Online Appendix

Spatial and Historical Drivers of Fake News Diffusion:
Evidence from Anti-Muslim Discrimination in India

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A Data Appendix

A.1 Details on fake news and keywords

In this section, we report the list of fake news we collected from the website AltNews (Table A1) and the full list of English keywords we employed to identify tweets reporting fake news (Table A2). These keywords were also translated in other 11 languages. Keywords in other languages are availble upon request. Finally, in Table A3 we report a list of keywords that we have used to identify tweets associated with other events that occurred in the weeks following the Tablighi shock.[1] If a tweet contains any of these keywords, we never include it in the sample of tweets reporting fake news related to the *Tablighi Jamaat* Convention.

[1] Around April 11, the end of the lockdown was approaching and many states started discussing about extending the lockdown. Around April 16, Babita Phogat (a famous wrestler and politician) posted a controversial anti-Muslim tweet that sparked a heated debate. On the same date, 73 cops were quarantined in Moradabad, a city in Uttar Pradesh with a long history of Hindu-Muslim riots. Finally, around April 27, Tablighi participants who had recovered from COVID-19 volunteered to donate their blood for plasma therapy for the treatment of other patients.

Table A1: Fake News with ”Muslim” in the Title or Abstract

Date	Origin	Fake News
02Mar		Suresh Chavhanke falsely claims Muslim community in Paris torched railway station
02Mar		Muslim girl raped by Hindu mob in Delhi? Pak propaganda website runs fake news
02Mar		Muslim shops sell biryani laced with birth control pills to Hindus? Fictional story viral
04Mar		AAP offers monetary relief to only Muslim victims of Delhi riots? Dainik Jagran clipping morphed
12Mar	05Mar	Delhi riots: Times Now misreports man firing at Muslim mob as attack on police
13Mar		First Muslim woman SP in Maharashtra? No, image of Women's Day celebration viral
16Mar	14Mar	Public TV falsely claims Muslim youths in Karnataka refuse coronavirus testing for "religious reasons"
30Mar		Old, unrelated video shared as Muslims licking utensils to spread coronavirus infection
01Apr		Video of Sufi ritual falsely viral as mass sneezing in Nizamuddin mosque to spread coronavirus infection
02Apr		Old video falsely viral as Muslim man spitting on food at Indian restaurant in the backdrop of coronavirus pandemic
02Apr		Coronavirus: Video of an undertrial in Mumbai falsely viral as Nizamuddin markaz attendee spitting at cop
04Apr		Video of Muslim vendor's unhygienic handling of fruits falsely linked with spreading coronavirus
04Apr		Old video of racist heckling falsely viral as Muslim man spits on passenger in New York metro
05Apr		Viral audio: False conspiracy theory about Modi govt introducing 'vaccine' to kill Muslims
06Apr		Video from Pakistan falsely viral as Muslims punished in India
06Apr		Video of Muslims exiting quarantine centre: Not Vinayaka Temple but residential lodging
07Apr		Old video from Philippines shared with false claim of Muslim man spitting on bread
07Apr		Viral audio falsely claims Muslim vendors have sprung up in Surat to spread coronavirus
08Apr		Old video where salon attendant applies saliva on customer's face falsely shared with Muslim angle
09Apr		Communal attack in Bawana shared with false claim of Muslim man injecting fruits with spittle
09Apr		Death of health worker in MP falsely communalised as attack by Muslims in UP ”Islamic jihadis”
11Apr		Video viral with false claim that Muslims scatter notes on the road to spread coronavirus
11Apr		Video from Pak falsely linked with Hindu man's alleged murder by Muslim men in Rajasthan
13Apr		Alt News video verification: Muslim vegetable vendor assaulted in Badarpur, Delhi
13Apr		UP police's mock drill video shared as 'corona Jihadis' arrested during lockdown
14Apr		Image of Muslims offering namaz on rooftops in groups is from Dubai
15Apr	06Apr	Video of fruit vendors in Indore shared with false anti-Muslim angle
15Apr	13Apr	Pakistani Mufti provoking people to flout lockdown shared to target Indian Muslims
16Apr	13Apr	Video of women spitting inside houses in Rajasthan's Kota given false Muslim angle
18Apr		False claim suggests Bandra mass gathering accused Vinay Dubey's father is Muslim
20Apr		Video of currency notes in Indore falsely viral as 'Muslim conspiracy' to spread coronavirus
20Apr		Videos viral with false claim of poor slum dwellers and Muslims hoarding food in Meerut
24Apr	21Apr	Video from Bijnor viral with false allegation that elderly Muslim vendor sprinkled urine on fruits
27Apr		Disabled Muslim man hounded for accidentally dropping currency, accused of spreading coronavirus
27Apr		Zee News publishes 2015 story with false claim of human faeces served to 'non-Muslims'
29Apr		Old video falsely shared as Muslims spitting on relief food during lockdown

Notes: The Table reports the list of fake news containing the keyword "Muslim" in their titles or excerpts, as reported by the popular Indian fact-checking website AltNews in March and April 2020. For each fake news more details can be seen by clicking on the green link. In red we highlight keywords that directly refer to Muslims as vehicle of COVID-19 contagion.

Table A2: English Fake News Keywords

#BioJihad	#BiologicalJihad	#coronaJehad	#IslamicCoronaJehad
#Islamiccoronavirusjihad	#IslamicRepublicVirus	#IslamicVirus	#jahiljamati
#JamaatKaCoronaDisaster	#JamaatkiGundagardi	#JamaatKoBanKaro	#JAMATI_CORONA_JEHAD
#JamatVirus	#JehadiVirus	#JihadiJamat	#MarkazCOVIDSpread
#MuslimsSpreadingCorona	#muslimvirus	#MuslimVirus	#NizamuddinIdiots
#NizamuddinMarkaj	#nizamuddinterrorists	#QuranaVirus	#TablighiJamatVirus
#TablighisInHiding	bio jihad	biological jihad	Corona J-had
corona jihaad	corona jihad	covid jehad	covid J-had
covid jihaad	covid jihad	covidjehad	covidjihad
islamic virus	jamat virus	jehad jamat	jihaad jamat
jihad jamat	muslim corona	Muslim infect	muslim infected
muslim infecting	muslim infects	muslim lick	muslim licked
muslim licking	muslim licks	Muslim pee	muslim peeing
muslim pees	muslim spat	Muslim spit	muslim spits
muslim spitting	Muslim sprinkle	muslim sprinkled	muslim sprinkles
muslim sprinkling	muslim stones	Muslim urine	muslim virus
muslims corona	muslims infect	muslims infected	muslims infecting
muslims lick	muslims licked	muslims licking	muslims pee
muslims peed	muslims peeing	muslims spit	muslims spitted
muslims spitting	muslims spread	muslims spreaded	muslims spreading
muslims sprinkle	muslims sprinkled	muslims sprinkling	muslims stones
muslims urine	muslin peed	Nizammuddin jihad	qurana virus
Tablighi excreted	Tablighi crime	Tablighi grope	Tablighi harass
tablighi harassed	tablighi harassing	Tablighi lewd	Tablighi naked
tablighi virus	Tabligi 1000 positive	#IslamicJihad	muslim jihad
CrushTablighiSpitters	tableeghi	CoronaBombsTablighi	markazcovidspread
Tablighi Talibani crime	CoronaTerrorism	jihadi weapon	MuslimMeaningTerrorist
corona bomb	islamiccoronajehad	jamaatkacoronadisaster	nizamuddincoronacases
crushtablighispitters	jihadivirus	markaznizamuddin	nijamuddinmarkaz
nizammudin	nizamuddinfiasco	nizamuddinmarkaz	tableeghijamaat
tableegi	tablighijamat	tablighijammat	tablighis
tablighivirus	tablighjamaat	tablighsuperspreader	tabligi
terrorist tablighi	tabligih traitors	bantablighdebate	markazvirus
MuslimDistancing	human bombs		

