Rural Internet and Religious Identities *

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Abstract

Social identities determine who we consider as 'us' and who as 'them'. Diverse nation states are confronted with an ongoing challenge to unite communities behind a shared national identity trumping local, ethnic, or religious identities. Information technologies spread narratives that can influence the weights of these different identities. This paper examines the consequences of the arrival of fast internet on Hindu-Muslim divisions in rural Indian communities. It leverages the staggered roll-out of the largest rural government broadband program in the world in a spatial Regression Discontinuity Design (RDD). It introduces precise data on 175,157 broadband connections in villages and combines it with data on violent acts by extreme individuals, distortions in welfare provisions by powerful local village heads, and voting behavior at the polling station level. The estimates document a surge in discrimination of the religious out-group by village heads at the household level considering novel data on over 5 million registered households in Jharkhand. Muslims receive 12.5% fewer work days under a non-Muslim village head and gain 29.2% under a Muslim village head relative to Muslims in neighboring villages with the respective village head but without fast internet. Further results highlight a rise in violent acts and divisions in voting behavior between Muslim and non-Muslim villages.

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1 Introduction

Uniting people from different cultures, religions, languages, and ethnicities behind a broader sense of "we" is a fundamental principle of nation-states (Anderson, 1983; Putnam, 2007; Bazzi *et al.*, 2019). Who is encompassed in the "imagined political community" that represents a nation is an ongoing and re-emerging struggle in many countries such as China (Uighurs), Turkey (Kurds), United Kingdom (Scots), India (Muslims) or Myanmar (Rohingyar). Information technologies have a central function in spreading a common narrative to create this imagined community where citizens, even without personal interactions, feel a sense of connection. The internet creates shared experiences and connects people as if in a national, or even *global village* (McLuhan and Powers, 1989; Depetris-Chauvin *et al.*, 2020). At the same time, it provides a platform for emotional appealing populists, echo chambers, and misinformation (e.g., Campante *et al.*, 2018; Vosoughi *et al.*, 2018; Levy, 2021). Overall, the *aggregate* impact of internet access on unity in diverse communities remains unclear.

Rural areas have only sparsely received information on politics and social debates via traditional media sources (Correa *et al.*, 1997). National controversies have thus hardly trickled down. Not anymore. Rural areas in developing countries, home to 3.1 billion of the world population, experience a dramatic change in the information environment as fast internet connects them to the nation (ITU, 2020; World Bank, 2021). The leap-frog technology has suddenly exposed a considerable share of inexperienced, mostly uneducated media users to highly sophisticated content creators. A very different experience to most study subjects who are: well-educated, urban, media-experienced individuals and who learned to navigate the increasingly sophisticated online world early.[1] The consequences of connecting the periphery to the core remain to be understood.

This paper focuses on India, which provides a unique setting to causally assess the impact of fast internet on its over 900 million people in rural areas (World Bank, 2021). The largest country in the world is home to a sizeable Muslim minority, making up 14.2% (170 million) of the population according to the 2011 census. Their peaceful coexistence has once more come under threat as the Hindu nationalist Bharatiya Janata Party (BJP) around Prime Minister Narendra Modi rose to power in 2014 (New York Times, 2019). Hate messages and misinformation have spread quickly via social media leading to lynch mobs targeting Muslims, which have forced social media giants like WhatsApp to restrict the viral potential of Indian messages (Time, 2019).

[1] The difference does not stop at the internet user, the safeguards within the internet are different as well. According to internal documents, Facebook invests 87% of its time resources on fact-checking content in the US, where only 10% of its user base resides (New York Times, 2021). In addition, Facebook has only recently improved its automatic hate speech detection algorithms in Hindi and Bengali - two of the main languages spoken in India (its largest user market).

Rural India is increasingly exposed to these messages as internet penetration more than doubled within four years from 12% in 2015 to 30% in 2019 (TRAI, 2018, 2019; World Bank, 2021). The sudden exposure of diverse rural areas to the national online discourse surrounding India's identity creates an interesting setting.

In this paper, I study the impact of fast internet on religious divisions in rural communities in India. Specifically, I examine the consequences of broadband connections established in 2017 on local conflict (2017-2022, village council level), the allocation of scarce welfare benefits to Muslims by local officials (2019-2022, individual level in Jharkhand), and voting behavior along religious lines (2019 national election, polling station level in Jharkhand). The study focuses on rural areas at the periphery, which get connected to the core. I introduce new data on the location and roll-out of 175,157 broadband connections as part of the largest rural government broadband initiative (called BharatNet) (Zimmermann, 2014). To identify the causal impact of fast internet, I exploit spatial discontinuities in internet availability that arose in 2017 due to the staggered roll-out of BharatNet. The study of several dimensions elicits the influence on different groups in the population: only extreme individuals resort to conflict, while favoritism by local officials in the allocation of welfare benefits is more common, and lastly, changes in voting behavior paint a picture of the general population. In sum, I aim to further our understanding of the Internet's impact on divisions in rural communities through the lens of different dimensions, which I discuss in more detail below.

To identify the causal impact of the internet, I introduce a new identification strategy based on spatial discontinuities in internet availability. The distribution of internet access is highly endogenous since wealthy, densely populated, and urban places are more profitable and thus connected first. I isolate exogenous variation in internet availability by exploiting discontinuities created by BharatNet. BharatNet is a flagship initiative of the Indian government that aims to connect every Gram Panchayat (GP or village council) to the fiber optic network.[2] It is designed to enable all households in a village with internet speeds of 2-20Mbps. Due to capacity constraints, the roll-out was split into two phases. 100,000 GPs were allocated to phase I (connected between 2014-2017), 150,000 to phase II (ongoing as of July 2023). The allocation took place at the block level (third highest administrative level) and was determined by minimizing the length of additional optical fiber that needed to be installed in phase I (Satyanarayana *et al.*, 2015).[3] I obtained data on the exact location where a GP gets connected to the fiber optic network, as well as in which phase. To isolate exogenous variation in internet availability, I exploit

[2] A GP consists of 2.5 villages on average and is the lowest level of government.

[3] The roll-out of BharatNet is combined with the set-up of public Wifi hotspots which create extremely local discontinuities in internet access.

discontinuities in fast internet between neighboring villages on two sides of the phase boundary in a spatial regression discontinuity design (RDD). Further specifications combine these spatial jumps in internet availability with individual-level data differentiating between Muslims and non-Muslims. In particular, they leverage discontinuities in the differential treatment of Muslims in villages on both sides of the boundary in a difference-in-discontinuity framework. In a final step, I compare discontinuities in the differential treatment of Muslims in villages with a non-Muslim GP president to villages with a Muslim GP president.[4] Following Gelman and Imbens (2019), all specifications estimate a local linear RD polynomial based on a sample of villages, polling stations or individuals located within a small distance of 10km from a boundary as in Dell and Olken (2020). The results are robust to alternative bandwidths, alternative weights, and a quadratic RD polynomial. I check the plausibility of the identifying assumptions by testing for discontinuities in a large number of variables, and outcomes pre-treatment and at a placebo boundary. In sum, combining this novel source of internet data and the unique variation in local internet access creates new avenues for the identification of the consequence of fast internet in a large developing country.

I discuss the impact of fast internet on several dimensions of divisions now one by one in more detail. I start by examining the causal influence of fast internet availability on violent conflict. The effectiveness of divisive messages transmitted via radio or movies to create violence against the targeted community has been documented in several contexts (e.g., see Wang, 2021; Ang, 2023; Esposito *et al.*, 2023 for the U.S., DellaVigna *et al.*, 2014 for Croatia, Adena *et al.*, 2015 for Nazi Germany and Yanagizawa-Drott, 2014 for Rwanda). Others have shown that uniting messages and shared experiences can lower tensions (e.g., see Blouin and Mukand, 2019 in Rwanda, Armand *et al.*, 2023 in the US and Depetris-Chauvin *et al.*, 2020 in Africa). The impact of messages transmitted online are less understood but points in a similar direction (e.g., an increase in hate crimes is found in response to Trump's tweets by Müller *et al.*, 2022 and, Russian social media by Bursztyn *et al.*, 2019). In contrast to the literature on traditional media, they attribute the impact to two channels: i) easier coordination and ii) a change in the information set. Altogether, these studies highlight the power of narratives spread via the media but also point to the importance of content. Naturally, this raises questions about the aggregate impact on rural communities.

The endogenous selection of content by the users makes the aggregate impact on uneducated, media-inexperienced villagers unclear. In contrast to the literature, this paper studies the impact on the periphery as it get closer to the core: do villagers unite behind being Indian as the

[4]The GP president is the elected head of the village council.

perceived distance to the rest of the nation shrinks or do they divide? Inflammatory religious content may be consumed by individuals in villages. However, they share a local community with members from different religions since they were born. Conditions that can lower stereotypes and foster mutual understanding (as highlighted in a different context by Bazzi *et al.*, 2019). To further our understanding of the overall impact on rural communities, I assess the Internet's impact on assaults, as well as riots and mobs by actors related to one of the two main parties: the Hindu nationalist BJP and the secular Indian National Congress (INC). I obtain data on 38,078 assaults over the 2008-2022 period from GDELT, and data on riots and mobs by supporters of the Hindu nationalist BJP and the secular INC from ACLED. I obtain information on 1,052 riots and 914 mobs by BJP supporters, and 382 riots and 281 mobs by INC supporters over the 2016-2022 period. I focus on low-intensity conflict events in order to capture escalating disagreements in local communities that often respond to a trigger (such as heightened divisions online). The findings based on the spatial RDD show a significant increase in the level and change of assaults and an increase in riots and mobs by BJP supporters but not by INC supporters both in the full sample and in the state of Jharkhand (which will be the focus of further results).[5] As in most moderate conflict settings, only a small set of villages is affected. The findings are therefore driven by a small number of extreme individuals who are willing to resort to violence and inflict catastrophic damage. Nevertheless, this can have broader consequences as local conflict can undermine trust and create fear in a larger set of people.

These findings serve as a motivation to assess the widespread consequences of rural internet on religious divisions. In particular, I estimate the causal impact of fast internet on the differential allocation of scarce welfare benefits to Muslims by GP presidents (*Sarpanch*).[6] A large literature shows widespread discrimination by individuals that have the power to punish or allocate resources in the name of the public (e.g., Hodler and Raschky, 2014; Burgess *et al.*, 2015; Goncalves and Mello, 2021). It remains unclear to what extent the internet influences the allocation decisions of local officials, but Grosjean *et al.* (2023) documents the amplification of discrimination of law enforcement officers through narratives spread via Trump campaign rallies. I study the allocation of paid work days within the largest rural welfare program in the world (Zimmermann, 2014), the National Rural Employment Guarantee Act (NREGA). NREGA is designed as a social protection mechanism for vulnerable rural households, which have the right

[5] Weidmann (2016) has argued that media availability is related to measurement error in conflict data. Although I cannot rule out the influence of media bias, the differential impact on BJP mobs and riots with the absence of any increase in INC mobs and riots makes it unlikely that the effects can fully be explained by media bias. Moreover, I do not find any increase in peaceful protests (results are available upon request).

[6] A GP president is the elected head of a village council (GP).

to a minimum of 100 days of work for the public at a fixed rate of pay, whereby the distribution of the work days falls within the responsibility of the GP. The program has suffered from supply constraints such that the demand for work cannot be matched, opening the door to discrimination and favoritism by the GP president (Dutta *et al.*, 2012).[7] As the potential consequences are serious and affect a large share of the population, the impact of the internet on more moderate expressions of group divisions is important.

The assessment of NREGA has several advantages. It allows a focus on Muslims, the largest religious minority, which has often been the target of hate. It is a program that large shares of the rural population rely on. Measurement error and spillovers are not likely. Finally, it can contribute to the isolation of an information channel.[8] I estimate a difference-in-discontinuity design to analyze whether the internet changes the treatment of Muslims relative to non-Muslims by GP presidents within NREGA. The outcome is based on the allocation of over 300 million NREGA work days between Muslims and non-Muslims. The information originates from over 5 million websites, which I webscraped and that document the universe of registered households (since 2006) and work days (2019-2022) within NREGA in Jharkhand.[9] I focus on a single state as the collection of the data is time-consuming and depends linearly on the number of registered households.[10] I link the work days to the respective GP president responsible for the allocation. To assess differential treatment by religion, I classify individuals and GP presidents as Muslim or non-Muslim based on their names. This allows me to obtain a unique perspective on the treatment of a minority by public officials at the individual level. The discontinuity in internet availability results in a sudden decrease in the number of new registrations of Muslims in NREGA and a significant decrease in the number of work days by 10.9% in villages with registered Muslims. Significantly fewer work days are allocated to Muslims in areas with internet compared to neighboring areas without internet, but only in villages with a non-Muslim president. The sign reverses in areas with a Muslim president, where significantly more work days are allocated to Muslims. Together, this is in line with the GP increasingly allocating scarce public goods based on religious group identities.

[7] Jeong *et al.* (2023) have documented personal favoritism of village heads in NREGA in the context of Uttarakhand.

[8] The literature found it difficult to isolate an information channel as two-way communication also enables better coordination of assaults, protests, or mobs. The preferred solution was therefore to assess only isolated information treatments online, which disguise the overall impact.

[9] In Jharkhand, a large share of households are registered within NREGA. In the median village, the cumulative sum of households that signed up between 2006 and 2022 is 1.16 times the number of households in the 2011 census.

