)	(0.000)	(0.010)	(0.010)
			[0.019, 0.059]	[0.012, 0.051]
Year FE	Yes	Yes	Yes	Yes
Shrid FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Kleibergen-Paap F Stat			13.82	12.94
Observations	157674	157674	157674	157674

(1), (2) Panel FE, (3), (4) IV 2SLS Regressions. Robust standard errors clustered at a shrid level in parentheses. Weak-instrument-robust projection-based Anderson-Rubin 90% CI in square brackets. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 3: Panel FE and IV 2SLS Regressions

To overcome these problems and induce causal inference, we use instrumental variables to isolate the exogenous variation in riots and mobile Internet speed. We instrument riot exposure with $Festival_{st-1}$ that records 1 if any state-specific Hindu festival falls on a Friday and 0 otherwise. We instrument average latency with $Lightning_{st-1}$, which is the SD in lightning stroke density in shrid s in year $t-1$. We instrument the interaction between riot exposure and average latency accordingly. Table 4 displays the first-stage regressions. The relevant Sanderson-Windmeijer (SW) F-statistic (Sanderson & Windmeijer 2016) is above the cut-off norm of 10 for each of the first stages.

We highlight the relevant coefficient estimates of interest in red. The coefficient estimate of the instrument $Festival_{st}$ on riot exposure in column (1) is positive and highly significant, aligning with the hypothesis that the coincidence of Hindu festivals on Friday increases the likelihood of riots. The coefficient estimate of the instrument $Lightning_{st-1}$ on average latency is positive and highly significant in column (2), aligning with our prediction that lightning interferes with the mobile network, and hence, mobile Internet speed. The coefficient estimate of $Festival_{st-1} \times Lightning_{st-1}$ in column (3) exhibits a significant, negative correlation. Hence, we can conclude that all the instruments satisfy the first requirement of being relevant, i.e., they are correlated with the endogenous variable. The second requirement is that they should be exogenous. Since Hindu festival occurrences depend on the Hindu lunar calendar, it is completely exogenous. The instrument for average latency is also exogenous because lightning is dependent on purely atmospheric conditions. The possibility of potential violation of exclusion restrictions (such as lightning damaging power infrastructure) is accounted for (see Section 4). Any other endogeneity introduced by the state-specific choice of festivals or location-inherent climate is eliminated in the fixed effects regression. The reduced form regression is provided in Appendix A.4.

Dep Var.	Riot'_{st-1}	Latency_{st-1}	$\text{Riot}'_{st-1} \times \text{Latency}_{st-1}$
Festival_{st-1}	0.031***	1.198**	1.242***
	(0.002)	(0.470)	(0.212)
Lightning_{st-1}	-1.379***	512.717***	-2.686
	(0.209)	(68.622)	(24.511)
$\text{Festival}_{st-1} \times \text{Lightning}_{st-1}$	-1.091***	-985.726***	-297.805***
	(0.261)	(83.173)	(29.984)
Year FE	Yes	Yes	Yes
Shrid FE	Yes	Yes	Yes
SW F Stat	59.66	43.68	40.52
Observations	157644	157644	157644

Robust standard errors clustered at a shrid level in parentheses. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 4: First Stage Regressions

Returning to Table 3, columns (3) and (4) show the fixed effects 2SLS regressions using Festival_{st-1}, Lightning_{st-1} and $\text{Festival}_{st-1} \times \text{Lightning}_{st-1}$ as instruments for Riot'_{st-1}, Latency_{st-1} and $\text{Riot}'_{st-1} \times \text{Latency}_{st-1}$, respectively. We find the signs of the coefficient estimates of Riot'_{st-1} and $\text{Riot}'_{st-1} \times \text{Latency}_{st-1}$ to be robust and statistically significant across specifications (3) and (4). We use the Kleibergen-Paap (KP) F-statistic to check for weak instrument bias since the standard errors are not i.i.d. but clustered at the level of shrids (Kleibergen & Paap 2006). The KP F-statistic are 13.82 and 12.94 for the IV 2SLS models without and with controls, respectively. They are slightly above the cut-off norm of 10, suggesting the presence of a possible weak instrument bias. To overcome this problem, we follow the recommendations of Guriev et al. (2021) and report the weak-instrument-robust Anderson-Rubin 90% confidence intervals. The Anderson-Rubin $\chi^2(3)$ statistic for specifications in (3) and (4) is 133.61 and 125.05, respectively. Thus, we strongly reject the null hypothesis that all three endogenous variables are jointly zero. Overall, we can conclude that the IV results are robust despite the weak instrument issue.

The IV coefficients should be interpreted as Local Average Treatment Effects (LATE). The effect of Riot'_{st-1} is the average effect of the increase in the probability of riots that occur because of Hindu festivals falling on Fridays. The effect of Latency_{st-1} is the average effect of an increase in latency that occurs because of a marginal increase in lightning stroke density. We find that a 0.1 unit increase in riot exposure reduces nightlights in the next year by 19.61%. The interesting takeaway from the result is that a 1 ms *decrease* in average annual mobile network latency amplifies the marginal (negative) effect of riot exposure on nightlights by approximately 1.2 - 5.1 percentage points. To illustrate, if we move from right to left on the horizontal axis in Figure 9, in the direction of decreasing latency, the average marginal effect of riot exposure on nightlights decreases. In other words, a marginal decrease in latency (i.e., a marginal increase in mobile Internet speed) amplifies the negative economic effect of riot exposure on nightlight in the following year.

Figure 9: Average Marginal Effects

Our result aligns with the intuition of Manacorda & Tesei (2020), Ackermann et al. (2021) and Ahmed et al. (2025), who found that ICTs, such as mobile phone coverage and television signal strength, are instrumental to mass mobilisation, conflicts and communal violence, respectively. Generally, faster Internet increases economic activities and growth by reducing the cost of obtaining information and coordination (for example, DeStefano et al. (2023), Sanchis-Guarner et al. (2025)). However, in the event of a riot, places with better Internet infrastructure are hit more.