Notes: The Table reports the list of keywords used to identify anti-Muslim fake news in our sample of tweets. We converted all keywords to lower-case and we removed hyphens and underscores. Note that some of the keywords consists of multiple tokens. In these cases, we searched all their possible permutations, allowing for any number characters to separate two tokens. First, we searched the keywords in the text of the tweet; in this case we added a regex anchor for the word boundary in front of each tokens. Then, we separataly searched the keywords in the set of hashtags for each tweet; in this case, we omitted the regex anchor.

Table A3: Hashtags related to other events

#Tablighi_donating_plasma	#Tablighiheros	#TablighiHeros	#TablighiJamaatHeroes
#TablighiJamaatPlasma	#Tabligi_Hereos	#Tabligi_Heroes	#tabligiHeros
#TabligiHerose	#TabligiJamaatherous	#TabligiJamaatPlasma	#TabligiPlasmaDonaters
#tabligshero	#Plasma	#PlasmaTherapy	#TablighiJamaatPlasma
#Tabligi_Hereos	#Tabligi_Heroes.	#tabligiHeros	#TabligiHerose
#TabligiJamaatherous	#TabligiJamaatPlasma	#TabligiPlasmaDonaters	#tabligshero
#Plasma	#PlasmaTherapy	#LockdownExtended	#Lockdownextention
#lockdownextension	#LockdownKeDushman	#LockdownkeDusman	#CoronaWarriors
#lockdownhustle	#Lockdown2	#ISupportBabitaPhogat	#ISupport_BabitaPhogat
#babitaphogat	#iSupportBabitaPhogat	#DontSuspendBabitaPhogat	#ISupportBabitaPhogatTruth
#SuspendBabitaPhogat	#SupportBabitaPhogat	#babitaphogatrashtrbhakt	#IsupportBabitaFogat
#SupportBabitaphogat	#geeta_phogat	#IndiaSupportsBabitaPhogat	#IStandwithBabitaPhoghat
#ISuportBabitaPhogat	#ISupport_BabitaPhogat.	#suspendedbabitaphogat	#suspendgeetaPhogat
#DontSuspendBabitaPhogat	#Moradabad	#Muradabad	#MoradabadViolence
#muradabad			

Notes: The Table reports the list of hashtags used to identify tweets associated with other events that occurred in the weeks following the Tablighi shock.

A.2 Summary Statistics

Table A4: Summary Statistics

Variable	Obs	Mean	Std dev	Median	Min	Max
Time-variant Variables, 3 days:						
N. Tweets Anti-Muslim Fake News	3756	3.04	19.7	0	0	552
Share Tweets Anti-Muslim Fake News	3352	0.012	0.033	0	0	0.7143
New COVID Deaths	3756	0.014	0.17	0	0	5
Time-variant Variables, 7 days:						
N. Tweets Anti-Muslim Fake News	8764	2.08	14.6	0	0	552
Share Tweets Anti-Muslim Fake News	7828	0.0082	0.027	0	0	0.71
New COVID Deaths	8764	0.012	0.17	0	0	8
Dist. New Delhi (x1000)	8764	0.98	0.56	0.95	0.0093	2.26
New Delhi Region	8764	0.034	0.18	0	0	1
Time invariant variables:						
Delhi Dummy	8764	0.0016	0.040	0	0	1
Std.Twitter Conn. to Delhi	8750	-0.000000015	1.00	-0.095	-1.03	4.56
Std.Born in Delhi	8750	-1.9e-10	1.00	-0.18	-0.20	14.2
Muslim Attack	8764	0.14	0.34	0	0	1
Non-Muslim Attack	8764	0.070	0.26	0	0	1
ln(0.01+Luminosity)	8764	0.70	1.49	1.01	-4.61	4.14
ln(Population density), 1990	8764	5.50	1.16	5.57	-1.44	10.6
Ln Sh.Muslim	8764	-2.77	1.29	-2.57	-6.10	-0.015
Ln Sh.Hindu	8764	-0.50	0.90	-0.16	-4.76	-0.0061
Ln Sh.Literated Pop. (2011)	8764	-0.47	0.17	-0.47	-1.21	-0.11
Ln Sh.Urban Pop. (+0.01 2011)	8764	-1.58	0.72	-1.57	-4.61	0.0100
N.Tweets pre-shock	8764	207.8	906.0	48.6	0	15383.7
Latitude	8764	23.4	5.74	24.6	8.31	34.5
Longitude	8764	81.1	6.26	79.2	69.8	96.8
Altitude	8764	486.9	718.0	253.1	4	4914.9
Ruggedness	8764	102007.0	165566.0	35094.4	773.7	851959.5
Precipitation	8764	1354.3	675.0	1161.6	200.2	4245.3
Land quality	8764	0.46	0.29	0.53	0	0.97
Dry rice suitability	8764	620.7	591.4	789.3	0	1722.7
Wet rice suitability	8764	1430.1	791.5	1403.3	0	2826.9
Wheat suitability	8764	636.8	578.7	608.9	0	2914.7
Malaria risk	8764	0.11	0.33	0.033	0	2.81
Dist. Muslim (x1000)	8764	494.7	446.5	385.2	0	1862.8
Distance: Border	8764	402403.3	473726.9	218057.5	0	1862808.9
Clinics per 1K inh.	8764	3.20	38.7	0.30	0.034	892.9
Doctors per 1K inh.	8764	0.31	0.27	0.25	0.0029	3.32
Hospital Doctors per 1K inh.	8764	0.068	0.12	0.041	0	2.46
Paramed. per 1K inh.	8764	0.89	0.77	0.72	0.0058	7.75
Hospitals per 1K inh.	8764	0.013	0.017	0.0072	0.00029	0.17
COVID tests per 1K (5Apr)	8764	1.06	2.25	0	0	18.8
Police per 1K inh.	8764	0.0039	0.019	0.00060	0	0.37
Police per 1K inh. (Passport)	8764	0.014	0.016	0.011	0.00054	0.13
Neolithic settlements	8764	0.38	1.58	0	0	20
Chacolithic settlements	8764	0.31	1.42	0	0	19
Cultural sites (300-700 CE)	8764	0.16	0.46	0	0	4
Cultural sites (8th-12th centuries)	8764	0.69	1.25	0	0	10
Ln(1+ Urban population in 1000)	8764	0.071	0.89	0	0	11.5
Distance: Coast	8764	410445.1	342190.6	333208.2	0	1246877.5
River	8764	0.60	0.49	1	0	1
Irrigation Potential	8652	0.20	0.33	0.00053	0	1
CV Rainfall : Delaware	8764	0.23	0.072	0.22	0.095	0.53
Percent Forest	8764	21.3	24.5	11.3	0	94.0
ln Distance Petroleum	8764	5.48	0.77	5.63	1.78	6.69
ln Distance Diamond: Primary	8764	6.69	0.56	6.83	3.71	7.48
ln Distance Gem	8764	4.96	0.87	5.09	2.21	6.35
ln Distance Gold Placer	8764	6.30	0.71	6.55	3.54	7.17
British direct rule	8428	0.65	0.48	1	0	1
years_british	8764	87.9	72.7	112	0	286
Year of First Railroad	6706	1886.2	18.0	1886	1853	1931
Medieval port	8764	0.064	0.24	0	0	1
Duration of Muslim rule	8764	368.3	235.7	387	0	995
Religious Polarization	8764	0.47	0.26	0.44	0.024	0.99
Linguistic fractionalization	8764	0.46	0.28	0.47	0.014	4.21
Religious fractionalization	8764	0.26	0.16	0.23	0.012	0.72
Scheduled Caste share	8764	0.15	0.091	0.16	0	0.50
Scheduled Tribe share	8764	0.18	0.27	0.044	0	0.99
Ganges	8764	0.083	0.28	0	0	1
Roads (Kms)	8764	688.8	497.1	567.5	0	3062.6
Railroad (Kms)	8764	101.5	96.2	84.7	0	599.4