[10] The analysis focuses on Jharkhand due to the following characteristics: it has a sizeable Muslim minority of 14.5%, similar to the Indian average, and it has a large phase boundary distributed across several areas in the state.

Finally, I turn to political divisions created by the internet differentiating between polling stations in Muslim and non-Muslim villages. Identity-based voting can have detrimental consequences (e.g., Banerjee and Pande, 2007). The results discussed so far have highlighted an increase in discrimination and conflict brought about by the internet. Increasing discrimination and violence can result in increases in group-based voting as promised benefits are allocated along group lines (e.g., Carlson, 2015; Hadzic *et al.*, 2020). At the same time, the content consumed online can have a direct influence on voting behavior (see Zhuravskaya *et al.*, 2020 for a review). In the U.S. and Europe, studies show that populists have benefited especially from the internet and voters were exposed to a high degree of online misinformation (Mocanu *et al.*, 2015; Campante *et al.*, 2018; Grinberg *et al.*, 2019; Guriev *et al.*, 2021). Assessments of the spread of misinformation find that especially old (unexperienced) users re-share political misinformation (Guess *et al.*, 2019). This makes an impact on political divisions involving many voters new to the internet seem likely.

I test the political implications of access to fast internet in the context of Jharkhand. Therefore, I assemble the 2019 national election results for 29,464 polling stations in Jharkhand. Although Muslims are a sizeable minority in India, there is no Muslim party that pools their votes behind them. Rather secular parties, most importantly the INC, are the main opponents to the rising movement of Hindu nationalist parties led by the BJP. The evolution of political polarization in India is fundamentally shaped by the dichotomy between secularism and Hindu nationalism (Sahoo, 2020). Therefore, I assess the political consequences along these lines in addition to assessing the changes in the differential support of Muslim candidates by Muslim villages. Overall, villages with internet shift towards Hindu nationalist parties and away from secular parties in non-Muslim villages. The shift is absent in villages with a high Muslim share, where they increasingly favor secular parties and Muslim candidates. These patterns are in line with a higher resilience of Muslim villages against Hindu nationalist messages, which can be explained by more common interactions between members of different groups.

So far, I have attributed the exacerbation of divisions to content exposure online. Alternatively, conflicts could arise if the potential economic impact of the internet favors Muslims. Mitra and Ray (2014) have documented an increase in violence against Muslims after they fared better economically relative to other groups. If Muslims benefited disproportionately from internet access in villages with a non-Muslim president and benefited less in villages with a Muslim president, then the patterns shown could be attributed to an economic mechanism. I test the plausibility of this alternative mechanism based on DHS data (2019-2021) covering over 2 million individuals (and over 280,000 Muslims). The difference-in-discontinuity estimates do not show any differential increase in wealth for Muslims and no significant difference in the economic status of Muslims in GPs with and without a Muslim president. This alleviates concerns that the increase in divisions is driven by the internet's economic impact. In contrast, poor Muslims seem to fare worse a pattern consistent with an increase in the discrimination of Muslims in general (and within NREGA) due to the exposure to new information online.

This paper makes several contributions to the literature. First, it documents the divisive influence of fast internet on rural areas in a large developing country. The internet has transformed developing economies, creating new jobs (Hjort and Poulsen, 2019) and increasing consumption (Bahia *et al.*, 2020).[11] These economic effects have been accompanied by changes in political dynamics. While mobile internet has been shown to coordinate protests (Acemoglu *et al.*, 2018; Manacorda and Tesei, 2020), decrease government approval (Guriev *et al.*, 2021) and crowed out offline interactions of politicians (Bessone *et al.*, 2022), I highlight the implications for the unity of rural communities. As isolated, inexperienced villagers get connected to the nation's core, heated national debates spill over. The consequences for extreme individuals, local representatives, and the general population have not been understood.

Second, I further our understanding of group divisions. A large literature has investigated shifting identities and the determinants of tensions between groups in diverse nation-states (e.g., Laitin, 1998; Bazzi and Gudgeon, 2021; Gehring, 2022). Exposure to inflammatory messages can foster hate crimes (Müller *et al.*, 2022), but shared experiences and personal interactions can form a common identity and build trust among groups (Bazzi *et al.*, 2019; Depetris-Chauvin *et al.*, 2020; Lowe, 2021). Even tough personal interactions and personal knowledge are likely high in rural communities. I show that on aggregate fast internet availability does not bind the community closer together but fuels divisions.

In the following, I give an overview of recent changes in the political discourse in India regarding Muslims offline and online in section (2). I present the data and outcomes in section (3), followed by the empirical strategy in section (4). The results are described in section (5), an alternative mechanism is discussed in section (6), while section (7) concludes.

2 Background

Many nation-states struggle to define their relation to religion (e.g., Turkey, Iran, or Afghanistan). India, a state with a large minority of 170 million Muslims, is a prime example. The rise of the

[11] A related literature on mobile phones has similarly documented widespread gains (for a review see Aker and Mbiti (2010).

BJP in recent years has ignited discussions about the secular fabric of India. A party deeply rooted in Hindu nationalist ideology, the BJP has sought to redefine India's identity along religious lines.[12] As a consequence, the notion that Indians are defined based on their place of birth is more frequently replaced with a definition based on Hindu culture (Sahoo, 2020). Secularism, a principle enshrined in the Indian constitution, guarantees equal rights and freedom to all religions, thereby separating religion from the state's matters. Following a period dominated by the secular Indian National Congress (INC) governing India for 54 years since independence, the rise of the BJP has challenged this principle, leading to tensions within India's diverse population.

These developments have been linked to increases in religious violence and hate crimes (New York Times, 2019). The rise of the BJP has made divisive and inflammatory language common among high-ranking government officials. A case in point are debates around killings (of mostly Muslim herders) by Hindu mobs in the name of cow protection.[13] The chief minister of Chhattisgarh (Raman Singh, BJP) proclaimed in 2017, for example: "We will hang those who kill cows" and a BJP lawmaker in Uttar Pradesh (Vikram Saini) stated a month earlier: "I had promised that I will break the hands and legs of those who do not consider cows their mother and kill them" (Human Rights Watch, 2019, p. 5). The Wire (2019) analyzed 34 campaign speeches of Uttar Pradesh's chief minister (Yogi Adityanath, BJP) and found over 100 instances of hate speech and religious polarization.

These inflammatory messages have reached a rapidly increasing rural audience. Previously isolated villages have rapidly adopted digital technologies. Rural India has gained 53 million new internet users every year since 2017, totaling 399 million in 2022 (Kantar, 2021, 2023). Internet consumption skyrocketed to 17 GB per day per user in 2021 according to the India Mobile Broadband Index, as an increasing network was combined with the worldwide fifth lowest prices per Gigabyte (0.17$ in 2022 according to cable.co.uk) (Nokia, 2022). The new users are uneducated, unexperienced and not informed about politics (CSDS, 2022).[14] They are confronted with a political discourse that is dominated by the BJP. Narendra Modi has been labeled India's first "social media Prime minister" in 2014 (Financial Times, 2014) and won the first "WhatsApp election" in 2019 (Financial Times, 2019). His party outspent its main rival the INC by a

[12] The party's leader, Narendra Modi, faced international criticism for his role in the 2002 Gujarat riots during his tenure as the state's Chief Minister. In 2005, he was denied a diplomatic visa to the U.S. on the grounds of "severe violations of religious freedom." This incident spotlights the BJP's stance towards religious minorities.

[13] The cow has a sacred status under Hinduism. A Human Rights Watch Report documents 44 killings in the name of cow protection between 2015 and 2018.

[14] Via their phone, they consume religious, political, and ethnic information in specialized chatgroups that spread national cleavages throughout the country (CSDS, 2022). Another issue has been violent acts based on misinformation spreading online. The BBC analyzed English-language media reports and identified a rapid increase in fatal mob attacks triggered by rumors originating from WhatsApp. While they found 0 in 2015 and 2016 the number increased to 31 in 2017 and 2018.

factor of 15 on social media in 2019 (Hindustan Times, 2019) and relies on a network of millions of volunteers who spread the BJPs messages in customized WhatsApp groups throughout the country (Time, 2019). This has likely impacted the online discourse. Leaked internal documents from Facebook document widespread misinformation including hate messages against Muslims and an internal memo from Facebook employees identifies ”misinfo that are connected to real world harm, specifically politics and religious tensions” as the main request from users in India (New York Times, 2021). In sum, the inexperienced villagers are confronted with an information environment that combines state-of-the-art online communication strategies with lax data protection rules during a time when religious tensions are high on a platform with limited tools to delete hate messages.

3 Data and Outcomes

Rural areas in the developing world have only very recently gained access to fast internet. I leverage the following data sources to capture emerging divisions in rural communities.

Internet Data: The Indian government proposed in 2011 to integrate its lowest level of government (Gram Panchayats) into its fiber optic infrastructure. This initiative now known under the name BharatNet, is proclaimed to be the largest rural government broadband connectivity program in the world. It aims to connect all 250,000 GPs in India to fiber optic internet.

Bharatnet is a central pillow of the National Telecom Policy of 2012 that aims to provide all households the opportunity of a broadband connection between 2 Mbps and 20 Mbps on demand (Satyanarayana *et al.*, 2015). Telecommunication providers and other companies can use the fiber optic infrastructure at highly subsidized rates. Major telecommunication providers have made use of the broadband infrastructure and more than 100,000 Wifi hotspots have been installed (Economic Times, 2017; Ministry of Communications, 2021).

The connection of GPs to broadband internet is implemented in a staggered manner due to capacity constraints. In phase I, which was completed in December 2017, 100,000 GPs were connected (Krishnan, 2018). The connection of the remaining 150,000 GPs is still ongoing as of July 2023.

I obtained lists of GPs by phase from Bharat Broadband Network Limited including the exact location where the GP is connected to the broadband internet. The raw data includes 208,512 connections for GPs located in 37 states and union territories.[15] Information is sparse for Karnataka, Tamil Nadu and Goa.

I cross-check the locations of the GPs by automated searches for a given GP on onefivenine – a village repository that provides local information about villages including their location. I update the location information if the location is unique in the repository and the sum of the absolute difference between the coordinates is larger than 0.05 (5.5km at the equator). In a second step, I manually check all GPs that were located outside of their district or were more than 1 degree (about 111 km at the equator) away from the mean location of the other villages in the block. The final dataset consists of 175,157 GPs - 94,023 in phase I and 81,134 in phase II - as illustrated in Figure (1).

Internet Usage: I collect data on internet usage, in order to confirm that the rural broadband program led to an increase in internet consumption. Measuring internet usage directly is inherently difficult due to a lack of fine-grained internet usage data, which is partially why I collect and rely on variation in internet availability in the first place.[16] Nevertheless, I use a feature in the Facebook Marketing API provided by Meta to commercial users for targeted advertising. Specifically, Meta shows a commercial user the number of active users on Meta's social media platforms in the last month for parameters (including location) that can be specified. Therefore, I feed the location of each village to the API and set all other parameters to the most general values to retrieve the number of active Facebook and Instagram users between 13 and 65 years that live (or have recently lived) in the location in 2020.[17] A limitation of that approach is that Meta has set the minimum value it reports to 1000 users to protect the privacy of its users, after 1000 the number of users is reported in steps of 100. Since 1000 active users is a prohibitively high number for many villages, I use a workaround to improve the accuracy of the number of users. I request the number of users in an Indian GP and a specific town in the US (which approximately has 1000 active users) jointly. This lowers the de facto minimum number of reported users to 0. Since the Marketing API restricts the shape of the area to a circle, I approximate the area of a GP as follows: I ask for the number of users within a 2km radius which captures space slightly smaller than the average GP.[18]

[15] Some GPs are listed in both phases. I follow the instruction of Bharat Broadband Network Limited and delete duplicate GPs from phase II.

[16] Studies evaluating the Internet's impact in developing countries at a large scale have relied on mobile coverage data based on the GSM Association's data which is not available in India or temporal variation due to connections via undersea cables (e.g., Hjort and Poulsen, 2019; Guriev *et al.*, 2021).

[17] API calls were made between October and December 2020.

[18] The average GP in Jharkhand covers an area of 18.39km^2 while I collect Facebook activity for an area of 12.57km^2.

The Meta data have the advantage of highlighting variation in internet usage that exposes individuals likely to national political debates around religion. However, their relative coarseness makes slightly stronger assumptions for identification necessary. Therefore, I supplement the data with information on internet availability in all schools of Jharkhand in 2019.[19] The data originate from the District Information System for Education (DISE) and include the exact location of all schools. In total, there are 45,782 schools, 29.61% reporting internet access. The high spatial granularity in combination with the indirect measure of usage, complement the strengths and weaknesses of the Meta data.

Conflict: To capture the most severe form of group divisions, I obtain data on assaults over the 2008-2022 period from the GDELT 1.0 Event Database (Leetaru and Schrodt, 2013). Assaults include physical and sexual assaults, destruction of property, torture, and death by physical assault. Assaults committed by the state (i.e., the police or the military) are excluded. The data highlight a drastic increase in assaults over time. While there are 7,050 recorded assaults in the 3 years before the start of BharatNet (2011-2013), there are 11,994 in the three years after phase I was completed (2017-2019). I complement the data with mob and riot events by supporters of the two main parties: the Hindu nationalist BJP and the secular INC from ACLED (Raleigh *et al.*, 2010). The data only start in 2016 and record 1,195 mobs and 1,434 riots over the sample period (2016-2022). Based on this data I construct the following outcomes: the natural logarithm of one plus the number of assaults, riots, or mobs (by party) within 1km around the broadband connection over the 2018-2022 period.