In support of the argument, we resort to the network model with imperfect information by Jackson & Yariv (2007), who argued that better connectedness induces enhanced coordination and enhanced information. Adapting their analogy to our context, agents having access to faster Internet (increased connectedness) are more likely to respond to changes in economic conditions (worsened communal dynamics in our context) due to enhanced information in the event of a riot. Further, agents become more responsive to changes in their connections' propensity to take action (e.g., deciding not to engage in inter-communal economic activities), which is attributed to enhanced coordination. Hence, faster Internet, through its enabling properties of enhanced coordination and information, worsens communal dynamics ex-post a communal riot, reducing the overall level of economic activities further.

5.1 Postestimation

We test for the joint significance of the exploratory variables (riot exposure, average latency, and their interaction) given in column (4) of Table 3, and strongly reject the null hypothesis, suggesting they are jointly different from zero. We further conducted a Hausman test, which suggested that IV is a better estimator than the baseline OLS.

In postestimation, we first perform a placebo test. Following standard practice, we *randomise* riot exposure and latency while keeping the central tendencies (mean and SD) of the *fake* variables consistent with the original ones. In principle, the randomisation should not affect nightlights. We generate our fake exploratory variables using a random-number generator function, and regress nightlights on them over the estimation sample.

Dep Var. Log Avg NL_{st}	(1)	(2)
$Riot'_{st-1}$	25.690	28.678
	(65.446)	(87.864)
$Latency_{st-1}$	0.003	-0.003
	(0.126)	(0.144)
$Riot'_{st-1} \times Latency_{st-1}$	-0.344	-0.383
	(0.599)	(0.791)
Year FE	Yes	Yes
Shrid FE	Yes	Yes
Controls	No	Yes
Kleibergen-Paap F Stat	0.10	0.07
Observations	157674	157674

Note the exploratory variables and their interaction are *randomised*.
Robust standard errors clustered at a shrid level in parentheses. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 5: Placebo Check

Table 5 shows the IV 2SLS regressions of nightlights on *randomised* riot exposure, latency, and their interaction. We instrument the fake exploratory variables using our (non-random) standard instruments from the main specification[15]. Confirming our prediction, we find statistically insignificant coefficient estimates.

Second, we run a sensitivity analysis. We check whether our instruments are correctly identifying the exogenous variations in communal riots and mobile Internet. In principle, the instruments should *fail* if we use different exploratory variables. Thus, we substitute Hindu-Muslim riots with all forms of protests that occurred in India between 2019 and 2023. Similarly, we substitute mobile network latency with *fixed* network latency, where a fixed network refers to a non-cellular connection type (e.g., WiFi, Ethernet).

[15]The standard instruments that we use for the study are: Festival, SD in lightning stroke density, and their interaction, respectively.

We extracted events classified as "Protests" by ACLED, derived their coordinates, and calculated protest exposure using the riot exposure methodology. For consistency, protest exposure is measured in 70 km of SD. Analogously, we use fixed network latency from Ookla. We then estimate an IV 2SLS regression of nightlights on protest exposure, fixed latency, and their interaction over the estimation sample, using the same set of instruments as in the main specification (1). Figure 10 plots the coefficient estimates.

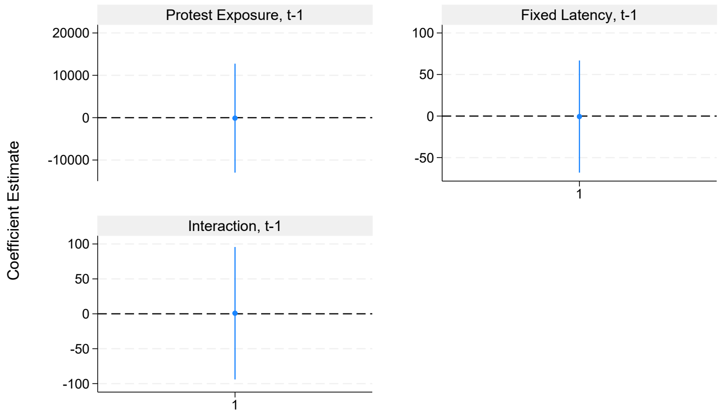

Figure 10: Sensitivity Analysis

We find no significant effects with protests and fixed Internet speed. This is because the standard instruments fail to identify exogenous variation in the exploratory variables, as they are *specifically* designed for Hindu-Muslim riots and mobile Internet speed. Failure to identify all the alternative variables suggests that our instruments are correctly identifying Hindu-Muslim Riots and mobile network latency following our predicted direction of correlation (refer to the First Stage Regressions in Table 4).

The lack of robust, significant estimates from both the placebo and sensitivity test suggests that our main model, given in specification (1), along with the relevant instruments, is correctly picking up causal effects rather than spurious correlation.

6 Mechanism

In this section, we discuss the mechanism through which mobile Internet speed amplifies the negative economic effects of riots. To build our argument, we resort to the network model with imperfect information by Jackson & Yariv (2007) and argue in line with Manacorda & Tesei (2020).

Adapting the network model to our context, we assume that agents maximise their payoff by taking a certain action (i.e., deciding how much to engage in inter-communal economic activities). Their action depends positively on the number of connections taking that same action through strategic complementarities and negatively on the cost of engaging in inter-communal economic activities. The latter depends on the current state of communal dynamics, as worse communal dynamics reduce the opportunity cost of engaging in inter-communal economic activities by promoting spiteful narratives.