Notes: The Table reports the number of nonmissing observations and the summary statistics (mean, standard deviation, median, minimum and maximum) for the variables used in our analysis.

A.3 Twitter Connectedness and Physical Distance between Indian Districts

Following Bailey et al. (2020) in this Section we study more systematically the relationship between Twitter connectedness and physical distance in Indian districts. To do this, we constructed the entire district-to-district matrix of social media interactions between district-pairs and estimate the following equation:

$$log(TwitterConnectedness_{i,j}) = \beta log(Distance_{i,j}) + \phi \mathbf{X}_{i,j} + \gamma_i + \delta_j + \varepsilon_{i,j}$$

where $log(TwitterConnectedness_{i,j})$ is the log of Twitter connectedness of district i to district j (for each $i \neq j$), computed as the share of replies and quotes posted in district i in response to tweets originally posted in district j, over the period from December 1, 2019 to January 31, 2020, $log(Distance_{i,j})$ denotes the log of the geographic distance between the centroids of districts i and j, $X_{i,j}$ include measures of the dissimilarity of the two districts along baseline socio-economic dimensions (i.e., the log of luminosity (+0.01) averaged between 1992-2010, the log of population density in 1990, the log share of Muslim and Hindu population in 2011, the log share of literate and urban population in 2011, and the average number of tweets before March 31).[2] Moreover, we control for a dummy taking the value one if both districts ever experienced a Muslim attack and for a dummy taking the value one if both districts ever experienced a precolonial conflict in which Muslim groups were not the aggressors. To account for district-specific unobserved characteristics, we add γ_i and δ_j fixed effects for districts i and j, respectively.

Table A5 shows the regression results, which progressively add to the unconditional specification in column 1 the district fixed effects (column 2) and the control variables (columns 3 to 5). Across all specifications, Twitter connectedness is negatively correlated with distance, corroborating the idea that Twitter connections are less frequent between pairs of individuals who live far apart from each other.

[2] Dissimilarity is computed by taking the absolute value of the difference between the value of the variable in district i and the value of the variable in district j. Details and sources on all baseline control variables are reported in Section 4, footnote 24, and Appendix A.2.

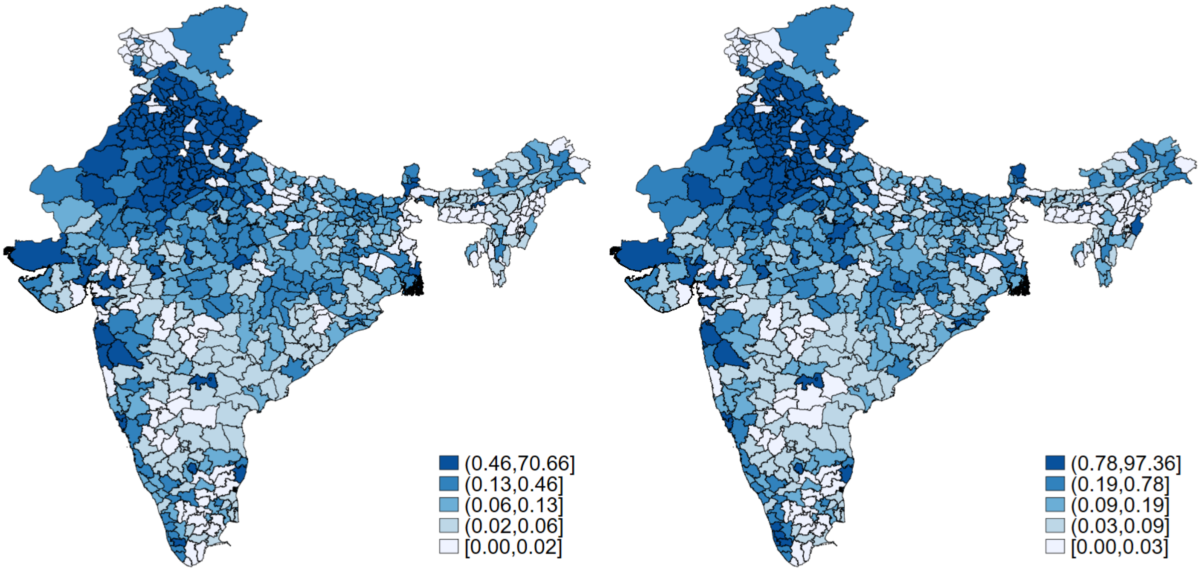
Table A5: Twitter Connectedness and Physical Distance between Indian Districts