Social Welfare: To capture subtle but relevant consequences of changing group divisions, I obtain data on the largest public employment program worldwide: NREGA (Zimmermann, 2014). Its primary goal is the "social protection of the most vulnerable people" in rural India by guaranteeing every household a minimum of 100 days of wage employment per fiscal year (Ministry of Rural Development, 2014, p.1). The program is implemented at the local level, where the GP is responsible for generating enough public works, registering households, and allocating work. The program is known to face supply issues such that demand for work days exceeds supply in all states as highlighted in Dutta *et al.* (2012). Assessing excess demand based on the National Sample Survey 2009-10, they find that 51,7% of rural households in Jharkhand

[19] The data on schools was obtained from http://schoolgisjharkhand.nic.in/education and last accessed on April 4, 2023. Although information on internet availability in schools exists country-wide, their latitude and longitude is only accessible in Jharkhand.

wanted to work in NREGA, of which 62.8% did not get any work.[20] Excess demand leaves the allocation of work among villagers at the discretion of the GP opening the door to favoritism. The presence of which is highlighted by Jeong *et al.* (2023) in the state of Uttarakhand, where GP presidents that barely won the election assign themselves three times more work days than those that barely lost.

To obtain public employment via NREGA, members of a household in a given village can register for a job card within their GP. A job card, in turn, enables members of the household to request public employment. To foster transparency, job cards are in the public record online. They include the name of the household head, the village and GP, the date of registration, and lists the days on which public employment was provided. I webscrape 5.41 million websites, including the universe of job cards in every village of Jharkhand.[21] 57.86% percent (3.13 million) of job card holders received employment between 2019 and 2022, totaling 324 million days of employment.

To assess changes in group divisions, I capture the differential treatment of Muslims in NREGA. Therefore, knowledge of the religious affiliation of individuals seeking employment is necessary. This type of information is scarce in Indian data and only available at large aggregates - the district - in the Indian census. Therefore, similar to Ash *et al.* (2021), I infer the religion based on the first and last names of villagers. I employ machine learning trained on over 41 million land records in Bihar, which Jharkhand used to be part of until the year 2000. The algorithm has been shown to predict whether an individual is Muslim with an accuracy of over 97% on unseen names in the context of Bihar (Chintalapati et al. 2022).[22] In total, 648,068 of the households (11.97%) registered in NREGA are Muslim.[23] 88% of GPs have at least one registered Muslim and they make up more than 10% of registered individuals in 33% of GPs. To further test whether the differential treatment of Muslims in NREGA is driven by deepening discrimination, I exploit the group affiliation of the GP president. Strengthening group identities along religious lines would lead to Muslims being disadvantaged in villages governed by a non-Muslim GP president and advantaged in those governed by a Muslim president. To test this hypothesis, I

[20] Such high levels of excess demand are characteristic of India's poor states where local and regional supply constraints bind. Although the main fiscal costs are provided by the national level, the supply, organization, and allocation of work and workers require skilled labor at the local and regional levels. While no state meets the demand for public employment within NREGA, others report more modest supply shortages resulting in a national average of 44.4% excess demand (Dutta *et al.*, 2012).

[21] Webscraping a large number of websites can be time-consuming due to computational constraints on both ends (the hosting server, as well as the CPU of the scraping machine). I webscraped the data between January and May 2023.

[22] The algorithm was developed by Rajashekar Chintalapati, Aaditya Dar, and Gaurav Sood and can be accessed via the pranaam package in Python.

[23] This is close to 14.53%, the Muslim share reported in the 2011 census for Jharkhand.

webscrape the GP president's name at the very end of their 5-year term in 2022 for all villages in Jharkhand reporting it online, 3,928 out of 4,345.[24] Again, I use the machine learning algorithm to classify presidents into Muslim and non-Muslim. Overall, 1,427 villages (4.41%) are governed by a Muslim president.

Finally, in order to locate the GPs I fuzzy merge them based on their name and the block and district information to the SHRUG village shapefile (Asher *et al.*, 2021). I am able to identify 89.4% of the locations. I then calculate the minimum distance of the centroid of the GP to the next phase boundary segment.

I construct the following outcomes: the share of Muslims that registered in a year for NREGA, as well as the natural logarithm of one plus the number of work days allocated to a specific household. This enables me to capture the allocation of work days to Muslims relative to others within NREGA differentiating between villages governed by a Muslim relative to villages governed by a non-Muslim GP president.

Voting: Next, I obtain voting data of the 2019 national election for Jharkhand at the polling station level.[25] Overall, there are 29,464 polling stations documenting the choices of 14.8 million voters. There are 57 parties most of which are small. The three most successful parties were the BJP with over 7.5 million, the INC with more than 2.3 million, and the JMM with over 1.7 million votes. Form-20 reports votes by candidate and polling station and includes a unique polling station ID. It does not report the name or location of a polling station, however.[26] In order to link each polling station to a location, I identify the name of each polling station through the Chief Electoral Officer in Jharkhand after verifying that the IDs did not change between the national and state elections in Jharkhand that both took place in 2019.[27] To assign a location based on a polling station name, I exploit that the majority of polling stations are situated in school buildings. I recover the precise coordinates of 17,031 polling stations via a fuzzy match with the District Information System for Education (DISE) - a data set containing every school and its coordinates.[28] In order to capture the political consequences of rural internet access which

[24] The information was obtained from https://gpdp.nic.in/PPC/sarpanchWithDetailsReport.html, last accessed on April 21, 2023. I obtain the information based on the last year in office as reporting in previous years was low. The election of that term took place between September and December 2017 and thus mostly before phase I was completed.

[25] The data have been accessed via Form-20 of the Election Commission on October 7, 2019.

[26] I tested several data sets containing the ID as well as latitude and longitude for polling stations that are based on https://gis1.jharkhand.gov.in/Election_GIS, but have found that the quality of the coordinates was too low.

[27] Source: https://ceojh.jharkhand.gov.in/mrollpdf1/aceng.aspx.

[28] The data set of schools have been accessed via http://schoolgisjharkhand.nic.in/education on April 4, 2023. In order to match the building name of the polling station, I first assign weights to each word based on the term frequency-inverse document frequency (tf-idf). A technique commonly used in text analysis. Thereby, I aim to

can accelerate group divisions, I assess voting behavior at polling stations in villages based on the share of Muslims present. I use the share of registered Muslims in NREGA since 2006 as a proxy. I group votes as follows: First, shift in votes towards Hindu nationalist parties.[29] Second, the share of votes received by secular parties. Third, the share of votes received by Muslim candidates.[30] Finally, I present the vote shares received by the two main national parties: the Hindu nationalist BJP and the secular INC. Thereby, I aim to capture emerging divisions in voting behavior along religious lines.

4 Empirical Strategy

Identification: To further our understanding of the causal impact of the internet on the cohabitation of religious communities in India, several challenges to identification need to be addressed. In particular, internet providers usually roll out their services gradually under demand and supply side considerations. On the demand side, more dense and wealthy areas are connected first. On the supply side, right-of-way, distance, and already available infrastructure are taken into consideration. Therefore, a simple comparison between areas with and without internet access usually implies a comparison of very different individuals. In contrast, I assess variation in rural internet availability due to the staggered roll-out of BharatNet, a large rural broadband connectivity program by the Indian government. The program divided villages into early and late receivers based on supply-side considerations at the block level (third administrative unit) as stated by Satyanarayana *et al.* (2015) p.25:

> "In Phase I, the Blocks to be connected were selected based on the least length of incremental optical fibre to be laid."

(incremental optical fiber refers to the length of connections that need to be built to connect the existing optical fiber network between cities to the GPs within a block). To the extent as supply and demand side factors are uncorrelated, this mitigates concerns related to vast differences in wealth, education, and population density between early- and late-treated areas. Nevertheless, early treated areas are more populated and educated (see Table 8 in the appendix). The roll-out

increase the quality of the match by assigning low weights to words that are common across observations (like *school*, *primary* or *secondary*) and high weights to words that are rare across observations and thus particular informative (usually the name of the village). Then I use fuzz matching based on a nearest neighbor algorithm.

[29] Hindu nationalist parties in the 2019 general election in Jharkhand: BJP; secular parties: INC, All India Trinamool Congress, Communist Party of India, Communist Party of India (Marxist, Liberation), Communist Party of India (Marxist-Leninist, Red Star).

[30] Again, I have used the same procedure as described above to assign a religion to each candidate running based on their name.

was combined with the set-up of over 100,000 Wifi hotspots which makes the internet readily accessible and creates highly localized variation in internet access. I isolate quasi-exogenous variation in fast internet by exploiting the discontinuous change in internet availability at the phase boundary. I use a range of approaches to examine the impact of fast internet on group divisions, which I describe one by one below.

4.1 RDD

To eliminate concerns regarding the correlation of supply and demand side factors, I exploit the discontinuous change of internet availability at the boundary in a spatial RDD:

$$y_v = \alpha + \beta_1 phase_v + f(dist_v, phase_v) + g(long_v, lat_v) + \sum_{s=1}^{1614} seg_{iv}^s + e_v, \tag{1}$$

where y denotes one of several outcomes capturing divisions at the GP or polling stations level v. $phase$ is a binary variable that takes on the value one if the GP received a broadband connection in the first phase and is zero if it will receive a broadband connection in the second phase. I follow Gelman and Imbens (2019) and account for smooth changes in the outcomes by including a local linear polynomial that is estimated separately for both phases. In addition, $g(long_v, lat_v)$ is a local polynomial that controls for the location of the GP in two-dimensional latitude-longitude space. In order to exploit local discontinuities, I divide the boundary into 1614 segments of 20km length (100 segments in the case of Jharkhand). This ensures that I only compare neighboring GPs located on either side of the same segment. To avoid comparisons across state boundaries, I add state fixed effects in the full sample and I apply a small bandwidth of 10km as in Dell and Olken (2020) (and similar to Dell *et al.*, 2018; Lowes and Montero, 2021; Méndez and Van Patten, 2022). β_1 captures then the causal impact of fast internet if divisions would have evolved smoothly in the absence of BharatNet. Section (4.4) assesses the plausibility of this assumption.

4.2 Difference-in-Discontinuity

Several outcomes allow me to differentiate between Muslims and non-Muslims. This enables an analysis of the impact of fast internet on Muslims relative to non-Muslims. In particular, I estimate the following model in a difference-in-discontinuity framework (similar to Grembi *et al.*, 2016 and Bluhm and Pinkovskiy, 2021):

$$
\begin{aligned}
y_{iv} = \alpha + \beta_1 phase_v + \beta_2 phase_v \times muslim_{iv} + \beta_3 muslim_{iv} + \\
f(dist_v, phase_v) + g(long_v, lat_v) + \sum_{s=1}^{100} seg_v^s + e_{iv},
\end{aligned}
\tag{2}
$$

where y_{iv} is the natural logarithm of one plus the number of work days received by individual i living in GP v, $phase_v$ is a binary variable that denotes whether the individual lives in a GP part of the first roll-out phase, whereby $muslim_{iv}$ identifies Muslims. Consequently, β_1 captures the average impact of broadband internet for non-Muslims, whereby $\beta_1+\beta_2$ estimate the influence for Muslims. My coefficient of interest is then β_2 capturing any change in the differential treatment of Muslims (e.g., in NREGA) due to internet availability. As in model (1), $f(dist_i, phase_i)$ is a local linear polynomial that is estimated separately for both phases and $g(long_i, lat_i)$ is a local polynomial that controls for the location of the GP in two-dimensional latitude-longitude space. 20km boundary segment fixed effects restrict the comparisons to close-by villages. Observations are weighted using triangular kernel weights. The model is estimated within a small bandwidth of 10km. The causal interpretation of β_2 requires slightly different assumptions compared to model (1). Namely, the absence of other discontinuities that affect Muslims and non-Muslims differently and a constant difference in outcomes between Muslims and non-Muslims. Thus, the difference-in-discontinuity design accounts for factors that affect Muslims and non-Muslims in the same way. This mitigates concerns regarding compound treatment effects due to the overlap with a low-level administrative boundary.

4.3 Difference-in-Difference-in-Discontinuity

The analysis of the allocation of NREGA benefits allows me to assess how fast internet changes the treatment of Muslims relative to non-Muslims depending on the religion of the GP president. Therefore, I estimate the difference-in-difference-in-discontinuity between GPs with a Muslim president and a non-Muslim president. I adapt model (2) as follows:

$$
\begin{aligned}
y_{iv} = \alpha + \beta_1 phase_v + \beta_2 phase_v \times muslim_{iv} + \beta_3 phase_v \times muslim_{iv} \times muslim\_pres_{iv} + \\
\beta_4 muslim_{iv} \times muslim\_pres_{iv} + \beta_5 muslim_{iv} + \beta_6 muslim\_pres_{iv} + \\
f(dist_v, phase_v) + g(long_v, lat_v) + \sum_{s=1}^{100} seg_v^s + e_{iv},
\end{aligned}
\tag{3}
$$

where $muslim\_pres_{iv}$ identifies a Muslim GP president and all other variables are defined as in model (2). The main identifying assumption changes accordingly. To interpret β_3 causally, in the absence of BharatNet, there should be no discontinuity in the difference in difference in outcomes between Muslims and others in villages with a Muslim president and without a Muslim president. If the assumptions are valid, then β_3 captures whether Muslim GP presidents change their treatment of Muslims due to internet availability differently relative to non-Muslim GP presidents.

