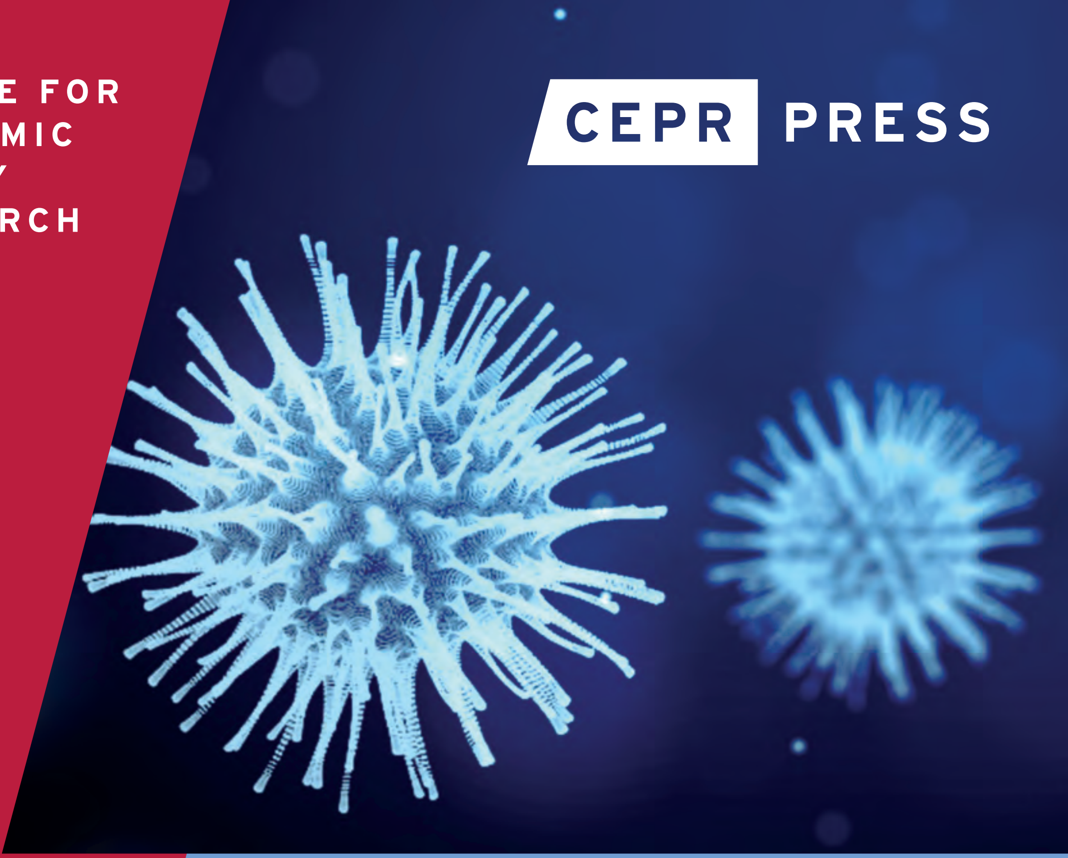
CENTRE FOR ECONOMIC POLICY RESEARCH

CEPR PRESS



COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 25
3 JUNE 2020

CEPR PRESS

Covid Economics Issue 25, 3 June 2020

Contagion and conflict: Evidence from India[1]

Rahul Mehrotra[2]

Date submitted: 31 May 2020; **Date accepted:** 2 June 2020

Covid Economics 25, 3 June 2020: 122-140

The health, economic and security impacts of the Covid-19 pandemic are playing out in volatile and potentially catastrophic ways, especially in conflict-affected states. The disease arrived in India during a period of heightened public protests, riots and religious polarization. In this paper, I document early evidence of the causal impact of Covid-19 proliferation on conflict risks across Indian districts. I use text-mining of conflict event descriptions to define two new measures of religious and pandemic-related conflict in addition to the standard measures of real-time conflict events provided by The Armed Conflict Location & Event Data Project (ACLED). Event study analysis indicates a sustained decline in conflict after the first Covid-19 case is reported, driven by a decrease in religious conflict and public protests. However, I also document a countervailing increase in the probability of Covid-19 related conflict. Poor districts and districts with low health infrastructure in particular demonstrate an increase in riots. These real-time findings are of first-order importance for policymakers and public administrators straddling a narrowing stringency corridor between maintaining public health and tolerance of containment policies.

1 Thanks to seminar participants at the Graduate Institute's online development economics seminar for comments and suggestions. This research is made possible by detailed and real-time data from the Covid19India.org project (https://api.covid19india.org/) and The Armed Conflict Location and Event Data Project (ACLED). The final database, Stata and R files used for this analysis can be shared with academic reviewers and journalists upon request.