Dep.Var.:	Ln Twitter Connectedness				
	(1)	(2)	(3)	(4)	(5)
Log. Distance	-0.15***	-0.15***	-0.12***	-0.12***	-0.12***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Diff. Log Lights			-0.06***	-0.03**	-0.03*
			(0.02)	(0.02)	(0.02)
			[0.00]	[0.04]	[0.05]
Diff. Pop. Density			-0.12***	-0.07***	-0.07***
			(0.03)	(0.01)	(0.01)
			[0.00]	[0.00]	[0.00]
Diff. Literacy			-0.28***	-0.32***	-0.32***
			(0.07)	(0.07)	(0.07)
			[0.00]	[0.00]	[0.00]
Diff. Urbanisation			-0.30***	-0.16***	-0.16***
			(0.08)	(0.04)	(0.04)
			[0.00]	[0.00]	[0.00]
Diff. Hindu Shares			-0.01	0.01	0.01
			(0.02)	(0.02)	(0.02)
			[0.74]	[0.60]	[0.62]
Diff. Muslim Shares			-0.02**	-0.02**	-0.02**
			(0.01)	(0.01)	(0.01)
			[0.02]	[0.02]	[0.02]
Diff. Average N. Tweets Pre-March 31				-0.00***	-0.00***
				(0.00)	(0.00)
				[0.00]	[0.00]
Both Historically Attacked by Muslim					0.17
					(0.12)
					[0.18]
Both Historically Attacked but not by Muslim					0.37**
					(0.15)
					[0.02]
District i and j FE	No	Yes	Yes	Yes	Yes
R-squared	0.00	0.24	0.25	0.27	0.27
Observations	391250	391250	391250	391250	391250

Notes: OLS estimates. Observations are district-pairs. In all specifications, the dependent variable is the log of Twitter connectedness of district i to district j (for each $i \neq j$) computed as the share of replies and quotes posted in district i in response to tweets originally posted in district j, over the period December 1, 2019 – January 31, 2020. Log(Distance) is the log of the geographic distance between district i and j. Unconditional estimates are reported in column 1; column 2 adds districts i and j fixed effects, column 3 further includes the absolute difference between the values of relevant baseline socio-economic controls in districts i and j, and column 4 adds the difference in the average number of tweets in the week before March 31, 2020. Column 5 adds two dummy variables tracking if both districts have ever experienced an attack by a Muslim group and precolonial conflict not involving Muslim aggressors, respectively. See Section 3 and footnote 24 for details on all variables. Standard errors in parentheses are clustered by each district i and j in a district-pair. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

A.4 Personal Ties to Delhi

Figure A1: Personal Ties to Delhi



(a) Share Population Born in Delhi (b) Share Population Previously Residing in Delhi

Notes: The Figure reports the share of population born in the Delhi state (Panel a) and the share of population whose prior residence was in the Delhi state (Panel b). In both panels, data are reported per thousand inhabitants. The Delhi state is excluded from the set of observations. Source: 2011 Indian census.

B Robustness: Fake news spread spatially from Delhi

Table B1: Delhi and the Tablighi Shock

Period:	Three Days		Seven Days	
Dependent variable:	N. Tweets FN		N. Tweets FN	
	(1)	(2)	(3)	(4)
Delhi Dummy × Post	142.48***	142.96***	83.38	83.50
	(24.59)	(21.22)	(82.81)	(82.59)
	[0.00]	[0.00]	[0.31]	[0.31]
Time-variant controls	Yes	Yes	Yes	Yes
Time-invariant controls	Yes	No	Yes	No
State FE	Yes	No	Yes	Yes
District FE	No	Yes	No	Yes
Day FE	Yes	Yes	Yes	Yes
R-squared	0.95	0.96	0.80	0.81
Observations	3756	3756	8764	8764

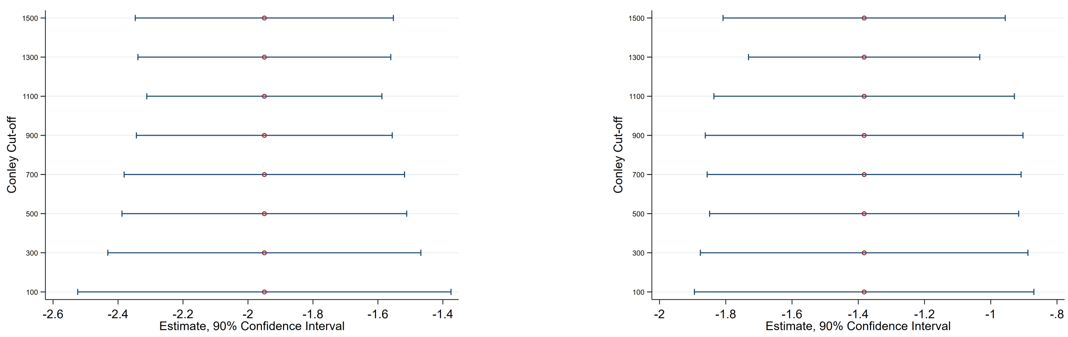
Notes: OLS estimates. Columns 1–2 focus on the March 28–April 2 period and columns 3–4 focus on the March 24–April 6 period. The analysis is carried out at the day-district level, the dependent variable is the number of tweets with anti-Muslim fake news and the main explanatory variable is the interaction between the *Delhi Dummy* and an indicator equal to one after March 30. In all specifications, the time invariant controls include the log of luminosity (+0.01) averaged between 1992-2010, the log of population density in 1990, the log share of Muslim and Hindu population in 2011, the log share of literate and urban population in 2011, and the average number of tweets before March 31, latitude, longitude, altitude, ruggedness, precipitation, land quality, dry rice suitability, wet rice suitability, wheat suitability, malaria risk, distance to the border, and distance to the closest border between Pakistan and Bangladesh. In all specifications the time-variant controls include the daily number of COVID deaths and the average number of tweets before March 31 interacted with the indicator equal to one after March 30. Columns 1 and 3 add state fixed effects, while columns 2 and 4 control for district fixed effects. See Section 3 and footnote 24 for details on all variables. Standard errors in parentheses are clustered to account for spatial correlation up to 250 km in the cross-section, and for both spatial and serial correlation in the panel specifications. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Number of Anti-Muslim Fake News Tweets in Space, Further Results with the New Delhi Region