4.4 Plausibility of Identifying Assumptions

The central assumptions behind model (1), (2), and (3) build on each other. While model (1) requires the absence of all discontinuities at the boundary that impact the outcome, model (2) and model (3) require the absence of discontinuities at the boundary that affect the difference in outcomes between Muslims and non-Muslims (or the difference in difference for model (3)). Model (2) and (3) thus do not require the absence of discontinuities that affect all individuals equally. However, any test of model (1) increases the plausibility of model (2) and (3).

Absence of other discontinuities: I test for discontinuities in a range of variables at the village level, which I obtained from SHRUG (Asher *et al.*, 2021). These include 2001 and 2011 census data on total population, number of households, size of the scheduled caste population, size of the scheduled tribal population, size of the literate population, number of primary, middle, secondary, and senior secondary schools, and number of colleges. In addition to total nightlights, average nightlights, electricity, rural consumption, as well as the information on the timing and length of rural road upgrades. The results reported in Table (1) and (10) do not show any evidence for discontinuities for Jharkhand and none for the full Indian sample except for the growth rate of the scheduled tribe population (significant at the 5% level) and the number of colleges (significant at the 10% level). This is to be expected by chance when testing for discontinuities in 72 different variables in total. It is therefore no evidence for a systematic deviation from the continuity assumption.[31]

Absence of pre-treatment discontinuities: I test whether there are any detectable differences in the outcomes before the start of BharatNet. This can be seen as a test for the presence of any pre-existing discontinuities that do affect the outcome. Limited data availability in the years before BharatNet restrict this test to conflict outcomes based on GDELT data and the registration of NREGA households. Table (2), columns 1 and 2 show the results and do not

[31] Nevertheless, it does present a random deviation. Table (11) in the appendix highlights that the results do not depend on it.

highlight any discontinuities.[32]

Falsification (Placebo Boundary): I construct a plausible placebo, not across time, but across space. This allows testing for the absence of discontinuities for outcomes that are not available before the start of BharatNet. Furthermore, it serves as a test of the additional assumptions in model (2) and (3).

A simplistic approach would just shift the boundary by a given amount or use random block boundaries as a placebo. This would ignore the non-random selection of blocks, however. Therefore, to construct a realistic counterfactual, I leverage information on the selection process of blocks into the treatment.

BharatNet will connect all GPs to the fiber optic network but split the project into two phases. It selected blocks, containing in sum 100,000 GPs, for phase I based on minimizing the length of additional cables that need to be built. The selection process can thus be visualized in two steps: first, all blocks are sorted based on the length of additional cables that need to be built, and second, the number of GPs is summed up across blocks moving from the block with the shortest additional cable need to the longest until 100,000 GPs are reached. That is then where the cut-off is, which determines the geographic phase boundary used in the spatial RDD. Now, imagine a thought experiment in which we move further up the sorted sequence of blocks, changing the arbitrary number of GPs that determine the cut-off to 175,000 (see Figure (3) for an illustration). Like any other number, this would then generate a plausible counterfactual boundary.

Since I lack information on the need for additional cables by block, I have to approximate this thought experiment. First, I use all 2011 census variables listed in Table (1) to estimate a block's propensity to be in phase I. Second, I split all district boundaries dividing phase II areas that do not intersect with state boundaries into 20km segments and assign the block on each segment with the higher predicted propensity to the placebo treatment.[33] I then test for discontinuities across the placebo boundary using model (1), (2), and (3).

The results reported in Table (2), columns 3-6 do not show any evidence for discontinuities. This supports the main identifying assumption of model (1), (2) and (3), namely the absence of other discontinuities and constant differences for model (2) and (3). It also mitigates concerns about compound treatment effects due to the overlap between phase boundaries and low-level

[32] Another approach to indirectly test for pre-existing discontinuities assesses the smoothness in the density of observations around the cutoff (Cattaneo *et al.*, 2020). Figure (5) presents the density of NREGA GPs and shows, confirmed by a formal test, no evidence for a discontinuity at the cutoff.

[33] For specifications that are restricted to Jharkhand, I use all district boundaries where the treatment status doesn't change as opposed to only non-treated areas to construct the counterfactual. This ensures enough (placebo) identifying variation.

administrative boundaries.

RD bandwidth: In the baseline, I restrict the sample to a small bandwidth of 10km (following other spatial RDD applications such as Dell *et al.*, 2018; Dell and Olken, 2020; Lowes and Montero, 2021; Méndez and Van Patten, 2022). The choice of the bandwidth can be seen as a trade-off, where small bandwidths allow for a good approximation of any functional form by the linear RD polynomial, while larger bandwidths increase the power (Cattaneo *et al.*, 2019). Tables (12) and (13) show the results for alternative bandwidths of 7.5km and 12.5km. Figure (6) extents the test for my preferred specification, estimating model (3) for a range of bandwidths starting with 30km and moving down in 1km steps to the point where the power is insufficient at 5km.

RD Kernel Weights: The baseline specifications apply triangular kernel weights. Thus, they put more weight on observations close to the boundary. Table (14), Panel B highlights that the main results, based on NREGA outcomes, are robust to giving equal weight to all observations.

RD Polynomial: All specifications apply local linear RD polynomials. A low-order polynomial is recommended in the literature to avoid overfitting and bad performance at the cut-off (Gelman and Imbens, 2019). Table (14), Panel C applies a quadratic RD polynomial to the main specifications, based on NREGA outcomes. The results are overall robust, only the discontinuity in the share of Muslim registrations loses its significance. The magnitude and the sign of the coefficients of interest remain very similar.

5 Main Results

I begin by documenting the impact of internet availability on usage in Section (5.1). I then examine whether fast internet divides rural communities. Section (5.2) assesses the influence on conflict. The treatment of the main religious minority - Muslims - in India's biggest public works program is analyzed in Section (5.3) and finally voting behavior in villages with and without Muslims is assessed in Section (5.4).

5.1 Internet Usage

The connection of phase I GPs to the fiber optic network does not necessarily cause a discontinuous jump in internet access at the phase boundary. I confirm the presence of a discontinuity based on social media usage and school internet data. First, Facebook and Instagram (Meta) usage in 2020 within 2km of the point of connection are examined. Points closer than 2km are dropped in the estimation to avoid an overlap between the radius and the boundary. Figure (4) highlights a strong discontinuity in monthly active Meta users at the boundary. The number increases by 1,135 on average India-wide and by 6,050 within Jharkhand.[34] Second, I test for discontinuities in internet availability in Jharkhand's schools. Precise locations of the schools allow me to test this at a very local level. Figure (4) documents a discontinuous increase in the likelihood of internet availability. Schools in phase I close to the boundary are 19.9 percentage points more likely to have internet compared to neighboring schools just across the boundary.

These results confirm the uptake of the broadband infrastructure documented in several media and government reports. The Economic Times, for example, announced in 2017 that major telecommunication providers like Reliance Jio, Airtel, Vodafone India, and Idea Cellular have made use of the broadband infrastructure and until 2021, 104,310 GPs had public Wifi hotspots installed, 510,559 homes were connected and 36,000km of unused fiber ("dark fiber") were leased (Ministry of Communications, 2021).

5.2 Conflict

This section reports the impact of the fast internet on extreme forms of divisions. It estimates model (1) on the level and change of assaults, as well as the number of riots and mobs by BJP and INC supporters. Table (3), Panel A shows overall an increase in the number of assaults by 0.5% on average in the full sample, as well as an increase in the growth rate by 0.43%. The increase is considerably more pronounced in Jharkhand, where assaults increase by 12.79% and the growth rate rises by 13.08%.[35] These estimates mirror the large increase in internet usage documented in Jharkhand in Section (5.1).

Columns 3-6 report the impact on riots and mobs by party. If inflammatory online messages by the BJP drive parts of the increase in divisions, one would expect an increase in conflict events by their supporters. Columns 3 and 4 show an 0.11% increase in the number of riots and an

[34]The average in the full sample is 6,924. The higher increase in Jharkhand mirrors state-wide numbers. A McKinsey Global Institute (2019) report includes Jharkhand among the five states with the fastest growth in internet penetration between 2014 and 2018.

[35]Note that the magnitude but not the sign of these coefficients depends on the bandwidth. The increase is 8.89% and 9.83% for a 12.5km bandwidth.

0.1% increase in the number of mobs by BJP supporters India-wide significant at the 5% level. Again, the increase is more dramatic in Jharkhand where BJP riots and mobs rise by 3.01%. In contrast, fast internet does not increase riots or mobs by INC supporters, if anything the number of mobs declines slightly by 0.1% in the full sample.

These patterns are consistent with an increase in violent divisions driven by the exposure to divisive debates on the internet. This increase seems to be partly driven by the BJP, although the increase in BJP riots cannot explain the full increase. Fast internet does not impact divisions driven by the INC. Although I cannot rule out that measurement bias influences the magnitude of the estimates, the negative point estimate for INC violence makes it unlikely that they explain the full result. These findings serve as a motivation to explore emerging religious divisions in other dimensions in more detail in the next sections.

5.3 Internet and Public Works

The impact of the fast internet on the allocation of scarce welfare benefits is examined in this section. If the exposure to internet affects the salience of group identities, it can affect the allocation decisions of local officials. Analyzing divisions based on administrative data on welfare benefits has several advantages: Firstly, it allows me to isolate the information channel from the coordination channel potentially present in the conflict results. Secondly, it provides an opportunity to explicitly focus on Muslims. Thirdly, measurement errors are unlikely. Fourthly, variation in the GP president responsible for the allocation enables an assessment of the supply channel.

I start with the examination of Muslim entries into NREGA relative to non-Muslims. Supply constraints do not bind for entries such that fast internet can affect entries differently due to multiple reasons. Most importantly in this context, the results will inform the reader on the internet's impact on the religious composition of registered households among which NREGA work days are distributed. The RDD results are reported in Table (4) and show a 2.8 percentage point decline in the share of Muslims among households that registered between 2017 and 2022. The result is significant at the 5% level and appears immediately in 2017. The differential decline in registrations could be explained by an increase in need or a decrease in the expected benefit (if discrimination is anticipated). The quick materialization of the pattern speaks to a psychological rather than an economic channel (I examine further evidence for the economic channel in Section (6) and find no support).

Next, I turn to the allocation of scarce NREGA work days among registered households differentiating between Muslims and non-Muslims. The fast internet could influence the GP president's allocation decision. Table (4), column 3 reports the estimates based on the difference-in-discontinuity model. The point estimate is negative but insignificant such that there is no evidence for a differential treatment of Muslims on average (conditional on being registered).

The average picture hides important differences, however. Since NREGA is constrained on the supply side, allocation based on group identities would differ based on the religious affiliation of the GP president. Therefore, I focus on GPs with at least one registered Muslim resident but with no Muslim president first. I examine to which extent the internet changes the treatment of Muslims by non-Muslim presidents relative to the treatment of non-Muslims. Column 4 highlights the result. Muslims receive 10.9% fewer NREGA days than non-Muslims in villages that have fast internet. Next, I turn to GPs with a Muslim president. If the internet affects Muslims in general differently, the effect should remain. This is not the case, the sign of the coefficient reverses in GPs with a Muslim president. In particular, Muslims get 22.1% more work days relative to non-Muslims, significant at the 1%-level. These patterns are in line with a heightened awareness of Muslims due to the exposure to heated national debates, which ultimately affect the GP president's allocation decision.

Finally, I re-estimate the relationship in model (3) on a sample of all villages with at least one registered Muslim. I directly contrast the treatment of Muslims (relative to non-Muslims) by Muslim GP presidents in neighboring villages across the internet boundary and compare it to the treatment of Muslims (relative to non-Muslims) by non-Muslim GP presidents in neighboring villages across the internet boundary. The difference in difference-in-discontinuity confirms the earlier pattern. Muslims receive overall 12.5% fewer days relative to non-Muslims in GPs without a Muslim president but receive 29.2% more days in GPs with a Muslim president on average significant at the 1%-level. Overall, these patterns suggest an increase in discrimination against individuals belonging to a different religious group, in particular Muslims. These findings highlight the power of a changing media environment that can produce unfair outcomes even within long-existing rural communities.

5.4 Political Impact

I turn to the political implications of rural internet availability, next. The exposure to divisions online and offline (documented before) can impact voting behavior. Around the world, ethnically fractionalized countries vote often based on identity as opposed to merit. Therefore, I examine the internet's impact on the extent to which the vote share for Muslim candidates is related to the share of Muslims in a GP (approximated by the share of Muslims registered in NREGA since 2006). The results are presented in Table (5), column 3 and show a significant increase in the relation. The results are consistent with an increase in voting based on religious identity, such that Muslims more likely vote for a Muslim if exposed to fast internet.[36] The impact is limited, however. Muslim candidates do not play an important role nationally.