Therefore, inter-communal economic activities will decrease if communal dynamics worsen (enhanced information). This mechanism is enhanced further through strategic complementarities. Agents iterate over their connections' best responses, knowing that if communal dynamics are worsened, their neighbours will be more likely to reduce inter-communal economic activities as well, amplifying the reduction further (enhanced coordination). Thus, if we attribute faster Internet to increased connectedness (Manacorda & Tesei 2020), then faster mobile Internet will unambiguously amplify the negative effects of Hindu-Muslim riots on economic activities through worsened communal dynamics.

It is important to note that the independent effect of faster mobile Internet on economic activities may well be positive. However, that does *not* detract from this mechanism.

Riots changed Hindu-Muslim dynamics in NE Delhi. For some, it's 'hateful beyond repair' now

Many riot victims, from both Hindu & Muslim communities, say they've stopped interacting with those from the other faith. Others say hatred was fuelled by rioters, rumours.

FATIMA KHAN and BISMEE TASKIN 24 February, 2021 12:01 pm IST

Most Popular

Representational image | Local people in Chand Bagh area in Northeast Delhi | Photo: Manisha Mondal | ThePrint

Source: The Print, dated 24/02/2021

Figure 11: Instance of Worsening Communcal Dynamics

In this section, we show that communal dynamics are worsened during Hindu-Muslim riots. The snapshot of a report covering the instance of such a riot in northeastern Delhi, eroding the state of Hindu-Muslim relations, is provided in Figure 11. What is more important is that faster mobile Internet, through its enabling features of enhanced coordination and enhanced information, *amplifies* such dynamics, leading to a fallout in overall economic activities[16].

We capture communal dynamics by exploiting the records of inter-communal interaction events. For this purpose, we use the Global Database on Events, Location and Tone

[16]For example, Fisman et al. (2020) argues that exposure to religion-based communal violence intensifies intergroup animosity, which, in turn, leads to lending decisions that are more sensitive to a borrower's religion.

(GDELT) Project (Leetaru & Schrodt 2013). The GDELT Project is a large, open-source dataset that relies on automated textual analysis of news sources in print, broadcast, and web formats from around the world. The project uses Textual Analysis by Augmented Replacement Instructions (TABARI) algorithm to classify events into CAMEO (Conflict and Mediation Event Observations) codes and assigns an average *tonality* of the event based on the verbs and sentiments detected in the first report of that event.

To give an example of this process, take an incident of communal violence on 02/07/2022 in Udaipur, Rajasthan, where locals assaulted two Muslims accused of killing a Hindu man (Source: ACLED). The event triggered broader communal tensions, and GDELT subsequently records a report by The Wire (14/07/2022), which states that on 14/07/2022, more than 300 Hindutva activists in Manesar, Haryana, organised a protest in response to the Udaipur killing, calling for the boycott of Muslims and advocating the use of weapons if needed. The report involves a threat towards the Muslim community; hence, GDELT assigned it an average tone of -2.22, approximately, following the TABARI algorithm. A snapshot of the report is given in Figure 12.


ANALYSIS COMMUNALISM

After 'Boycott Muslims' Call Comes VHP Threat of Killings, 'Will Repeat Gujarat if Situation Demands'

Astha Savyasachi
14/Jul/2022 · 5 min read

Days after Manesar 'boycott Muslims' event, local Hindutva leaders say Hindus need to arm themselves and prepare for war, and claim the Modi government is giving them moral support.

Devender Singh, VHP, Manesar addressing the Hindu panchayat in Manesar, Haryana. Photo: Astha

Source: The Wire, dated 14/07/2022

Figure 12: GDELT Average Tone Assignment: -2.22

We extract all geo-referenced, CAMEO-coded news events of Hindu-Muslim interactions that had a negative tone that occurred in India between 2019 and 2023. By quantifying tone, we proxy for communal dynamics (i.e., the ongoing state of Hindu-Muslim relations), such that increased negative tonality of events concerning Hindu-Muslim interactions implies worsening communal dynamics.

We finally regress the following specification,

$$\begin{aligned} \text{Log Tone}'_{st} = \beta_0 + \beta_1 \text{Riot}'_{st} + \beta_2 \text{Latency}_{st} \\ + \beta_3 (\text{Riot}'_{st} \times \text{Latency}_{st}) \\ + \text{X}_{1st} + \text{X}_{2dt} + \lambda_s + \delta_t + \epsilon_{st} \end{aligned} \tag{2}$$

where subscripts and notations have their usual meaning.

The dependent variable, Tone'_{st}, is tone exposure (calculated similarly to riot exposure). We applied a natural logarithmic transformation for simplified interpretation.

Note that we use tone exposure in 210 Km of SD in specification (2) because it provides the best fit. Accordingly, we use riot exposure in 210 Km of SD. We instrument latency with the *mean* lightning stroke density instead of SD in lightning stroke density because it has a higher explanatory power (a higher KP F-statistic). See the Appendix A.5 for details.

Dep Var.	Log Tone'_{st}	Log Tone'_{st}	Log Avg NL_{st}	Log Avg NL_{st}
Riot'_{st}	1.530***	1.492***		
	(0.250)	(0.257)		
Latency_{st}	0.007**	0.005*		
	(0.003)	(0.003)		
$\text{Riot}'_{st} \times \text{Latency}_{st}$	-0.026***	-0.024***		
	(0.006)	(0.006)		
Tone'_{st-1}			-2.190***	-2.082***
			(0.210)	(0.206)
Year FE	Yes	Yes	Yes	Yes
Shrid FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Kleibergen-Paap F Stat	20.19	19.56	687.68	684.83
Observations	135395	135395	157674	157674

Robust standard errors clustered at a shrid level in parentheses. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 6: Mechanism Analysis

The first two columns of Table 6 show the regression outputs of tone exposure on riot exposure, average mobile network latency, and their interaction. We use Festival_{st}, Lightning_{st}, and $\text{Festival}_{st} \times \text{Lightning}_{st}$ as instruments for Riot'_{st}, Latency_{st}, and $\text{Riot}'_{st} \times \text{Latency}_{st}$ respectively. The KP F-statistic is above the cut-off norm of 10, meaning weak-instrument bias is not an issue. The coefficient estimates are consistent across specifications in the first and second columns. The results imply that a marginal increase in riot exposure increases exposure to Hindu-Muslim events with a negative tone, worsening communal dynamics. Further, that higher mobile network latency dampens the marginal effect of riots on such dynamics by approximately 2.4 percentage points. Since higher mobile network latency means slower Internet, the result analogously implies that faster Internet *worsens* communal dynamics in the presence of riots by approximately 2.4 percentage points. Figure 13 plots the average marginal effects of riot exposure on tone exposure for different levels of average mobile network latency.