Period:	Three Days					Seven Days				
Dependent variable:	N. Tweets FN					N. Tweets FN				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Delhi Region × Post	7.31***	7.14***	6.92***	1.44	1.32	5.22**	5.15**	5.00**	0.35	0.28
	(2.23)	(2.32)	(2.31)	(1.97)	(1.97)	(2.44)	(2.30)	(2.29)	(1.46)	(1.46)
	[0.00]	[0.00]	[0.00]	[0.46]	[0.50]	[0.03]	[0.03]	[0.03]	[0.81]	[0.85]
Std.Twitter Conn. to Delhi × Post			0.35***		0.29***			0.24***		0.19***
			(0.10)		(0.10)			(0.07)		(0.07)
			[0.00]		[0.00]			[0.00]		[0.01]
Std.Born in Delhi × Post				1.73***	1.71***				1.45**	1.44**
				(0.58)	(0.58)				(0.73)	(0.73)
				[0.00]	[0.00]				[0.05]	[0.05]
Time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-invariant controls	Yes	No	No	No	No	Yes	No	No	No	No
State FE	Yes	No	No	No	No	Yes	No	No	No	No
District FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.89	0.92	0.92	0.92	0.92	0.76	0.79	0.79	0.79	0.79
Observations	3750	3750	3750	3750	3750	8750	8750	8750	8750	8750

Notes: OLS estimates. Observations are districts in each day in two periods: March 28–April 2 in columns 1–5, and March 24–April 6 in columns 6–10. We exclude Delhi from the set of observations. In all specifications, the dependent variable is the number of tweets with anti-Muslim fake news. In columns 1 and 6 the time-variant and time-invariant controls are as in columns 1 and 3 of Table 1, whereas in columns 2–5 and 7-10 they are as in columns 2 and 4 of Table 1. *New Delhi Region × Post* is a dummy taking the value one for districts located in the National Capital Region surrounding the Delhi state interacted with the *Post-March 30* dummy. *Std. Twitter Connectedness to Delhi × Post* computes for each district *i* the standardized share of quotes and replies to tweets posted in the Delhi state by users located in the state (excluding from the denominator the quotes and replies to tweets posted within the district) interacted with the *Post-March 30* dummy. *Std. Born in Delhi × Post* computes the (standardized) share district inhabitants who were born in the Delhi state interacted with the *Post-March 30* dummy. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Figure B1: Robustness: *Dist. New Delhi × Post* with Different Conley Thresholds



(a) 3 day windows

(b) 7 day windows

Notes: Each dot is the coefficient associated with the variable *Distance to New Delhi × Post* from estimating specification 4 in Table 1 with Conley standard errors at different distance thresholds (on the vertical axis). Horizontal bars indicate 90% confidence intervals.

Table B3: Robustness: Alternative Dependent Variables and Distance to New Delhi

Period:	Three Days			Seven Days		
Dependent variable:	Sh. Tweets FN	Ln(N. Tweets FN+1)	IHS N. Tweets FN	Sh. Tweets FN	Ln(N. Tweets FN+1)	IHS N. Tweets FN
	(1)	(2)	(3)	(4)	(5)	(6)
Dist. New Delhi ($\times$ 1,000) $\times$ Post	-0.004**	-0.115**	-0.157***	-0.004***	-0.104***	-0.143***
	(0.002)	(0.046)	(0.056)	(0.001)	(0.030)	(0.037)
	[0.023]	[0.013]	[0.005]	[0.001]	[0.001]	[0.000]
Time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.324	0.797	0.784	0.267	0.730	0.718
Observations	3346	3750	3750	7814	8750	8750

Notes: OLS estimates. Observations are districts in each day in two periods: March 28–April 2 in columns 1–3, and March 24–April 6 in columns 4–6. The dependent variable is the share of tweets with anti-Muslim fake news over the total number of tweets in columns 1 and 4, the log of (1+) the number of fake news tweets in columns 2 and 5, and the Inverse Hyperbolic Sine (IHS) of the number of fake news tweets in columns 3 and 6. In all specifications we control for districts and day fixed effects, and the baseline controls include the daily number of COVID deaths. Columns 2 and 5 additionally control for the log of (1+) the average number of tweets before March 31 interacted with the *Post* indicator, whereas columns 3 and 6 further include the Inverse Hyperbolic Sine of the the average number of tweets before March 31 interacted with the *Post* indicator. See Section 3 for details on all variables. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table B4: Number of Anti-Muslim Fake News Tweets and Government's Ability to Intervene (3-Days)

Period:	Three Days									
Dep.Var.:	Number of FN Tweets									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dist. New Delhi (× 1,000) × Post	-1.96***	-1.98***	-1.98***	-1.95***	-1.96***	-1.94***	-1.96***	-1.99***	-2.01***	-2.06***
	(0.32)	(0.32)	(0.32)	(0.32)	(0.32)	(0.32)	(0.32)	(0.34)	(0.32)	(0.33)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Doctors per 1K inh. × Post	0.28								-0.21	-0.28
	(0.64)								(0.63)	(0.58)
	[0.66]								[0.74]	[0.63]
Hospital Doctors per 1K inh. × Post		1.90							2.95	3.10*
		(1.53)							(1.81)	(1.72)
		[0.22]							[0.10]	[0.07]
Paramed. per 1K inh. × Post			0.08						-0.07	-0.11
			(0.20)						(0.22)	(0.21)
			[0.69]						[0.73]	[0.61]
Clinics per 1K inh. × Post				0.00***					0.00	-0.00
				(0.00)					(0.00)	(0.00)
				[0.00]					[0.51]	[0.68]
Hospitals per 1K inh. × Post					-7.80				-14.74***	-14.90***
					(4.78)				(5.04)	(5.34)
					[0.10]				[0.00]	[0.01]
COVID tests per 1K (5Apr) × Post						0.02			0.04	0.04
						(0.04)			(0.04)	(0.04)
						[0.58]			[0.35]	[0.30]
Police per 1K inh. × Post							1.96		6.81**	
							(2.30)		(3.23)	
							[0.40]		[0.03]	
Police per 1K inh. (Passport) × Post								5.32		12.30
								(6.17)		(7.48)
								[0.39]		[0.10]
Time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
Observations	3750	3750	3750	3750	3750	3750	3750	3750	3750	3750