Therefore, I examine vote shifts between the two main poles in the debate around India's religious identity: the Hindu nationalist BJP and secular parties (these two groups represent 68.1% of total votes). Again, I differentiate by the share of Muslims in a GP. It is a viable strategy for a targeted minority to combine their voting power behind an inclusive broader franchise as offered by the secular parties. An increase in religious divisions can then lead to an increase in votes for that franchise, while non-Muslims start favoring the other pole. Table (5) shows that polling stations in non-Muslim areas with fast internet report a shift of votes to the Hindu nationalist party. The shift is sizeable and declines with the share of Muslims. The discontinuity in the shift to the BJP is consistent with a general increase in Hindu nationalism due to the internet, but also with rewarding the government for the allocation of fast internet. The voting patterns for secular parties reveal a strong decrease at the boundary in villages with a Muslim share below the state average. The sign switches in GPs with a considerable Muslim share. The absence of individual-level voting data makes a conclusive interpretation difficult. Nevertheless, these patterns are consistent with the notion that a minority rallies behind a larger beneficial franchise if it cannot get the majority.

6 Alternative Mechanism

The results presented so far show an increase in divisions in rural communities. The increase can be attributed to a change in the information set as formerly isolated communities gain access to heated national debates online. The patterns can also be explained through a different mechanism, however. Hjort and Poulsen (2019) have shown an increase in employment in Sub-Sahara Africa after an area gets connected to broadband internet. Economic gains if unequally distributed can increase tensions between groups as shown by Mitra and Ray (2014) for the case of Muslims in India. Did the internet create inequalities that produced the patterns highlighted above? In the following, I discuss the evidence for this alternative mechanism.

In order to attribute the increase in NREGA work days for individuals of the same religion than the GP president to the internet's economic impact, the economic effects need to follow specific patterns. Firstly, they need to materialize quickly as a decline in the share of Muslims

[36]The small but significant effect of internet availability on votes for Muslim candidates in non-Muslim villages could be due to the imperfect measurement of a village's Muslims (as I rely on NREGA registrations).

is observable from 2017 onward. Secondly, the impact of the internet needs to reverse its sign in villages with compared to villages without a Muslim president. Thirdly, Muslims need to gain disproportionately in villages without and gain less than average in villages with a Muslim president. Although, it is not apparent why the impact of the internet would follow these patterns it is possible.

Therefore, I leverage the latest round of DHS data covering the 2019-2021 period to test the internet's differential impact on households' wealth and poverty status. I rely on individual-level data on 2,062,660 adults after restricting the sample to rural areas and residents of the interviewed household. To identify the impact of fast internet on Muslims relative to non-Muslims, I estimate model (2) and (3) on both, the full sample and Jharkhand for comparability. Table (6) presents the results. Columns 1 and 3 do not show any evidence for the hypothesis that poor Muslims benefit disproportionately from rural internet (India-wide and in Jharkhand), nor does it show that there are differential effects on Muslims in Jharkhand's villages with and without a Muslim president. In contrast, the likelihood that a Muslim is below the poverty line increases by 5.1 percentage points in the full sample and by 18.2 percentage points in Jharkhand. To take the whole distribution into account I assess the Internet's impact on wealth using DHS's rural wealth index. I do not find any significant differential impact of the internet on Muslim wealth relative to non-Muslims. The same holds true for the difference in the difference between villages with and without a Muslim president.

The interpretation of the magnitudes has to be considered carefully, however, since DHS clusters are randomly shifted in space. As this paper relies on fine-grained spatial discontinuities, measurement errors in the location can considerably impact the result. To protect the respondent's confidentiality DHS shifts a cluster in a random direction and random distance between 0 and 5km from the true location for 99% of rural DHS clusters and up to 10km for the remaining 1%. Importantly for this paper, DHS assures that the clusters are not displaced across district boundaries. This ensures that points are never shifted across the internet boundary in the case of Jharkhand where the boundary intersects with district boundaries. One can therefore expect that the coefficients are upward biased (increasing the likelihood of detecting non-existent economic effects) as the continuity assumption might be violated.[37]

[37] Table (9) tests for significant differences in outcomes based on the 2011 census within 5km on both sides of the boundary. There are no significant differences in Jharkhand but slightly more schools in early treated areas in the full sample. This mitigates concerns regarding sizeable bias due to the displacement of DHS clusters.

7 Conclusion

Billions of people live in rural areas in developing countries. As they get access to the internet, they are joining national conversations that were once far removed. How does that impact the cohabitation of different groups in rural communities that have lived together for decades?

This paper analyzes the impact of the largest rural government broadband initiative worldwide on group divisions in rural communities. It collects new data on the location of 175,157 broadband connections that aim to connect every GP to the fiber optic network. In combination with Wifi hotspots and a staggered roll-out, the initiative creates spatial discontinuities in internet usage between villages receiving fast internet in phase I and those which receive it in phase II.

This paper examines several dimensions of divisions. It considers extreme outcomes and shows that the sudden increase in internet results in an increase in assaults, as well as an increase in riots and mobs by supporters of the Hindu nationalist BJP. These findings motivate more detailed assessments of moderate but widespread forms of divisions in the state of Jharkhand. I document increasing distortions in the allocation of NREGA welfare benefits along religious lines by GP presidents in a difference-in-discontinuity design. Non-Muslim GP presidents allocate fewer work days to Muslims. The reverse is apparent for Muslim presidents, which favor Muslims over others. Further specifications rule out a differential economic impact that could explain these patterns. Thus, the evidence suggests that the change in the information set brought by the internet leads elected representatives to allocate public goods based on group identities. In a final step, this paper explores the political consequences and shows an increase in votes for the Hindu nationalist BJP in villages without (in NREGA registered) Muslims and an increase in votes for the secular INC and Muslim candidates in villages with a sizeable Muslim share. Although the evidence varies in depth, in sum, it paints a coherent picture that reinforces itself. Fast internet divides rural communities.

The results suggest vast consequences for the developing world as rural communities gain internet access. They highlight that changes in the information environment can transfer national divisions to local rural communities. These results likely hinge on the national debate and the design of (social media) algorithms. They add to studies documenting costly unintended consequences of internet platforms (Bursztyn *et al.*, 2019; Grinberg *et al.*, 2019; Levy, 2021; Müller *et al.*, 2022). These should (but may not) be factored into the design decisions of algorithms developed by private companies.

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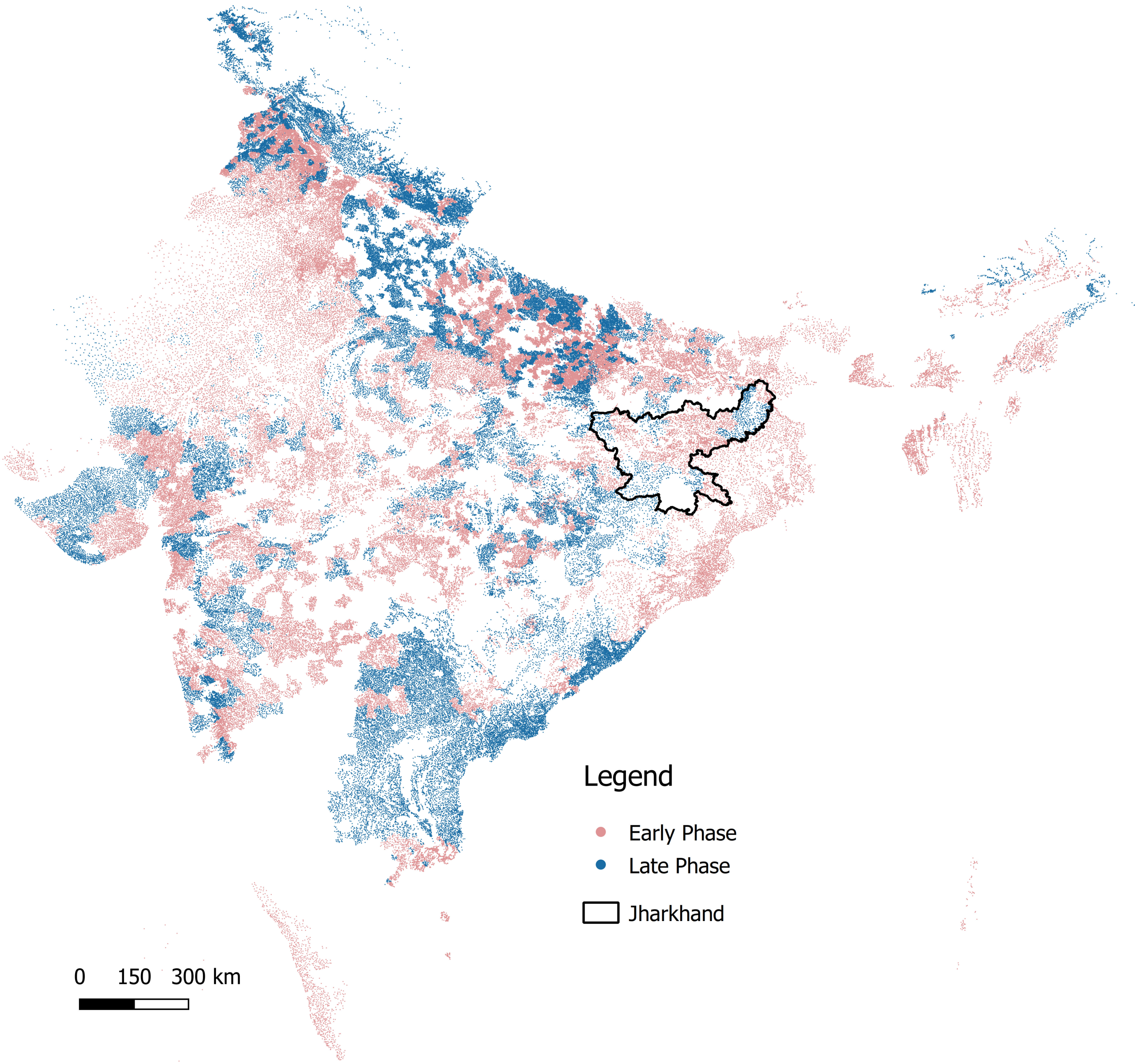
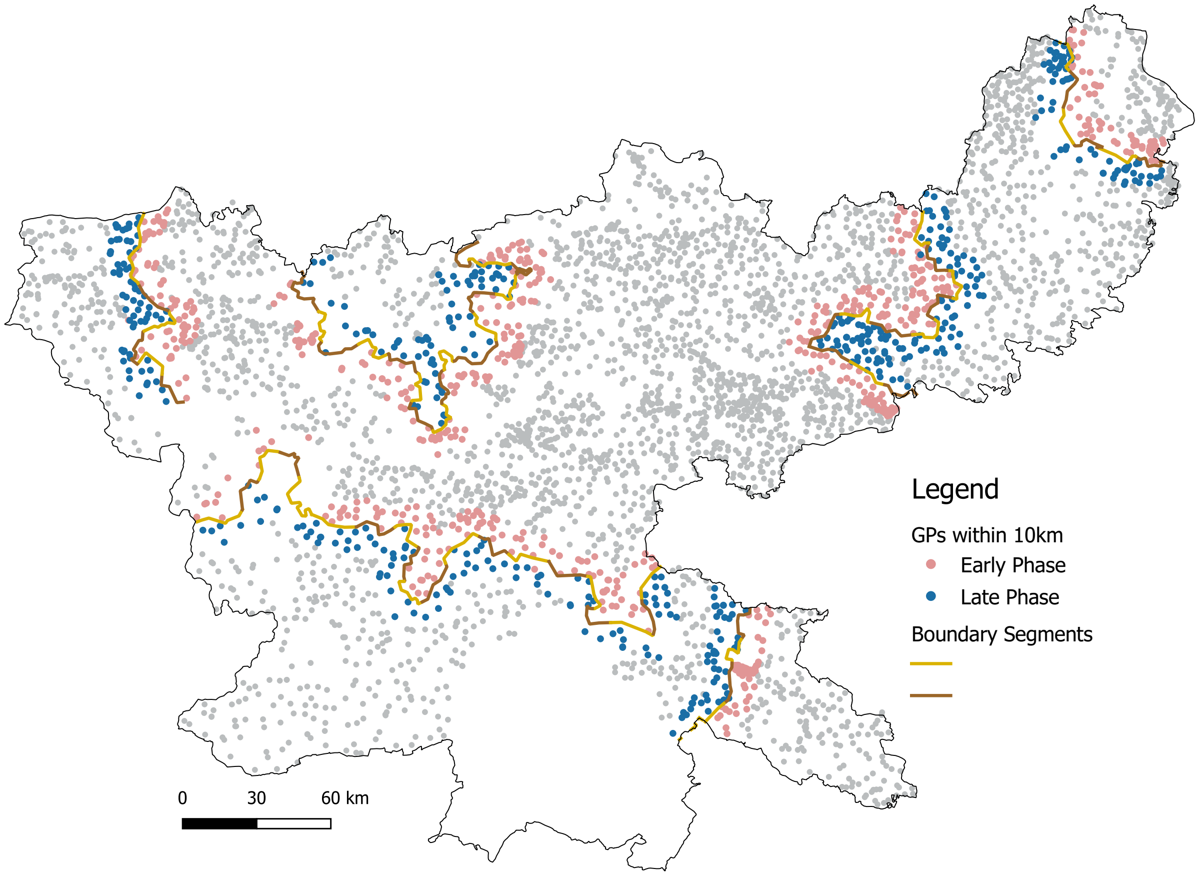
Figures and Tables