2 Graduate Institute of International and Development Studies.

Covid Economics 25, 3 June 2020: 122-140

1 Introduction

Natural disasters and their economic impacts can exacerbate underlying social tensions and increase violent conflict risks, especially in already polarized or fragmented societies (Bergholt and Lujala, 2012; Schleussner et al., 2016; De Juan et al., 2020). The health, economic and security impacts of the ongoing Covid-19 pandemic are similarly playing out in volatile and potentially catastrophic ways. The pandemic has *a priori* ambiguous impacts on conflict. First, the robust implementation of lockdowns and mobility restrictions implemented by state security services to contain viral transmission should reduce the incidence of violent events (Berman et al., 2020). However, there is also emerging evidence of a countervailing public backlash as the pandemic and containment measures impose asymmetric costs on different segments of society. This can contribute to further state-led violence to suppress public backlash.[1] Other theoretical considerations linking pandemics to conflict include the impact of resulting economic downturns on reducing individual opportunity costs of engaging in violence and limiting state capacity for counter-insurgency operations (Becker, 2000; Grossman, 1991; Dal Bó and Dal Bó, 2011; Fearon and Laitin, 2003). Evidence on which of these countervailing effects will dominate over the short to medium-term is a first order concern for public administrators and policymakers, especially in conflict-affected states with limited fiscal space to insulate their populations from the pandemic's economic shocks. As the contagion continues to proliferate, developing countries are facing a narrowing stringency possibility corridor between the health imperative to flatten the infection curve and the tolerance imperative to maintain law and order (Baldwin, 2020).

In this paper, I present early evidence of the causal impact of Covid-19 contagion on the probability of conflict across Indian districts. An event study research design with staggered treatment adoption is used to estimate short-term effects of Covid-19 contagion up to six weeks after the first case is reported in a district. My main findings are as follows: first, there is a sustained decrease in overall conflict risk after contagion is reported in an average district. This effect is primarily driven by a decline in public protests and religious violence. Second, there is a short-term, statistically significant increase in risk of Covid-19 related violence and riots for four weeks following district-level contagion. No statistically significant differences are observed in conflict pre-trends before contagion which supports a causal interpretation of the findings.

[1] For example, see: Kazmin, A. (2020, April 14). India's lockdown extension sparks migrant worker protests. Financial Times. Link

Finally, I explore heterogeneity across districts using nightlight intensity as a proxy for district-level wealth and medical beds per capita as a proxy for district-level health infrastructure. The results show an increase in riots in poor districts and in districts with low health infrastructure. On the other hand, districts with higher health infrastructure experience a decline in conflict.

The Covid-19 pandemic arrived in India in end-January 2020 during a period of elevated civilian protests and religious polarization. India accounted for approximately 60% of all conflict events recorded in South Asia between January - April 2020 predominantly involving protests and riots (more then 4,500 events reported), according to The Armed Conflict Location and Event Data Project (ACLED). This violence was driven by the policy proposals of the Hindu-nationalist central government of the Bhartiya Janata Party (BJP). Specifically, an amendment to Indian citizenship law (Citizenship Amendment Act, 2019) was passed in early-December 2019 allowing for religious criteria to grant citizenship to refugees from neighboring countries. Another proposed legislation aimed to establish a National Registry of Citizens based on verification of Indian residents' ancestral ties to the country. Combined, these measures ignited nation-wide protests driven by fears of religious persecution of minorities. The protests and riots were met with a strong response by state security forces. As a result of this action, India witnessed a steady decline in conflict from its peak in December 2019. This decline accelerated further with the arrival of the Covid-19 pandemic in end-January. However, this trend reversed again in early-April 2020, primarily driven by an increase in conflict events related to lockdown and quarantine zones imposed to contain Covid-19. The resulting economic crisis has in turn led to an internal migrant crisis whereby newly unemployed labour from locked down urban and industrial districts are aiming to return to their places of origin in violation of lockdown rules.[2] Moreover, there is evidence of renewed increase in religious polarization and discrimination against minorities who are accused of spreading the disease.[3]

Violent conflict is a major risk for public administration and medical workers aiming to safeguard local populations from the ongoing pandemic. This paper enters the broader discussion on the security implications of the ongoing global pandemic by providing novel, micro-evidence on the impact of Covid-19 contagion on conflict risks across Indian districts. Overall, the evidence pre-

[2]For example, see: Singh, J., & Kazmin, A. (2020, April 30). India: The millions of working poor exposed by pandemic. https://on.ft.com/2VMG8Vi

[3]For example, see: Agrawal, R. (2020, April 7). Islamophobia Is Making the Coronavirus Crisis Worse. Foreign Policy. Link

Covid Economics 25, 3 June 2020: 122-140

sented indicates the need for continued emphasis on maintaining public law and order, specifically by addressing the social and economic segments of society particularly affected by the pandemic. Low medical capacity districts require urgent attention for both health and security reasons. While these findings should be treated as preliminary and focusing on short-term effects, the longer-term security implications of the pandemic also represent an urgent concern in India. The root causes for the elevated public disturbance and conflict remain unchanged in terms of the religious and nationalist policy agenda of the central government. These have been further supplemented by new concerns regarding the economic crisis, internal migrant crisis and religious polarization resulting from the Covid-19 pandemic. As more disease, conflict and containment policy data emerges, we can expect to get more precise and generalizable analyses on the security impacts of the crisis.