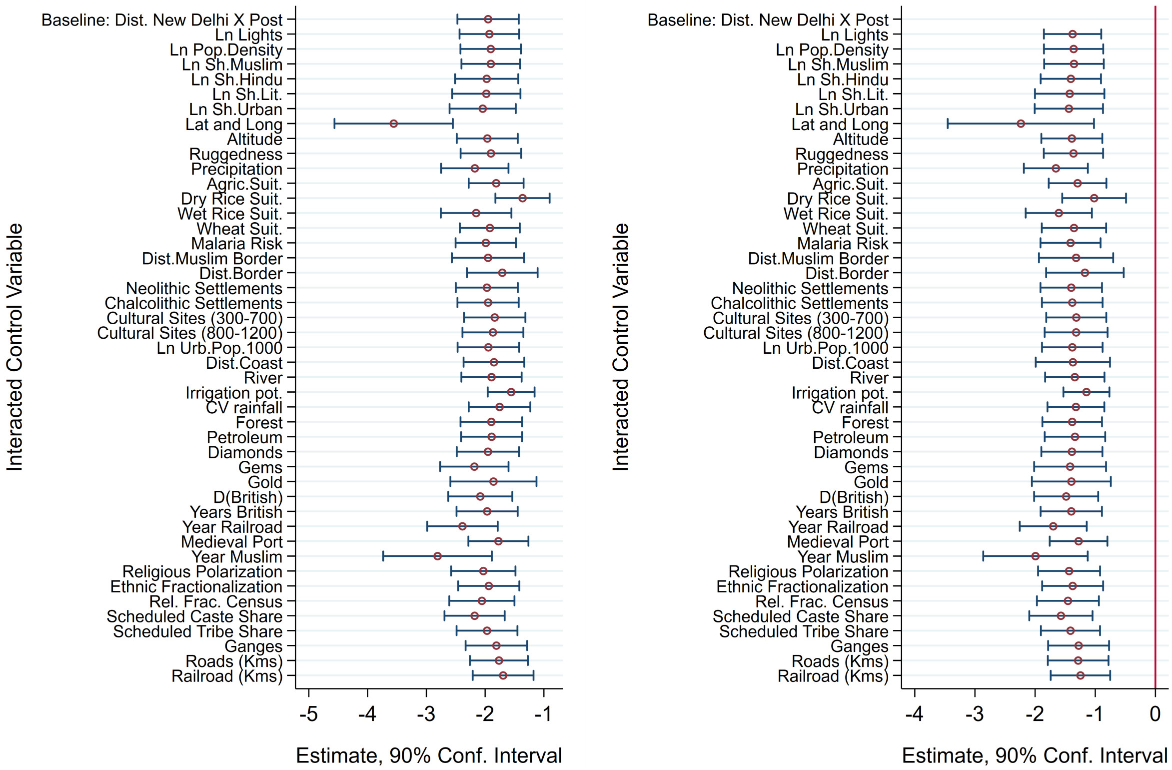
Notes: OLS estimates. Observations are districts in each day in the period March 28–April 2. In all specifications we exclude Delhi from the set of observations. In all specifications, the dependent variable is the number of tweets with anti-Muslim fake news, and the time variant and invariant controls are as in even specifications of Table 1. *Distance New Delhi (× 1,000) × Post* is the distance from each district's centroid to the coordinates of New Delhi (per 1,000 km) interacted with the *Post-March 30* dummy. Each column additionally controls for the following variables (per thousand inhabitants) interacted with the *Post-March 30* dummy: availability of doctors (column 1), hospital doctors (column 2), paramedics (column 3), clinics (column 4), hospitals (column 5), the number of COVID tests in early April (column 6), reported number of police stations (column 7) and number of police stations issuing passports (column 8). Columns 9 and 10 include in the specification all health-related variables and the reported number of police stations (column 9) or the number of police stations issuing passports (column 10). All variables are computed at the district level except COVID tests which are at state level. See Section 3 and 5.1 for details on all variables. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table B5: Number of Anti-Muslim Fake News Tweets and Government's Ability to Intervene (7 Days)

Period:	Seven Days									
Dep.Var.:	Number of FN Tweets									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dist. New Delhi ($\times$ 1,000) $\times$ Post	-1.39***	-1.39***	-1.39***	-1.39***	-1.39***	-1.37***	-1.39***	-1.42***	-1.41***	-1.45***
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.32)	(0.32)	(0.33)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Doctors per 1K inh. $\times$ Post	0.08								-0.09	-0.15
	(0.62)								(0.64)	(0.61)
	[0.90]								[0.89]	[0.80]
Hospital Doctors per 1K inh. $\times$ Post		0.67							1.12	1.28
		(2.25)							(2.96)	(2.83)
		[0.77]							[0.71]	[0.65]
Paramed. per 1K inh. $\times$ Post			0.03						-0.02	-0.06
			(0.19)						(0.17)	(0.16)
			[0.89]						[0.91]	[0.72]
Clinics per 1K inh. $\times$ Post				0.00					0.00	-0.00
				(0.00)					(0.00)	(0.00)
				[0.26]					[0.70]	[0.85]
Hospitals per 1K inh. $\times$ Post					-3.83				-7.64	-8.11
					(4.91)				(6.39)	(6.16)
					[0.44]				[0.23]	[0.19]
COVID tests per 1K (5Apr) $\times$ Post						0.03			0.04	0.05
						(0.04)			(0.04)	(0.04)
						[0.35]			[0.25]	[0.23]
Police per 1K inh. $\times$ Post							1.73		4.39	
							(2.45)		(3.61)	
							[0.48]		[0.22]	
Police per 1K inh. (Passport) $\times$ Post								5.14		10.03
								(7.28)		(8.69)
								[0.48]		[0.25]
Time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79
Observations	8750	8750	8750	8750	8750	8750	8750	8750	8750	8750

Notes: OLS estimates. Observations are districts in each day in the period March 24–April 6. In all specifications we exclude Delhi from the set of observations. In all specifications, the dependent variable is the number of tweets with anti-Muslim fake news, and the time variant and invariant controls are as in even specifications of Table 1. *Distance New Delhi ($\times$ 1,000) $\times$ Post* is the distance from each district's centroid to the coordinates of New Delhi (per 1,000 km) interacted with the *Post-March 30* dummy. Each column additionally controls for the following variables (per thousand inhabitants) interacted with the *Post-March 30* dummy: availability of doctors (column 1), hospital doctors (column 2), paramedics (column 3), clinics (column 4), hospitals (column 5), the number of COVID tests in early April (column 6), reported number of police stations (column 7) and number of police stations issuing passports (column 8). All variables are computed at the district level except COVID tests which are at state level. Columns 9 and 10 include in the specification all health-related variables and the reported number of police stations (column 9) or the number of police stations issuing passports (column 10). See Section 3 and 5.1 for details on all variables. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Figure B2: Sensitivity of Distance to New Delhi to Accounting for Further Controls Interacted with *Post March 30*