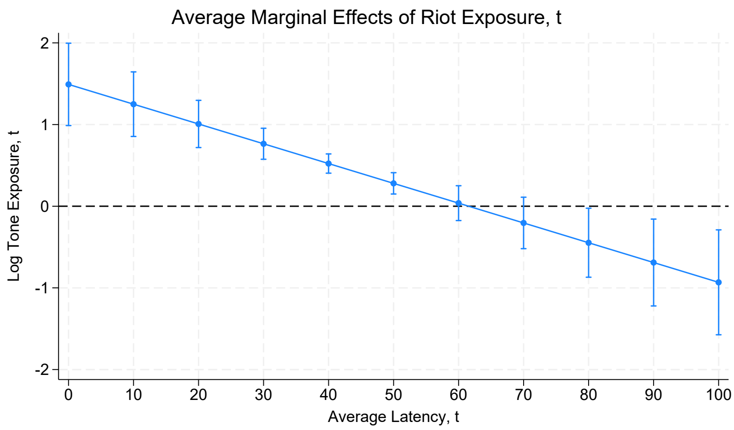

Figure 13: Average Marginal Effects

We finally regress nightlights on tone exposure in the previous year in the third and fourth columns to show the effect of communal dynamics on economic activities. Since most of the reports recorded in GDELT would cover riot events (e.g., the aftermath or damage inflicted), we instrument Tone'_{st-1} with Festival_{st}. The KP F-statistic is very high for the specifications, implying no possibility of weak instrument bias. The results imply that increased exposure to negatively-toned events (which reflects worsening communal dynamics) reduces nightlights (economic activity) in the following year, confirming our hypothesis.

Our exploration of the channel of mechanism illuminates how faster mobile Internet amplifies the negative economic effects of riots. Riots negatively affect communal dynamics, and faster mobile Internet, through enhanced coordination and enhanced information, amplifies such an impact. Since communal dynamics worsen, agents are discouraged from engaging in inter-communal economic activities as it becomes costlier (e.g., it might be difficult to trust an agent from the rival communal group after a riot), leading to an amplified decline in the overall level of economic activity.

7 Robustness Checks

We perform a series of robustness checks on our results to validate our argument that mobile Internet speed plays a catalytic role in amplifying the negative economic effects of riots. First, we employ alternative measures of Internet speed, namely, average download speed in megabytes per second (Mbps) and average upload speed in Mbps.

We study the following specifications,

$$\begin{aligned}\text{Log Avg NL}_{st} = \beta_0 + \beta_1 \text{Riot}'_{st-1} + \beta_2 \text{Download Speed}_{st-1} \\ +\beta_3(\text{Riot}'_{st-1} \times \text{Download Speed}_{st-1}) \\ +\text{X}_{1st} + \text{X}_{2dt} + \lambda_s + \delta_t + \epsilon_{st}\end{aligned} \tag{3}$$

$$\begin{aligned}\text{Log Avg NL}_{st} = \beta_0 + \beta_1 \text{Riot}'_{st-1} + \beta_2 \text{Upload Speed}_{st-1} \\ +\beta_3(\text{Riot}'_{st-1} \times \text{Upload Speed}_{st-1}) \\ +\text{X}_{1st} + \text{X}_{2dt} + \lambda_s + \delta_t + \epsilon_{st}\end{aligned} \tag{4}$$

where the subscripts and notations have their usual meaning.

Tables 7 and 8 present the regressions using alternative measures of Internet speed, namely, the average mobile Internet download speed and upload speed, respectively. It is important to note that, unlike average latency, higher download and upload speeds imply *faster* Internet. Hence, we should see the exact opposite coefficient estimates in terms of signs after running the regressions.

Dep Var. Log Avg NL_{st}	(1)	(2)
Riot'_{st-1}	1.670**	1.279
	(0.678)	(0.794)
	[0.607, 2.733]	[0.034, 3.769]
Download Speed_{st-1}	-0.018	-0.034*
	(0.018)	(0.021)
	[-0.074, 0.010]	[-0.098, -0.002]
Riot'_{st-1} × Download Speed_{st-1}	-0.114***	-0.097***
	(0.026)	(0.030)
	[-0.155, -0.073]	[-0.192, -0.049]
Year FE	Yes	Yes
Shrid FE	Yes	Yes
Controls	No	Yes
Kleibergen-Paap F Stat	6.41	5.71
Observations	157674	157674

Robust standard errors clustered at a shrid level in parentheses. Weak-instrument-robust projection-based Anderson-Rubin 90% CI in square brackets. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 7: Robustness Check using Average Download Speed

Columns (1) and (2) of Table 7 show signs of the coefficient estimates of Riot'_{st-1}, Download Speed_{st-1} and Riot'_{st-1} × Download Speed_{st-1} instrumented by Festival_{st-1}, Lightning_{st-1} and $\text{Festival}_{st-1} \times \text{Lightning}_{st-1}$, respectively. The signs are consistent with our main estimation (refer to Table 3) across specifications; however, the results are weak as the KP F-statistic is lower than the cut-off norm of 10.