Figure 1: BharatNet GPs by Phase



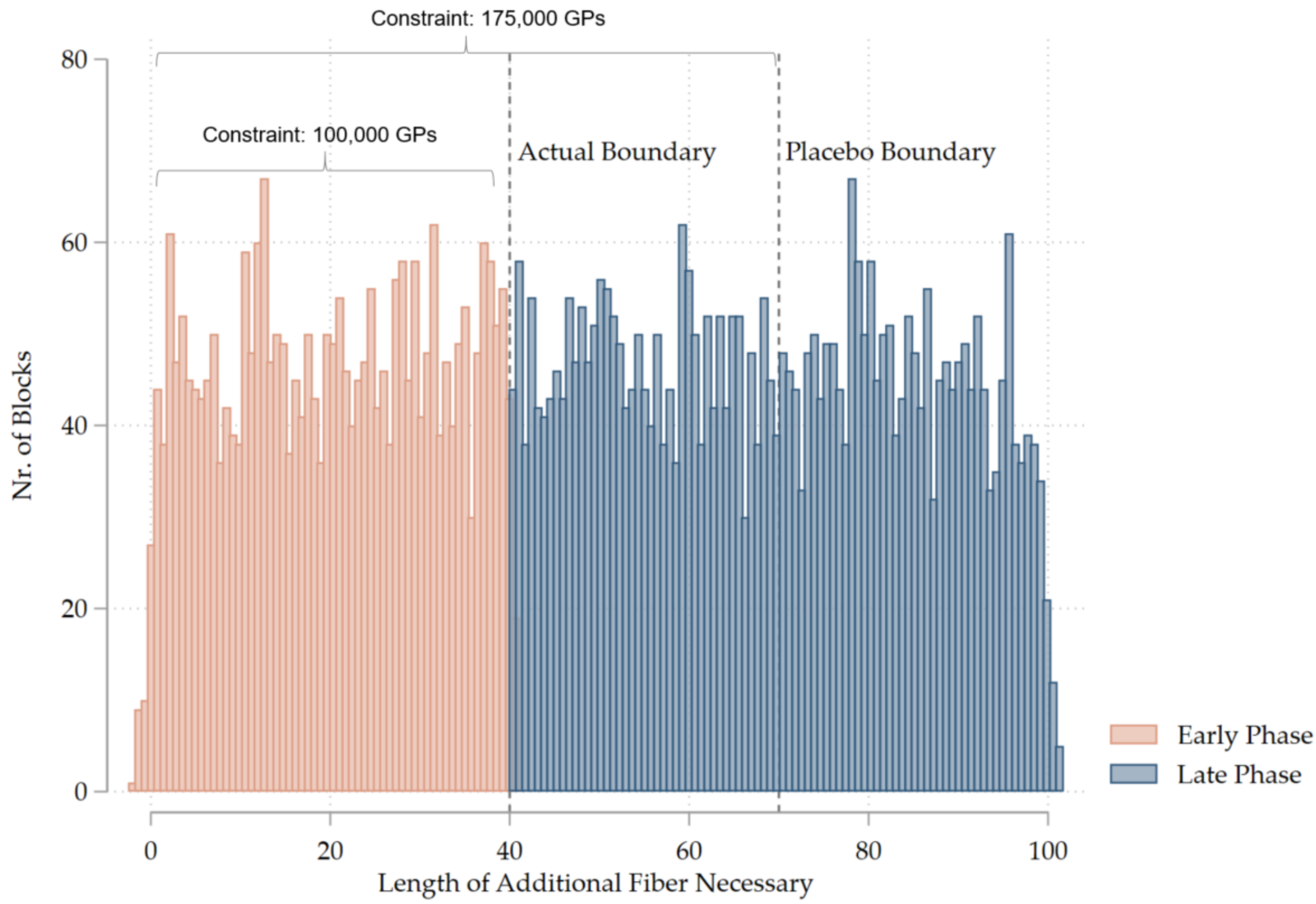
Notes: Each dot on the map represents a GP that gets connected to broadband internet via the government's rural broadband initiative BharatNet. Salmon dots denote GPs in phase I that got connected between 2014 and 2017. Blue dots denote GPs in phase II which is still ongoing (as of 2023). The data is publicly available at https://sites.google.com/view/johannes-matzat/data.

Figure 2: Visualization of RDD, Jharkhand



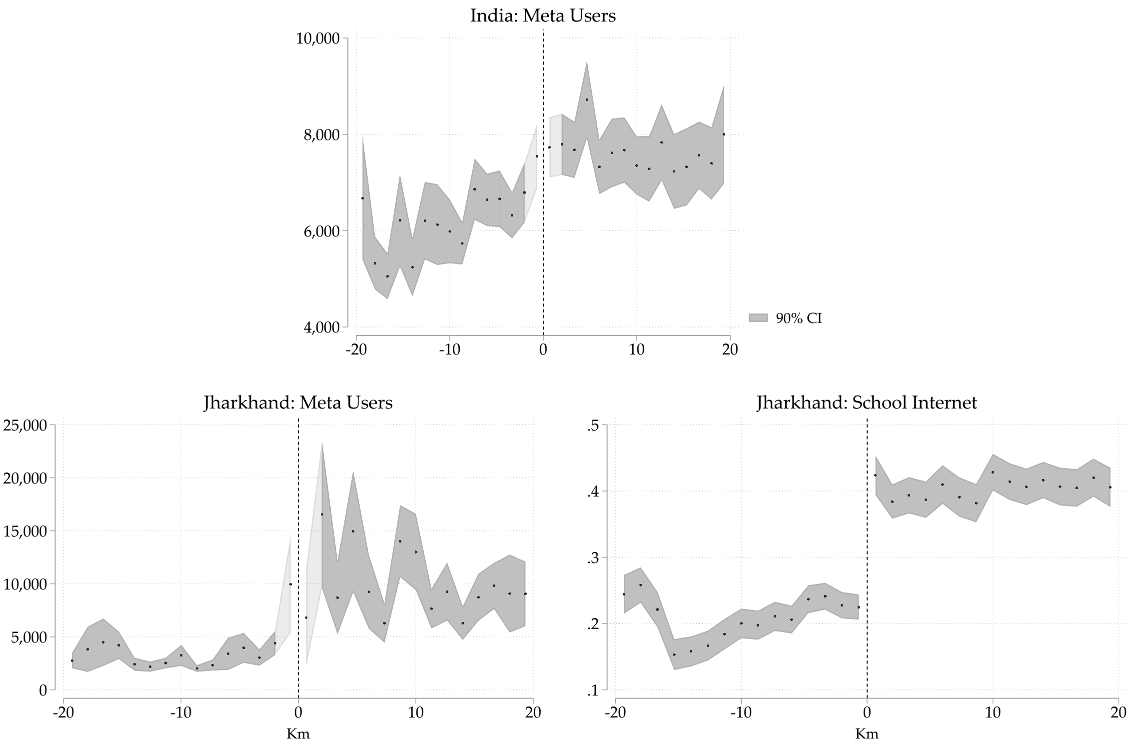
Notes: Each dot on the map represents a GP in Jharkhand that gets connected to broadband internet via the government's rural broadband initiative BharatNet. Colored dots are within 10km of the boundary. Salmon dots denote GPs in phase I that got connected between 2014 and 2017. Blue dots denote GPs in phase II which is still ongoing (as of 2023). The boundary is divided into 20km segments as highlighted by the two different colors.

Figure 3: Illustration of Placebo Boundary



Notes: The histogram illustrates the thought experiment behind the placebo boundary. It exemplifies the selection of the 6,697 blocks in India into phase I and II. According to Satyanarayana *et al.* (2015), all blocks were ranked based on the number of kilometers of fiber optic cable needed to connect each GP in a given block to the existing fiber optic network. The blocks with the lowest need were then selected subsequently into phase I until the number of GPs reached 100,000. A different constraint would have resulted in a different boundary, which still follows the same logic, however. Changing the constraint, therefore, generates plausible counterfactuals (the figure illustrates a counterfactual with a constraint at 175,000 GPs for phase I). Note, that the actual number of kilometers that each block needs to add is not known to me and the variable used here is hypothetical to illustrate the argument.

Figure 4: BharatNet and Internet Usage



Notes: The figure depicts on the y-axis the number of active monthly Meta users (Facebook and Instagram) within 2km of the connection point of the fiber-optic cable within a GP in a binned plot. The x-axis denotes the distance to the nearest boundary between phase I and phase II in kilometers. Positive values denote the distance for GPs in phase I (early internet); negative values denote the distance for GPs in phase II (late internet). Note that the number of active Meta users includes users on both sides of the boundary if the connection point of the fiber-optic cable lies within 2km of the boundary (area with confidence intervals in light grey). When I estimate model (1) in a donut-RDD such that observations within 2km of the boundary are excluded, internet availability increases active monthly Meta users by 1,135.0* for the full sample and by 6,050.0** for Jharkhand. The probability that the internet is available in a school in Jharkhand increases by 19.9*** percentage points at the boundary.

Table 1: Test for other Discontinuities - Census

	Panel A: India			*Panel B: Jharkhand*		
	(1) 2001	(2) 2011	(3) 2011-2001	(4) 2001	(5) 2011	(6) 2011-2001
Total Population	-64.889	-83.201	-13.352	-511.283	-801.588	-172.453
	(55.720)	(65.448)	(12.867)	(612.645)	(702.171)	(115.820)
No. of Households	-10.907	-14.838	-2.917	-92.519	-158.546	-43.192
	(10.082)	(13.020)	(3.392)	(112.877)	(143.854)	(33.613)
Literate Population	-34.608	-48.769	-10.851	-367.713	-529.999	-94.456
	(36.262)	(46.134)	(11.788)	(447.453)	(527.233)	(96.150)
Scheduled Caste Population	-10.154	-15.603	-4.567	-26.110	-82.953	-29.869
	(8.451)	(10.284)	(2.975)	(47.178)	(67.264)	(22.929)
Scheduled Tribe Population	1.193	-2.994	-3.828**	70.809	70.248	-0.281
	(4.578)	(5.780)	(1.851)	(59.707)	(73.110)	(18.501)
No. of Primary Schools	-0.023	-0.052	-0.026	-0.254	-0.263	0.059
	(0.025)	(0.035)	(0.025)	(0.180)	(0.335)	(0.220)
No. of Middle Schools	0.007	0.002	-0.003	-0.117	-0.436	-0.304
	(0.014)	(0.025)	(0.020)	(0.183)	(0.367)	(0.217)
No. of Secondary Schools	-0.001	0.008	0.010	-0.072	-0.105	-0.031
	(0.008)	(0.016)	(0.013)	(0.091)	(0.113)	(0.071)
No. of Sr. Secondary Schools	0.004	0.015	0.011	-0.026	-0.058	-0.028
	(0.006)	(0.012)	(0.009)	(0.020)	(0.039)	(0.033)
No. of Colleges	0.002	-0.008	-0.009*	0.004	-0.012	-0.007
	(0.002)	(0.006)	(0.005)	(0.020)	(0.013)	(0.013)
Observations	50,476	50,586	50,476	1,193	1,201	1,193

Note: This table tests for pre-existing discontinuities at the boundary. It estimates the main coefficient of interest (β_1) of model Y for a number of outcomes from the 2011 and 2001 censuses. The model is estimated at the GP level, restricted to locations less than 10km away from the boundary. Panel A reports coefficients for the full sample and includes 20km segment and state fixed effects. Panel B is restricted to Jharkhand and includes 20km segment fixed effects. Observations are weighted using triangular kernel weights. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$

Table 2: Internet, Conflict, and Public Works, Placebo

	(1) Assault	(2) Δ Assault	(3) BJP Riot	(4) BJP Mob	(5) INC Riot	(6) INC Mob
	Panel A: Conflict, India					
Placebo	-0.846	-0.941	0.003	-0.005	-0.046	-0.041
	(0.610)	(0.599)	(0.058)	(0.057)	(0.056)	(0.055)
Observations	19,772	19,710	19,772	19,772	19772	19,772
Bandwidth	10km	10km	10km	10km	10km	10km
Period	Pre	Pre	Post	Post	Post	Post
Placebo	Time	Time	Space	Space	Space	Space
	Panel B: Conflict, Jharkhand					
Placebo	-2.097	-2.256	0.086	0.086	0.086	0.086
	(2.637)	(2.633)	(0.065)	(0.065)	(0.065)	(0.065)
Observations	960	956	1,843	1,843	1,843	1,843
Bandwidth	10km	10km	20km	20km	20km	20km
Period	Pre	Pre	Post	Post	Post	Post
Placebo	Time	Time	Space	Space	Space	Space
	Registrations: Muslim Share	Registrations: Muslim Share	NREGA Work Days	NREGA Work Days	NREGA Work Days	NREGA Work Days
	Panel C: Public Works, Jharkhand					
Placebo	0.007	0.018	0.058	0.097**	-0.255	0.073*
	(0.021)	(0.043)	(0.040)	(0.038)	(0.156)	(0.038)
Muslim × Placebo			0.051	-0.085	0.063	-0.098
			(0.079)	(0.066)	(0.205)	(0.066)
Muslim Pres. × Muslim × Placebo						0.273
						(0.301)
Observations	2,735	763	5,650,320	4,285,068	429,824	4,749,420
GP presidents	All	All	All	Non-Muslim	Muslim	All
Bandwidth	10km	10km	10km	10km	12.5km	10km
Period	2009-2011	2011	2019-2022	2019-2022	2019-2022	2019-2022
Placebo	Time	Time	Space	Space	Space	Space