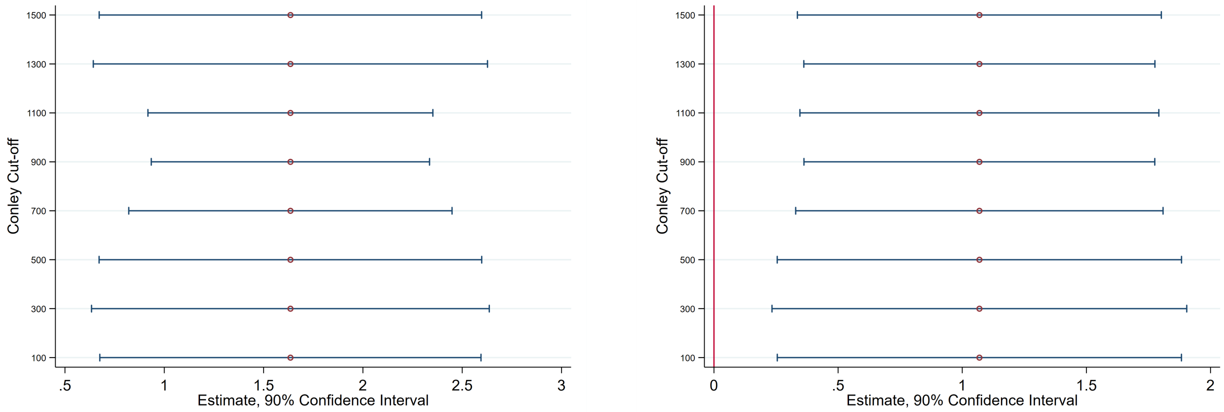


(a) 3 days window (b) 7 days window

Notes: The first dot displays the coefficient associated with the variable *Dist. New Delhi* × *Post* from estimating specifications 2 (panel a) and 4 (panel b) in Table 1 as baseline estimate. In each panel the other dots display the sensitivity of this estimate to further controlling for the variables indicated on the vertical axis (interacted with the *Post March 30* indicator). Horizontal bars indicate 90% confidence intervals.

C Robustness: the "Tablighi shock" and Muslim Attack-Districts

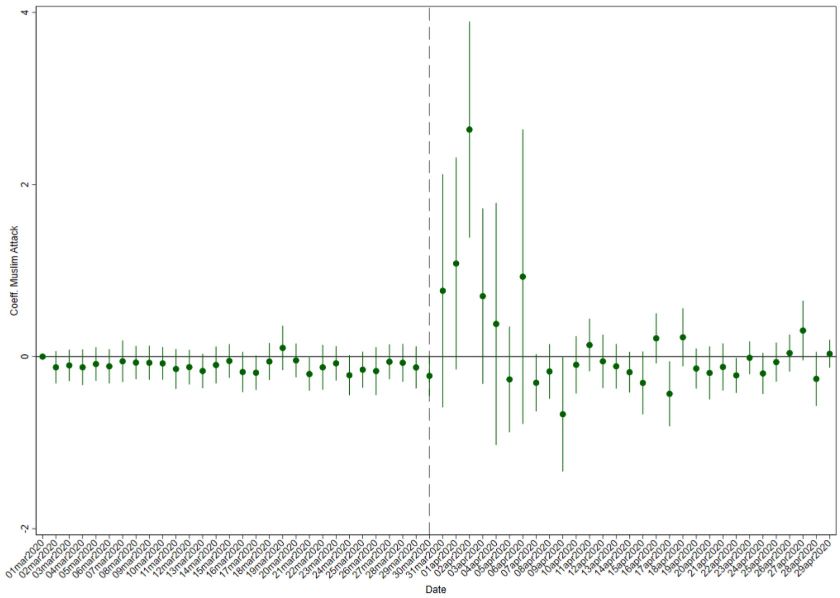
Figure C1: Robustness: *Muslim Attack* $\times$ *Post* with Different Conley Thresholds



(a) 3 day windows (b) 7 day windows

Notes: Each dot is the coefficient associated with the variable *Muslim Attack* $\times$ *Post* from estimating specification 4 in Table 3 with Conley standard errors at different distance thresholds (on the vertical axis). Horizontal bars indicate 90% confidence intervals.

Figure C2: Number of Tweets With Anti-Muslim Fake News and Historical Muslim Attacks – Event Analysis



Notes: Daily panel analysis in the March 1–April 29 period. Each dot is a coefficient from a version of specification 4 in Table 3 that replaces the dummy *Muslim Attack* interacted with the *Post March 30* indicator, with the dummy *Muslim Attack* interacted by each date dummy. The baseline period is March 1. The specification also controls for the average number of tweets in the week before the *Tablighi* shock and for a dummy taking the value one for districts that experienced precolonial conflicts in which Muslim groups were not the aggressors, both interacted by date dummies. Vertical bars indicate 90% confidence intervals.

Table C1: Robustness: Alternative Dependent Variables and Muslim Attacks

Period:	Three Days			Seven Days		
Dependent variable:	Sh. Tweets FN	Ln(N. Tweets FN+1)	IHS N. Tweets FN	Sh. Tweets FN	Ln(N. Tweets FN+1)	IHS N. Tweets FN
	(1)	(2)	(3)	(4)	(5)	(6)
Muslim Attack × Post	0.01***	0.10*	0.13*	0.01***	0.12***	0.16***
	(0.00)	(0.06)	(0.07)	(0.00)	(0.04)	(0.05)
	[0.01]	[0.09]	[0.08]	[0.00]	[0.00]	[0.00]
Time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.33	0.80	0.79	0.27	0.74	0.73
Observations	3352	3756	3756	7828	8764	8764

Notes: OLS estimates. Observations are districts in each day in two periods: March 28–April 2 in columns 1–3, and March 24–April 6 in columns 4–6. The dependent variable is the share of tweets with anti-Muslim fake news over the total number of tweets in columns 1 and 4, the log of (1+) the number of fake news tweets in columns 2 and 5, and the Inverse Hyperbolic Sine (IHS) of the number of fake news tweets in columns 3 and 6. In all specifications we control for districts and day fixed effects, and baseline controls include the daily number of COVID deaths. Columns 2 and 5 additionally control for the log of (1+) the total number of tweets interacted with the *Post* indicator, whereas columns 3 and 6 further include the Inverse Hyperbolic Sine of the total number of tweets interacted with the *Post* indicator. See Section 3 for details on all variables. Standard errors in parentheses are clustered to account for both serial correlation (up to 250 km) and spatial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table C2: Robustness: Alternative Definitions of Muslim-Related Conflict (3 days)