To overcome weak instrument bias, we report the Anderson-Rubin 90% confidence intervals, and we derive the weak-instrument-robust bounds. As a further test, we checked for the joint significance of the exploratory variables, which suggests that the estimates are jointly different from 0. Thus, we conclude that higher download speed (analogously, faster mobile Internet) amplifies the negative (marginal) effects of riots. A similar argument applies to the interpretation of Table 8 for average mobile Internet upload speed.

Dep Var. Log Avg NL_{st}	(1)	(2)
$Riot'_{st-1}$	3.169***	3.168**
	(1.210)	(1.590)
	[1.272, 6.963]	[0.674, 10.648]
Upload $Speed_{st-1}$	-0.023	-0.047
	(0.061)	(0.067)
	[-0.407, 0.073]	[-0.468, 0.058]
$Riot'_{st-1} \times$ Upload $Speed_{st-1}$	-0.619***	-0.642***
	(0.151)	(0.195)
	[-1.329, -0.383]	[-1.864, -0.336]
Year FE	Yes	Yes
Shrid FE	Yes	Yes
Controls	No	Yes
Kleibergen-Paap F Stat	3.55	3.50
Observations	157644	157644

Robust standard errors clustered at a shrid level in parentheses. Weak-instrument-robust projection-based Anderson-Rubin 90% CI in square brackets. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 8: Robustness Check using Average Upload Speed

Next, we use a different raster masking category[17] of nightlights as our dependent variable. Throughout our analysis, we have used VIIRS median raster masked nightlights. In the following robustness check, we use VIIRS average-masked nightlights.

Table 9 shows the regressions using average raster-masked nightlights as the dependent variable. Columns (1) and (2) show structural OLS regressions without and with controls, respectively. Columns (3) and (4) show the IV 2SLS regressions without and with controls, respectively. The KP F-statistic is marginally higher than 10; therefore, we report the weak-instrument-robust Anderson-Rubin 90% confidence intervals.

The coefficient estimates are significant across all specifications, aligning with our main findings presented in Table 3. The estimates in column (4) imply that a 0.1 unit increase in riot exposure in the previous year decreases nightlights in the current year by approximately 19.54%, and that the effect is moderated in the presence of higher mobile network

[17]Raster masking is the process of filtering certain pixels from the raw raster data following a given rule, e.g., using mean, median, SD, etc.

Dep Var. Log Avg NL$_{st}$	(1)	(2)	(3)	(4)
Riot'_{st-1}	-0.025**	-0.030***	-2.505***	-2.151***
	(0.011)	(0.011)	(0.471)	(0.444)
			[-3.611, -1.767]	[-3.195, -1.454]
Latency_{st-1}	-0.000***	-0.000***	-0.005	-0.002
	(0.000)	(0.000)	(0.003)	(0.003)
			[-0.011, -0.000]	[-0.009, 0.002]
$\text{Riot}'_{st-1} \times \text{Latency}_{st-1}$	0.001***	0.001***	0.036***	0.029***
	(0.000)	(0.000)	(0.010)	(0.010)
			[0.021, 0.059]	[0.013, 0.052]
Year FE	Yes	Yes	Yes	Yes
Shrid FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Kleibergen-Paap F Stat			13.82	12.94
Observations	157674	157674	157674	157674

(1), (2) Panel FE, (3), (4) IV 2SLS Regressions. Robust standard errors clustered at a shrid level in parentheses. Weak-instrument-robust projection-based Anderson-Rubin 90% CI in square brackets. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 9: Robustness Check using Average Raster-Masked Nightlights

latency (i.e., slower Internet). In other words, the coefficient estimates from Table 9 imply that a 1ms decrease in average annual mobile network latency amplifies the negative effects of riots on economic activities by approximately 1.3 - 5.2 percentage points. The findings are consistent with our main argument presented in Table 3.

To summarise, we use two alternative specifications for robustness in this section: first, we use alternative measures for Internet speed, namely, average download and upload speeds; second, we use a different raster-masking category of nightlights. We got consistent estimates across all specifications. Overall, we can conclude that our findings are robust.

8 Conclusion

To the best of our knowledge, our paper is the first to exploit the *intensive* margin of riots in the presence of varying mobile Internet speeds, emphasising the critical role of ICT quality in exacerbating the pervasive effects of religious riots.

Our motivation behind studying the role of mobile Internet as a facilitator primarily stems from Petrova & Tapsoba (2025). Given India's historical significance of communal violence, information plays a crucial role in shaping the aftermath of riot episodes. With the recent evolution of digital connectivity, the relationship between communal violence and economic activities has become more intricate. Digital news and public opinion spread faster, and so does communal hatred.

Examples of such events where localised riots gained national significance through social media are abundant (see Appendix A.1). In this paper, we show that the communal hatred among identity groups that forms after a riot episode is *amplified* by better connectivity, driving inter-communal economic activity further down.

Using an instrumental variable approach, we identify exogenous variations in *both* riots and mobile Internet speed to find their individual and interactive causal impact on economic activities (proxied by night-time lights). We instrument Hindu-Muslim Riots with the Iyer & Shrivastava (2018) instrument, and mobile Internet speed with standard deviation (SD) in lightning stroke density. To the best of our knowledge, our paper is the first to exploit the correlation between lightning and cellular network quality through electromagnetic interference. Our paper is also the first to exploit mobile Internet speed data from a publicly available source. Using speed provides us with a significant advantage in calculating the intensive margin of riots in the presence of varying Internet speeds.

In summary, we find that mobile Internet speed amplifies the negative marginal effect of riots on night-time lights in the following year by approximately 1.2 - 5.1 percentage points. Our findings align with the intuition presented in Manacorda & Tesei (2020), Ackermann et al. (2021) and Ahmed et al. (2025).