Notes: This table shows a falsification test. Columns 1-2 test for discontinuities in the pre-treatment period, while columns 3-6 test for discontinuities at a placebo boundary. Panel A and B estimate model (1) at the GP level. Columns 1-2 are based on GDELT and estimate the impact of BharatNet on the natural logarithm of one plus the (change in) number of assaults. The outcomes in columns 3-6 are based on ACLED and measure the natural logarithm of one plus the number of riots or mobs initiated by BJP or INC supporters, respectively. Mobs are a subset of riots. The bandwidth is always 10km except if there is not sufficient variation in which case I double the bandwidth. All coefficients in Panel A and B are multiplied by 100. In Panel C, columns 1 and 2 estimate model (1) at the GP-year level. The outcome is the share of Muslims among newly registered households in NREGA. Columns 3-5 estimate model (2) at the individual-year level. The outcome is the natural logarithm of one plus the number of workdays allocated within NREGA. Column 6 estimates model (3). Standard errors are clustered at the GP-year level for columns 3-6. All specifications include 20km segment fixed effects. Triangular kernel weights are applied. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$

Table 3: Internet and Conflict

	(1) Assault	(2) Δ Assault	(3) BJP Riot	(4) BJP Mob	(5) INC Riot	(6) INC Mob
	Panel A: India					
Internet	0.499*	0.430*	0.111**	0.104**	-0.095	-0.108*
	(0.267)	(0.234)	(0.044)	(0.043)	(0.060)	(0.058)
Observations	55,707	55,487	55,707	55,707	55,707	55,707
Bandwidth	10km	10km	10km	10km	10km	10km
	Panel B: Jharkhand					
Internet	12.785***	13.075***	3.006***	3.006***	-0.099	-0.099
	(4.093)	(4.099)	(1.049)	(1.049)	(0.069)	(0.069)
Observations	1,294	1,287	1,294	1,294	2,372	2,372
Bandwidth	10km	10km	10km	10km	20km	20km

Notes: This table estimates model (1) at the GP level. Columns 1-2 are based on GDELT and estimate the impact of BharatNet on the natural logarithm of one plus the (change in) number of assaults. The outcomes in columns 3-6 are based on ACLED and measure the natural logarithm of one plus the number of riots or mobs initiated by BJP or INC supporters, respectively. Mobs are a subset of riots. The bandwidth is always 10km except if there is not sufficient variation in which case I double the bandwidth. All coefficients are multiplied by 100. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$

Table 4: Internet and Public Works

	(1) Registrations: Muslim Share	(2) Registrations: Muslim Share	(3) NREGA Work Days	(4) NREGA Work Days	(5) NREGA Work Days	(6) NREGA Work Days
Internet	-0.028**	-0.056*	-0.013	-0.067	-0.494	-0.074
	(0.011)	(0.031)	(0.054)	(0.050)	(0.317)	(0.050)
Muslim × Internet			-0.056	-0.109**	0.221***	-0.125***
			(0.047)	(0.047)	(0.065)	(0.047)
Muslim Pres. × Muslim × Internet						0.417***
						(0.086)
Observations	6,697	1,128	6,865,104	5,589,676	487,120	6,091,712
GP president	All	All	All	Non-Muslim	Muslim	All
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period	2017-2022	2017	2019-2022	2019-2022	2019-2022	2019-2022

Notes: Columns 1 and 2 estimate model (1) at the GP-year level. The outcome is the share of Muslims among newly registered households in NREGA. Columns 3-5 estimate model (2) at the individual-year level. The outcome is the natural logarithm of one plus the number of workdays allocated within NREGA. Column 6 estimates model (3). Standard errors are clustered at the GP-year level for columns 3-6. All specifications include 20km segment fixed effects and are restricted to a bandwidth of 10km. Triangular kernel weights are applied. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$

Table 5: Internet and Voting

	(1) Hindutva-Shift	(2) Secular Votes	(3) Muslim Cand.	(4) BJP	(5) INC
	Panel A: All Villages				
Internet	0.056**	-0.032**	0.002***	0.024	-0.033***
	(0.027)	(0.012)	(0.000)	(0.019)	(0.012)
Muslim × Internet	-0.174***	0.123***	0.001**	-0.051	0.131***
	(0.058)	(0.024)	(0.001)	(0.049)	(0.022)
Observations	3,240	3,240	3,240	3,240	3,240
	Panel B: Non-Muslim Village				
Internet	0.081**	-0.031**	0.001***	0.049*	-0.028*
	(0.038)	(0.015)	(0.000)	(0.030)	(0.015)
Observations	1,187	1,187	1,187	1,187	1,187
	Panel C: Muslim Village				
Internet	0.018	-0.013	0.003***	0.005	-0.015
	(0.036)	(0.017)	(0.000)	(0.024)	(0.017)
Observations	2,044	2,044	2,044	2,044	2,044
	Panel D: Minority Muslim Village				
Internet	0.069	-0.065***	0.002***	0.004	-0.065***
	(0.046)	(0.023)	(0.000)	(0.028)	(0.023)
Observations	1,317	1,317	1,317	1,317	1,317
	Panel E: Majority Muslim Village				
Internet	-0.083	0.059***	0.003***	-0.024	0.047**
	(0.058)	(0.021)	(0.001)	(0.051)	(0.020)
Observations	724	724	724	724	724

Notes: Panel A estimates model (2) at the polling station level in Jharkhand. Panel B estimates model (1) on different subsets. In particular, polling stations located in non-Muslim villages (Panel B), Muslim villages (Panel C), and villages with a Muslim share below (Panel D) and above (Panel E) state average. The outcome in column 1 is the number of votes for Hindutva parties minus the number of votes for secular parties as a share of total votes. Column 2 assesses the impact on the vote share of secular parties, column 3 on the vote share of Muslim candidates, column 4 on the vote share of the BJP (the main Hindutva party) and column 5 on the vote share of the INC (the main secular party). All specifications include 20km segment fixed effects and are restricted to a bandwidth of 10km. Triangular kernel weights are applied. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$

Table 6: Internet and Economic Effects

	(1) BPL	(2) Wealth	(3) BPL	(4) Wealth
	India		*Jharkhand*	
Internet	-0.013	50.818*	-0.036	-142.152
	(0.017)	(30.674)	(0.064)	(102.243)
Muslim × Internet	0.043*	75.029	0.195***	-56.591
	(0.026)	(54.515)	(0.072)	(108.823)
Observations	288,866	289,380	26,557	26,614
Segment FE	Yes	Yes	Yes	Yes
Internet			-0.043	-162.923
			(0.063)	(108.137)
Muslim × Internet			0.181***	-71.077
			(0.069)	(116.716)
Muslim Pres. × Muslim × Internet			0.056	30.975
			(0.197)	(198.850)
Observations			26,557	26,614
Segment FE			Yes	Yes

Notes: The upper panel estimates model (2) at the individual level; the bottom panel estimates model (3). The outcome is a dummy denoting whether a household owns a below poverty line card in columns 1 and 3. The outcome is the rural DHS-Wealth index for columns 2 and 4. Columns 1-2 are estimated on the full sample, columns 3-4 only consider Jharkhand for comparability. All specifications include 20km segment fixed effects, are restricted to a bandwidth of 10km, and standard errors are clustered at the DHS-cluster level. Triangular kernel weights are applied. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$

Appendix

Table 7: Summary Statistics

	N	Sum	Mean	SD	Min	Max
	Panel A: India					
Early Phase	174,736	93,687	0.54	0.50	0	1
Distance (km)	174,736	2,196,091	12.57	72.68	-368.02	1,662.12
Absolute Distance (km)	174,736	6,452,036	36.92	63.85	0.01	1,662.12
Assaults (ln)	175,157	1,531.90	0.01	0.14	0	7.39
Δ Assaults (ln)	174,421	1,208.14	0.01	0.12	0	6.83
BJP Riots (ln)	175,157	449.86	0.003	0.06	0	3.26
BJP Mobs (ln)	175,157	403.15	0.002	0.05	0	3.22
INC Riots (ln)	175,157	191.18	0.001	0.03	0	1.95
INC Mobs (ln)	175,157	145.85	0.001	0.03	0	1.61
Wealth	2,062,660	1.05e+08	50.69	1,005.80	-2,556.24	3,186.81
BPL	2,059,595	1,105,883	0.54	0.50	0	1
	Panel B: Jharkhand					
Early Phase	4,336	2,797	0.65	0.48	0	1
Distance (km)	4,336	50,698	11.69	24.43	-62.05	84.69
Absolute Distance (km)	4,336	91,483.77	21.10	16.99	0.03	84.69
Assaults (ln)	4,337	65.62	0.02	0.16	0	2.56
Δ Assaults (ln)	4,304	49.32	0.01	0.14	0	2.20
BJP Riots (ln)	4,337	10.40	0.002	0.04	0	0.69
BJP Mobs (ln)	4,337	10.40	0.002	0.04	0	0.69
INC Riots (ln)	4,337	3.47	0.001	0.02	0	0.69
INC Mobs (ln)	4,337	3.47	0.001	0.02	0	0.69
Registration Muslim Sh.	21,242	2,684.32	0.13	0.21	0	1
NREGA Work Days (ln)	19,951,740	2.23e+07	1.12	1.72	0	5.55
Hindutva Shift (Sh.)	29,147	9,458.32	0.32	0.43	-1	1
Secular Votes (Sh.)	29,147	5,270.35	0.18	0.24	0	1
Muslim Cand. (Sh.)	29,147	71.26	0.002	0.007	0	0.27
BJP (Sh.)	29,147	14,728.67	0.51	0.29	0	1
INC (Sh.)	29,147	4,758.19	0.16	0.24	0	1
Wealth	81,467	-5.78e+07	-709.75	854.84	-2,526.35	2,764.01
BPL	81,329	53,759	0.66	0.47	0	1

Notes: This table shows summary statistics for the full sample in Panel A and Jharkhand in Panel B. Early Phase is a binary variable equal to one if a GP got internet in phase I, and zero if in phase II. Distance (km) denotes the distance (phase I: kilometer, phase II: kilometer$\times(-1)$) from the GP to the closest point on the boundary. Assaults captures (the change of) the natural logarithm of one plus the number of assaults. Riots captures the natural logarithm of one plus the number of riots by supporters of the BJP or INC. Mobs are a subset of riots. Registration Muslim Sh. captures the share of Muslims among newly registered households within a year and GP in NREGA. NREGA work days denote the natural logarithm of one plus the number of NREGA work days allocated to a household per year. Hindutva shift captures the number of BJP votes minus the number of votes for secular parties as a share of total votes. Secular votes is the share of votes to the INC, All India Trinamool Congress, Communist Party of India, Communist Party of India (Marxist, Liberation), Communist Party of India (Marxist-Leninist, Red Star). Muslim Cand. is the share of votes for Muslim candidates irrespective of the party. Wealth and BPL are based on the DHS (2019-2021) wave. Wealth denotes the rural DHS-Wealth index. BPL is a binary variable denoting whether a DHS-household has a below poverty line card.

Table 8: Balance Table, Pre-Treatment, Full Sample

	Panel A: India			*Panel B: Jharkhand*		
	Early Phase	Late Phase	Diff.	Early Phase	Late Phase	Diff.
Total Population	3316.2	2698.2	618.0***	3894.7	2525.5	1369.1*
No. of Households	672.7	558.3	114.4***	728.2	490.3	238.0
Literate Population	2171.4	1641.5	529.9***	2417.5	1358.7	1058.8*
Scheduled Caste Population	538.5	430.8	107.7***	477.1	292.0	185.1***
Scheduled Tribe Population	243.4	224.5	18.9***	568.3	660.9	-92.5
No. of Primary Schools	2.3	2.1	0.2***	1.9	1.7	0.2
No. of Middle Schools	1.2	0.9	0.3***	1.3	1.0	0.3
No. of Secondary Schools	0.6	0.4	0.2***	0.4	0.3	0.1*
No. of Senior Secondary Schools	0.3	0.2	0.1***	0.1	0.1	0.0
No. of Colleges	0.1	0.1	0.0***	0.0	0.0	0.0
Assault	0.1	0.1	-0.0	0.0	0.0	-0.0
Violent Protest	0.0	0.0	0.0	0.0	0.0	0.0
Peaceful Protest	0.0	0.0	-0.0	0.0	0.0	0.0

Notes: Columns 1 and 2 report means for phase I and phase II GPs. Column 3 reports the difference between phase I and phase II. Stars denote p-values from a t-test, where $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$. Columns 4-6 repeat the exercise for GPs in Jharkhand.