Dependent variable:	N. Tweets FN					
Specifications:	Radius 100	Radius 5000	1200-1757	1000-1840	Sub-Periods	Modern
	(1)	(2)	(3)	(4)	(5)	(6)
Exp. Muslim Attack × Post	15.87***	11.11***				
	(4.28)	(2.55)				
	[0.00]	[0.00]				
Muslim Attack × Post			1.92***	1.39***		
			(0.60)	(0.51)		
			[0.00]	[0.01]		
Muslim Attack 1000-1600 × Post					0.70	
					(0.74)	
					[0.35]	
Muslim Attack 1601-1757 × Post					1.88***	
					(0.70)	
					[0.01]	
Hindu-Muslim Conflict 1950-2000 × Post						1.61***
						(0.33)
						[0.00]
Time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	Yes	Yes	Yes	Yes	Yes	Yes
Observations	0.96	0.96	0.96	0.96	0.96	0.96
N	3756	3756	3756	3756	3756	3756

Notes: OLS estimates. Observations are districts in each day in the March 28 –April 2 period. Each specification substitutes *Muslim Attack* × *Post* from specification 4 of Table 3 with an alternative definition of historical exposure to Muslim attacks (interacted with the *Post March 30* dummy). Column 1 and 2 compute exposure to Muslim attacks as in Dincecco et al. (2022) over distances up to 100 and 5,000 km, respectively. Column 3 computes the dummy Muslim Attack over the 1200-1757 period whereas in column 4 the dummy is calculated over the 1000-1840 period. Column 5 includes in the same specification two dummies tracking Muslim attacks over the 1000-1600 and 1601-1757 period, respectively. Column 6 exploits more recent data on Hindu-Muslim clashes over the 1950-2000 period. See Sections 3 and 5.2 for details on all variables. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Robustness: Alternative Definitions of Muslim-Related Conflict (7 days)

Dependent variable:	N. Tweets FN					
Specifications:	Radius 100	Radius 5000	1200-1757	1000-1840	Sub-Periods	Modern
	(1)	(2)	(3)	(4)	(5)	(6)
Exp. Muslim Attack × Post	11.28***	8.11***				
	(3.68)	(2.24)				
	[0.00]	[0.00]				
Muslim Attack × Post			1.25**	0.87**		
			(0.50)	(0.44)		
			[0.01]	[0.05]		
Muslim Attack 1000-1600 × Post					0.63	
					(0.54)	
					[0.25]	
Muslim Attack 1601-1757 × Post					1.16*	
					(0.62)	
					[0.06]	
Hindu-Muslim Conflict 1950-2000 × Post						1.02***
						(0.34)
						[0.00]
Time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.81	0.81	0.81	0.81	0.81	0.81
Observations	8764	8764	8764	8764	8764	8764

Notes: OLS estimates. Observations are districts in each day in the March 24 –April 6 period . Each specification substitutes *Muslim Attack × Post* from specification 4 of Table 3 with an alternative definition of historical exposure to Muslim attacks (interacted with the *Post March 30* dummy). Column 1 and 2 compute exposure to Muslim attacks as in Dincecco et al. (2022) over distances up to 100 and 5,000 km, respectively. Column 3 computes the dummy Muslim Attack over the 1200-1757 period whereas in column 4 the dummy is calculated over the 1000-1840 period. Column 5 includes in the same specification two dummies tracking Muslim attacks over the 1000-1600 and 1601-1757 period, respectively. Column 6 exploits more recent data on Hindu-Muslim clashes over the 1950-2000 period. See Sections 3 and 5.2 for details on all variables. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

D Robustness using Observations at the Sub-District and Town Level

Table D1: Sub-District Level Analysis

Period:	Three Days		Seven Days	
Dependent variable:	N. Tweets FN		N. Tweets FN	
	(1)	(2)	(3)	(4)
Dist. New Delhi ($\times$ 1,000) $\times$ Post	-0.45***		-0.28***	
	(0.10)		(0.06)	
	[0.00]		[0.00]	
Muslim Attack $\times$ Post		1.65***		0.96***
		(0.56)		(0.32)
		[0.00]		[0.00]
Time-variant controls	Yes	Yes	Yes	Yes
Sub-District FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
R-squared	0.67	0.89	0.62	0.75
Observations	35496	35502	82824	82838

Notes: OLS estimates. Observations are sub-districts in each day in two periods: March 28–April 2 in columns 1-2, and March 24 –April 6 in columns 3-4. Columns 1 and 3 exclude Delhi from the set of observations. In all specifications the dependent variable is the number of tweets with anti-Muslim fake news. In odd columns the time-variant and time-invariant controls are as in column 2 of Table 1, whereas in even columns the sets of controls mimics that of columns 2 of Table 3. *Distance New Delhi ($\times$ 1,000) $\times$ Post* is the distance from each district's centroid to the coordinates of New Delhi (per 1,000 km) interacted with the *Post-March 30* dummy. *Muslim Attack $\times$ Post* is a dummy tracking districts that experienced precolonial conflict in which Muslim groups were the aggressors interacted with the *Post-March 30* dummy. See Section 3 for details on all variables. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table D2: Town-Level Analysis

Period:	Three Days		Seven Days	
Dependent variable:	N. Tweets FN		N. Tweets FN	
	(1)	(2)	(3)	(4)
Dist. New Delhi ($\times$ 1,000) $\times$ Post	-0.12***		-0.08***	
	(0.02)		(0.01)	
	[0.00]		[0.00]	
Muslim Attack $\times$ Post		3.28***		1.88***
		(1.11)		(0.60)
		[0.00]		[0.00]
Time-variant controls	Yes	Yes	Yes	Yes
Town FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
R-squared	0.57	0.91	0.57	0.77
Observations	46344	46350	108136	108150

Notes: OLS estimates. Observations are towns in each day in two periods: March 28–April 2 in columns 1-2, and March 24 –April 6 in columns 3-4. Columns 1 and 3 exclude Delhi from the set of observations. In all specifications the dependent variable is the number of tweets with anti-Muslim fake news. In odd columns the time-variant and time-invariant controls are as in column 2 of Table 1, whereas in even columns the sets of controls mimics that of columns 2 of Table 3. *Distance New Delhi ($\times$ 1,000) $\times$ Post* is the distance from each district's centroid to the coordinates of New Delhi (per 1,000 km) interacted with the *Post-March 30* dummy. *Muslim Attack $\times$ Post* is a dummy tracking districts that experienced precolonial conflict in which Muslim groups were the aggressors interacted with the *Post-March 30* dummy. See Section 3 for details on all variables. Standard errors in parentheses are clustered to account for both spatial correlation (up to 250 km) and serial correlation. P-values are reported in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.