We identify communal dynamics or narratives that follow a riot as the mechanism. We provide evidence that riots *erode* the prevailing state of Hindu-Muslim relations, and faster mobile Internet, through its enabling properties of enhanced information and enhanced coordination, *aggravates* the hateful narrative between communities beyond the afflicted region's spatial extent. Such a wider "broken atmosphere"[18] makes it costlier for agents to engage in inter-communal interactions even more. For example, members from rival communities might find it difficult to trust someone outside their group, reducing interactions and thus, economic activity (*viz.* the amplification). This emphasises the greater need for the government's role in positive messaging, given a better Internet.

While we present a robust argument backed by evidence, we acknowledge the limitations and outline their workarounds. First, our estimates might be fuzzy due to potential weak-instrument bias. We address the issue by using weak-instrument-robust inference. Second, we could not test our argument using alternative measures of economic activity due to the granularity of our analysis[19]. Satellite-based night-time lights were the only reliable proxy available for economic activities with enough (temporal and spatial) variation. Future research could test the robustness of our results using innovative data.

[18]Refer to The Print report (24/02/2021).

[19]Although public goods provision and/or employment data are available at the shrid level from the decennial Census, using them in our context is not informative because these variables lack sufficient variation.

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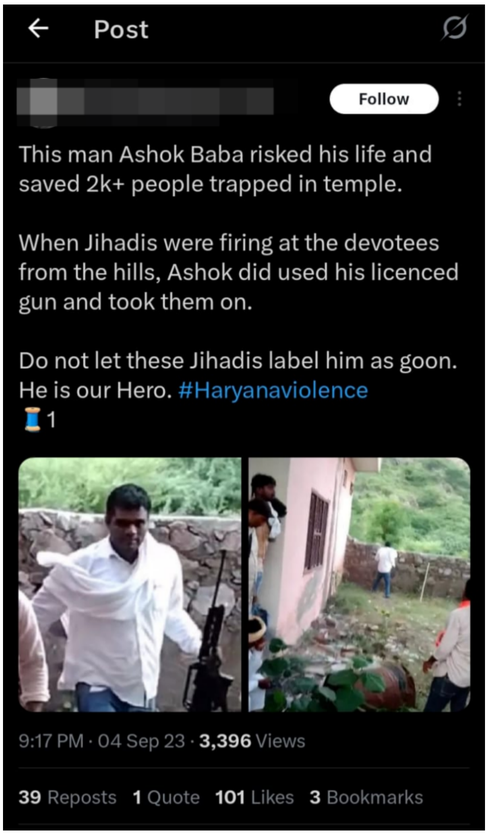
A Appendix

A.1 Tweets

This section shows an excerpt of the negative sentiments circulated in X (Twitter) following the Nuh, Haryana Violence (Source: Firstpost dated 03/08/2023), as discussed in the Introduction section.

It can be seen that communal narratives worsen following a riot. The anonymised tweet snapshots provided below show instances where people belonging to the Hindu identity groups exhibit strong hatred towards their Muslim counterparts. Referring to them as "Jihadis" (i.e., one who commits to *Jihad*, or the fight against the enemies of Islam) or "Terrorists", these tweets attempt to boycott Muslims, their businesses and products.

Aligning with our posited argument, with better mobile Internet connectivity, members of the Hindu community *beyond* Haryana's spatial extent should be exposed to these tweets. Thus, better connectivity should *amplify* the reductions in inter-communal interactions following a riot and hence, the overall level of economic activity.



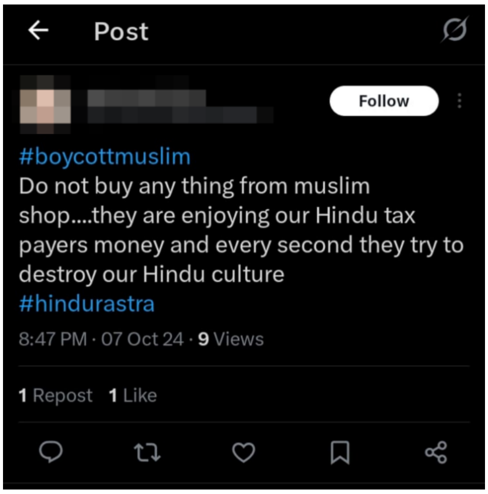
(a) Exhibit 1

(b) Exhibit 2

Figure A1: Tweet Examples

(c) Exhibit 3

(d) Exhibit 4



(e) Exhibit 5

Figure A1: Tweet Examples (contd.)

A.2 Choice of Hindu Festivals

State/UT	Festivals		
Andaman & Nicobar Islands	Pongal	Janmashtami	Vasant Panchami
Andhra Pradesh	Ramnavami	Durga Ashtami	Navami
Arunachal Pradesh	Shivratri	Holi	Durga Ashtami
Assam	Holi	Durga Ashtami	Navami
Bihar	Holi	Ramnavami	Navami
Chandigarh	Holi	Shivratri	Janmashtami
Chhattisgarh	Holi	Shivratri	Janmashtami
Dadra Nagar Haveli	Pongal	Holi	Ganesh Chaturthi
Daman Diu	Pongal	Holi	Ganesh Chaturthi
Goa	Shivratri	Vasant Panchami	Holi
Gujarat	Holi	Ramnavami	Navami
Haryana	Shivratri	Holi	Janmashtami
Himachal Pradesh	Holi	Shivratri	Ramnavami
Jammu & Kashmir	Shivratri	Ramnavami	Holi
Jharkhand	Shivratri	Holi	Durga Ashtami
Karnataka	Shivratri	Ganesh Chaturthi	Navami
Kerala	Shivratri	Janmashtami	Navami
Lakshadweep	Holi	Pongal	Shivratri
Madhya Pradesh	Holi	Ramnavami	Janmashtami
Maharashtra	Ramnavami	Ganesh Chaturthi	Navami
Manipur	Vasant Panchami	Navami	Shivratri
Meghalaya	Navami	Durga Ashtami	Vasant Panchami
Mizoram	Vasant Panchami	Holi	Navami
Nagaland	Shivratri	Navami	Durga Ashtami
NCT of Delhi	Holi	Shivratri	Navami
Odisha	Holi	Durga Ashtami	Navami
Puducherry	Pongal	Janmashtami	Vasant Panchami
Punjab	Holi	Ramnavami	Janmashtami
Rajasthan	Holi	Ramnavami	Janmashtami
Sikkim	Holi	Janmashtami	Navami
Tamil Nadu	Janmashtami	Ganesh Chaturthi	Navami
Tripura	Holi	Durga Ashtami	Navami
Uttar Pradesh	Ramnavami	Janmashtami	Navami
Uttarakhand	Shivratri	Holi	Navami
West Bengal	Holi	Durga Ashtami	Navami