Table 9: Balance Test, Pre-Treatment, 5km Bandwidth

	Panel A: India			*Panel B: Jharkhand*		
	Early Phase	Late Phase	Diff.	Early Phase	Late Phase	Diff.
Total Population	2260.9	2288.7	-27.7	2538.5	2989.3	-450.8
No. of Households	435.7	438.6	-2.8	480.0	581.8	-101.7
Literate Population	1351.9	1362.2	-10.3	1421.8	1552.3	-130.5
Scheduled Caste Population	409.0	391.7	17.3	351.1	297.3	53.8
Scheduled Tribe Population	171.0	172.7	-1.7	565.1	553.5	11.6
No. of Primary Schools	1.7	1.7	0.1	1.6	1.6	-0.0
No. of Middle Schools	0.9	0.8	0.1*	0.9	0.9	-0.1
No. of Secondary Schools	0.4	0.3	0.0*	0.3	0.2	0.1
No. of Senior Secondary Schools	0.2	0.2	0.0*	0.1	0.1	-0.0
No. of Colleges	0.0	0.0	-0.0	0.0	0.0	-0.0
Assault	0.0	0.1	-0.0	0.0	0.0	0.0
Violent Protest	0.0	0.0	-0.0	0.0	0.0	0.0
Peaceful Protest	0.0	0.0	-0.0	0.0	0.0	0.0

Notes: Columns 1 and 2 report means for phase I and phase II GPs located within 5km of the boundary. Column 3 reports the difference between phase I and phase II. Stars denote p-values from a t-test, where $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$. Columns 4-6 repeat the exercise for GPs in Jharkhand.

Table 10: Test for other Discontinuities - Other

	(1) Nightlights	(2) Avg. Nightlights	(3) Electricity	(4) Rural Consumption	(5) PMGSY Timing	(6) PMGSY Length
	Panel A: India					
Early Phase	-0.002	0.008	0.000	51.517	65.566	-0.193
	(0.021)	(0.012)	(0.006)	(59.252)	(66.312)	(0.226)
Observations	48616	48616	42296	48081	6700	5724
	Panel B: Jharkhand					
Early Phase	0.116	0.039	0.000	-424.857	-551.968	-0.965
	(0.146)	(0.091)	(.)	(355.860)	(344.055)	(1.426)
Observations	1162	1162	21	1106	309	219

Notes: This table tests for pre-existing discontinuities at the boundary. It estimates the main coefficient of interest (β_1) of model Y for a number of outcomes from SHRUG. The model is estimated at the GP level, restricted to locations less than 10km away from the boundary. Panel A reports coefficients for the full sample and includes 20km segment and state fixed effects. Panel B is restricted to Jharkhand and includes 20km segment fixed effects. Observations are weighted using triangular kernel weights. $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$

Table 11: Internet and Conflict, Robustness

	(1) Assault	(2) Δ Assault	(3) BJP Riot	(4) BJP Mob	(5) INC Riot	(6) INC Mob
	Panel A: Change in Tribal Population, Control					
Internet	0.419*	0.358	0.120***	0.112**	-0.098	-0.111*
	(0.251)	(0.220)	(0.045)	(0.044)	(0.061)	(0.059)
Observations	54,615	54,398	54,615	54,615	54,615	54,615
	Panel B: Change in Nr. of Colleges, Control					
Internet	0.417*	0.342	0.115**	0.109**	-0.099	-0.109*
	(0.251)	(0.220)	(0.045)	(0.044)	(0.061)	(0.059)
Observations	54,555	54,341	54,555	54,555	54,555	54,555

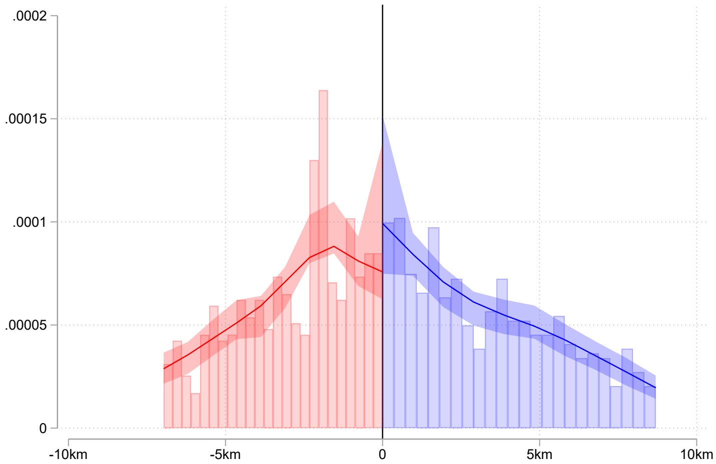
Notes: This table re-estimates Table (3) including the change in the tribal population (Panel A) and the change in the number of colleges (Panel B) as control variables. All coefficients are multiplied by 100. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$

Table 12: Internet and Conflict, Bandwidths

	(1) Assault	(2) Δ Assault	(3) BJP Riot	(4) BJP Mob	(5) INC Riot	(6) INC Mob
	Panel A: India					
Internet	0.571*	0.492*	0.098*	0.098*	-0.132*	-0.134*
	(0.330)	(0.289)	(0.053)	(0.053)	(0.075)	(0.072)
Observations	43,169	42,993	43,169	43,169	43,169	43,169
BW	7.5km	7.5km	7.5km	7.5km	7.5km	7.5km
Internet	0.499*	0.430*	0.111**	0.104**	-0.095	-0.108*
	(0.267)	(0.234)	(0.044)	(0.043)	(0.060)	(0.058)
Observations	55,707	55,487	55,707	55,707	55,707	55,707
BW	10km	10km	10km	10km	10km	10km
Internet	0.485**	0.396**	0.095**	0.087**	-0.075	-0.082*
	(0.229)	(0.202)	(0.038)	(0.037)	(0.052)	(0.050)
Observations	66,387	66,099	66,387	66,387	66,387	66,387
BW	12.5km	12.5km	12.5km	12.5km	12.5km	12.5km
	Panel B: Jharkhand					
Internet	18.758***	18.628***	3.678**	3.678**	-0.161	-0.161
	(5.703)	(5.727)	(1.453)	(1.453)	(0.100)	(0.100)
Observations	957	950	957	957	2,147	2,147
BW	7.5km	7.5km	7.5km	7.5km	17.5km	17.5km
Internet	12.785***	13.075***	3.006***	3.006***	-0.099	-0.099
	(4.093)	(4.099)	(1.049)	(1.049)	(0.069)	(0.069)
Observations	1,294	1,287	1,294	1,294	2,372	2,372
BW	10km	10km	10km	10km	20km	20km
Internet	8.892***	9.835***	2.364***	2.364***	-0.044	-0.044
	(3.183)	(3.156)	(0.829)	(0.829)	(0.047)	(0.047)
Observations	1,613	1,602	1613	1,613	2,593	2,593
BW	12.5km	12.5km	12.5km	12.5km	22.5km	22.5km
Internet	4.389**	5.386***	1.317***	1.317***	-0.099	-0.099
	(1.981)	(1.945)	(0.507)	(0.507)	(0.069)	(0.069)
Observations	2,372	2,353	2,372	2,372	2,372	2,372
BW	20km	20km	20km	20km	20km	20km

Notes: This table re-estimates Table (3) applying different bandwidths. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$

Figure 5: Density around the Cutoff



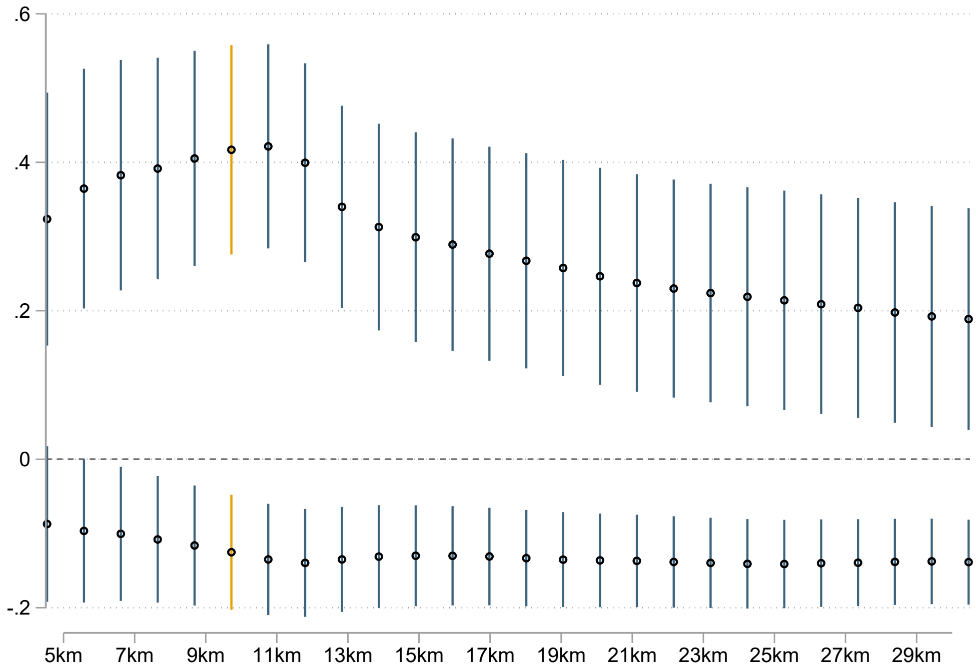
Notes: The figure shows the density of the observations (NREGA GPs in Jharkhand) with respect to their distance to the boundary. It tests whether there are significant differences in the density around the cutoff following Cattaneo *et al.* (2020). There is no evidence for a significant difference (p-value = 0.15).

Table 13: Internet and Public Works, Bandwidths

	(1) Registration: Muslim Share	(2) Registration: Muslim Share	(3) Work Days	(4) Work Days	(5) Work Days	(6) Work Days
Internet	-0.026*	-0.053	0.017	-0.057	-0.926**	-0.074
	(0.014)	(0.038)	(0.064)	(0.061)	(0.430)	(0.060)
Muslim × Internet			-0.058	-0.079	0.200***	-0.103*
			(0.052)	(0.052)	(0.069)	(0.053)
Muslim Pres. × Muslim × Internet						0.386***
						(0.092)
Observations	5,133	864	5,359,580	4,368,508	386632	4,755,140
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
BW	7.5km	7.5km	7.5km	7.5km	7.5km	7.5km
Internet	-0.028**	-0.056*	-0.013	-0.067	-0.494	-0.074
	(0.011)	(0.031)	(0.054)	(0.050)	(0.317)	(0.050)
Muslim × Internet			-0.056	-0.109**	0.221***	-0.125***
			(0.047)	(0.047)	(0.065)	(0.047)
Muslim Pres. × Muslim × Internet						0.417***
						(0.086)
Observations	6,697	1,128	6,865,104	5,589,676	487,120	6,091,712
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
BW	10km	10km	10km	10km	10km	10km
Internet	-0.021**	-0.050*	-0.034	-0.050	-0.319	-0.055
	(0.010)	(0.027)	(0.048)	(0.044)	(0.273)	(0.044)
Muslim × Internet			-0.074*	-0.125***	0.223***	-0.138***
			(0.043)	(0.043)	(0.062)	(0.044)
Muslim Pres. × Muslim × Internet						0.363***
						(0.082)
Observations	8,059	1,369	8,254,524	6,628,000	691,708	7,347,460
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
BW	12.5km	12.5km	12.5km	12.5km	12.5km	12.5km

Notes: This table re-estimates Table (4) for different bandwidths. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$

Figure 6: Internet and Public Works, Bandwidths



Notes: This figure re-estimates Table (4), column 6 for different bandwidths starting at 5km and moving in 1km steps to 30km. It presents the two coefficients of interest β_2 and β_3 based on model (3). 90% confidence intervals are displayed.

Table 14: Internet and Public Works, Robustness

	(1) Registration: Muslim Share	(2) Registration: Muslim Share	(3) Work Days	(4) Work Days	(5) Work Days	(6) Work Days
	Panel A: Main Specification					
Internet	-0.028**	-0.056*	-0.013	-0.067	-0.494	-0.074
	(0.011)	(0.031)	(0.054)	(0.050)	(0.317)	(0.050)
Muslim × Internet			-0.056	-0.109**	0.221***	-0.125***
			(0.047)	(0.047)	(0.065)	(0.047)
Muslim Pres. × Muslim × Internet						0.417***
						(0.086)
Observations	6,697	1,128	6,865,104	5,589,676	487,120	6,091,712
FE	Segment	Segment	Segment	Segment	Segment	Segment
	Panel B: Uniform Weights					
Internet	-0.020*	-0.049*	-0.071	-0.059	-0.373	-0.058
	(0.010)	(0.027)	(0.050)	(0.047)	(0.302)	(0.046)
Muslim × Internet			-0.078*	-0.174***	0.255***	-0.180***
			(0.041)	(0.041)	(0.060)	(0.042)
Muslim Pres. × Muslim × Internet						0.511***
						(0.081)
Observations	6,697	1,128	6,865,104	5,589,676	487,120	6,091,712
FE	Segment	Segment	Segment	Segment	Segment	Segment
	Panel C: Second-Order Polynomial					
Internet	-0.021	-0.045	-0.105	-0.066	-0.447	-0.124
	(0.020)	(0.052)	(0.087)	(0.089)	(0.350)	(0.085)
Muslim × Internet			-0.056	-0.107**	0.219***	-0.125***
			(0.047)	(0.047)	(0.065)	(0.047)
Muslim Pres. × Muslim × Internet						0.417***
						(0.086)
Observations	6,697	1,128	6,865,104	5,589,676	487,120	6,091,712
FE	Segment	Segment	Segment	Segment	Segment	Segment

Notes: This table re-estimates Table (4) applying uniform weights (Panel B) and a quadratic RD polynomial (Panel C). $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$