Important Hindu festivals in each state and union territory (UT). Dussehra and Diwali are common (and apply) for all, and hence not included in the list to avoid redundancy. All States and UTs are made consistent with the latest 2011 Indian Census.

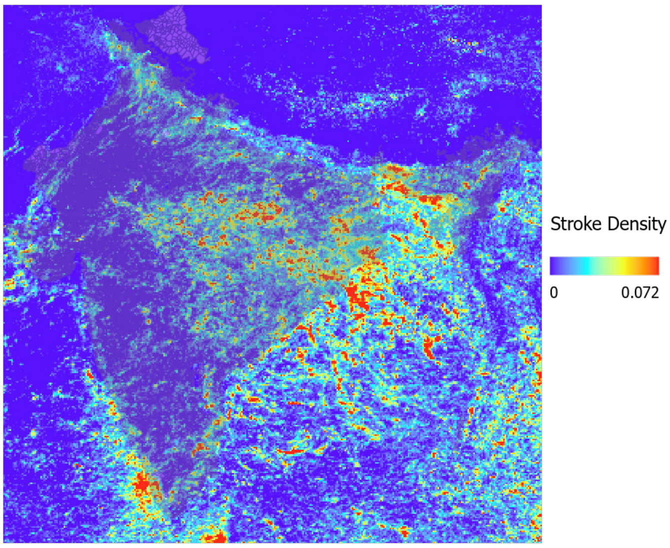
Table A1: List of Hindu festivals by state used in the instrument Festival

Iyer & Shrivastava (2018) listed five major Hindu festivals for the 16 largest Indian states in their analysis. The states they used were based on the 2001 Census. We use *all* states and union territories as of the (latest) 2011 Census. Hence, while keeping the list mostly consistent with Iyer & Shrivastava (2018), we add and update a few festivals to align with our broader coverage and more recent context. These additions and updates account for contemporary shifts in festival popularity, using information from the respective State/UT's Department of Cultural Affairs and Tourism.

A.3 Lightning Stroke Density

This section provides the raster images of lightning stroke density from The World Wide Lightning Location Network (WWLLN) Global Lightning Climatology (WGLC) and time series (Kaplan & Lau 2021, 2022, Kaplan 2025).

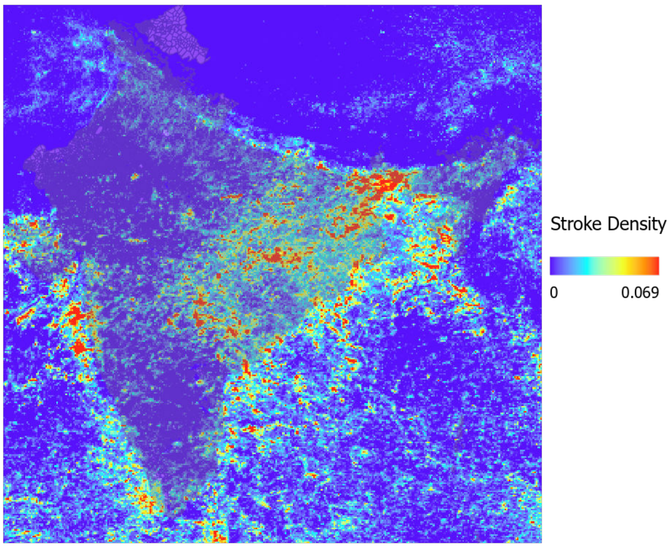
The dataset comprises NetCDF multidimensional files of lightning stroke density at 0.5-degree 5-arc-minute resolution at a monthly time dimension. The raster images provided below show the lightning stroke density (in $km^{-2}d^{-1}$)[20] for India, aggregated by standard deviation (SD) and clustered over years.



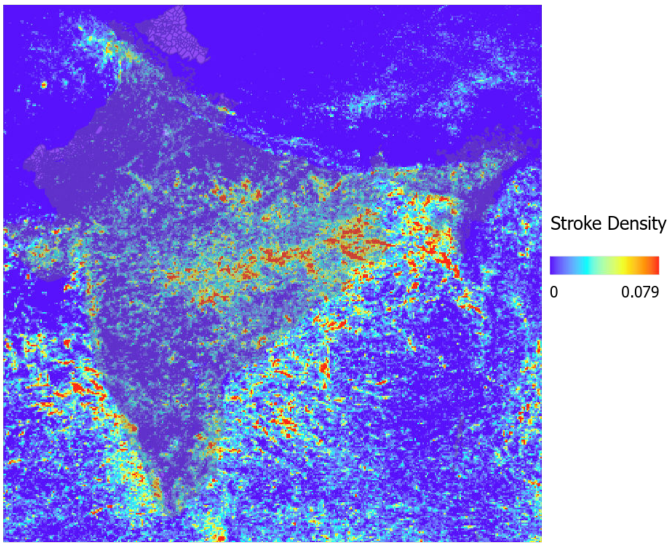
(a) 2019

Figure A2: SD in Lightning Stroke Density clustered over years

[20]Lightning stroke density is defined as the number of strokes per square Km of surface area per day detected at a particular location during a time period.

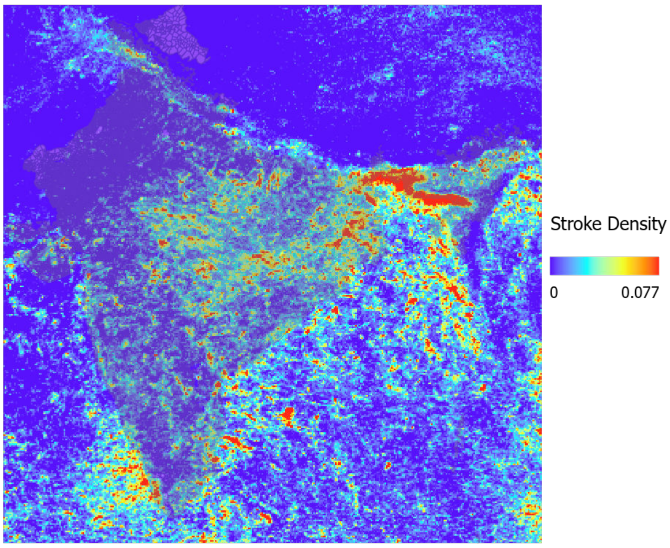


(b) 2020

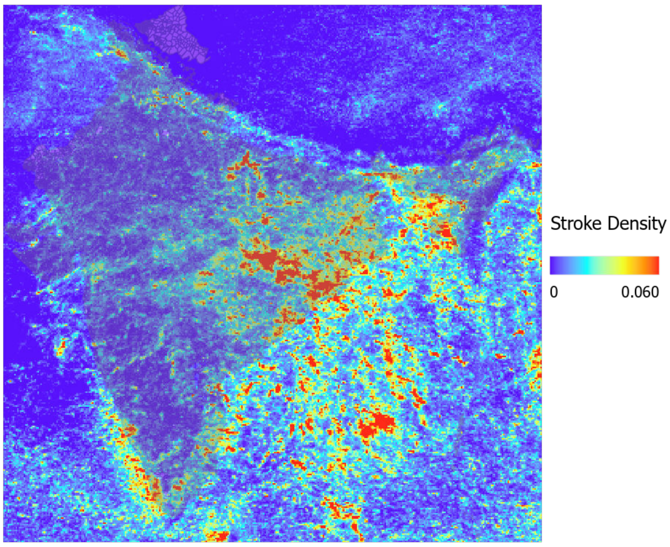


(c) 2021

Figure A2: SD in Lightning Stroke Density aggregated over years (contd.)



(d) 2022



(e) 2023

Figure A2: SD in Lightning Stroke Density aggregated over years (contd.)

A.4 Regression of Nightlights on Instruments

Dep Var. Log Avg NL_{st}	(1)	(2)
Festival_{st-1}	-0.036***	-0.033***
	(0.006)	(0.006)
Lightning_{st-1}	2.127**	2.469***
	(0.844)	(0.841)
$\text{Festival}_{st-1} \times \text{Lightning}_{st-1}$	-4.992***	-4.962***
	(1.206)	(1.208)
Year FE	Yes	Yes
Shrid FE	Yes	Yes
Controls	No	Yes
Observations	157674	157674

Robust standard errors clustered at a shrid level in parentheses. p-values *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table A2: Reduced Form Regression

A.5 Choosing the Mechanism Model

We regress Log Tone'_{st} on Riot'_{st-1}, Latency_{st-1} and $\text{Riot}'_{st-1} \times \text{Latency}_{st-1}$. The respective instruments for the exploratory variables are Festival_{st-1}, Lightning_{st-1} and $\text{Festival}_{st-1} \times \text{Lightning}_{st-1}$ respectively.

In Table A3, Lightning_{st-1} is the mean lightning stroke density, and in Table A4, it is the SD in lightning stroke density.

SD in Km	KP F-statistic	RMS	AIC	BIC
70	9.23	0.932	365290.7	365388.9
105	13.66	0.593	242972	243070.1
140	16.62	0.441	162604.9	162703.1
175	18.44	0.353	102453.2	102551.3
210	19.56	0.296	54195.15	54293.31

Lightning_{st-1} is the *mean* lightning stroke density.

Table A3: Regression results for different standard deviations for Tone Exposure

SD in Km	KP F-statistic	RMS	AIC	BIC
70	5.25	0.804	325116.7	325214.9
105	7.67	0.528	211153.1	211251.2
140	9.24	0.395	132424.2	132522.4
175	10.21	0.316	72223.76	72321.92
210	10.81	0.264	23404.53	23502.69

Lightning_{st-1} is the *SD* in lightning stroke density.

Table A4: Regression results for different standard deviations for Tone Exposure

Tables A3 and A4 show that tone exposure in 210 Km of SD provides the best fit according to minimum AIC, BIC, and RMS. For consistency, we use riot exposure in 210 Km of SD.

For the choice of the instrument Lightning_{st-1}, we compare the KP F-statistic of both tables. We see that Table A3 yields consistently higher KP F-statistics compared to Table A4; however, the best fit measure reflects the opposite. We perform a standard rule-of-thumb logic in this context, and prioritise instrument identification (KP F-statistic) over best fit (minimum AIC, BIC, and RMS). Therefore, we use mean lightning stroke density as our instrument for average mobile Internet latency in our Mechanism Analysis in Section 6.