2 Data and Research Design

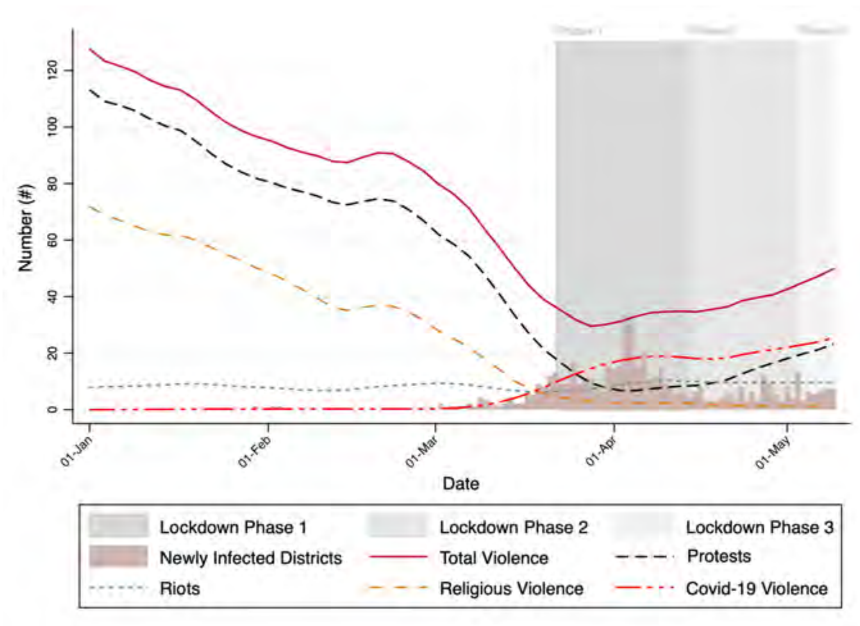


Figure 1: Contagion and Conflict in India (Jan 1 - May 9, 2020)

I use daily updated, patient-level data collected by the Covid19India project using government bulletins and official social-media announcements which is aggregated up to the district-level. Additional state-level, daily updates on the total number of Covid-19 cases, deaths and recoveries

Covid Economics 25, 3 June 2020: 122-140

Covid Economics 25, 3 June 2020: 122-140

are also collected[4] This information is combined with geo-located data on daily conflict events provided by The Armed Conflict Location and Event Data Project (ACLED). ACLED classifies violence events further into sub-categories, including protests, riots, violence against civilians, battles, explosions and strategic events.[5]

Furthermore, two new measures for religious and pandemic-related violence are generated using text-mining of ACLED event reports that describe each recorded event.[6] My first new measure of religious violence classifies all events which include references to participants' religious affiliations, religious group affiliations, places of worship or the Citizenship Amendment Act (2019). Similarly, my measure of Covid-19 violence identifies events which refer to coronavirus, Covid-19, quarantines or lockdowns. See Figure 2 and Figure 3 for word clouds containing the most commonly occurring terms in the event descriptions for religious and Covid-19 related violence, respectively.

I combine district-level data on nightlight intensity and medical infrastructure from The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG platform) compiled by Asher et al. (2019). Nightlight intensity data comes from the U.S. Air Force's Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS). I use the latest available complete data series from 2013 and designate districts above the median as rich districts and *vice versa* for poor districts. The medical infrastructure information comes from the 2011 Population Census of India and includes the total number of beds in government clinics and hospitals. The total number of beds is divided by the population to derive a per capita measure. Districts above the median are referred to as high medical capacity districts and *vice versa* for low medical capacity districts. Finally, I collect central and state government notifications to define a lockdown indicator at the district-day level.

See Figure 1 for a graphical representation of trends in violence and Covid-19 contagion across Indian districts from January 1st until May 9th 2020. The lines represent smoothed mean values from non-parametric local polynomial regressions with bandwidth of 7 days, while the bars represent the daily total of newly infected districts. The first three phases of the Indian lockdown are represented using the shaded background. The first states and districts went into lockdown

[4]See the project website: www.covid19india.org and database: api.covid19india.org. Data availability for Covid-19 testing is not of sufficient quality to be included in this analysis.

[5]See ACLED (2019) for the complete codebook and methodology used to compile this dataset.

[6]A similar measure of Covid-19 related violence is now also available directly from ACLED. However, I prefer my novel measure for this analysis since it distinguishes between Covid-19 and religious violence in India, unlike the ACLED measure.

Covid Economics 25, 3 June 2020: 122-140

Figure 2: Religious Violence

Figure 3: Covid-19 Violence

Covid Economics 25, 3 June 2020: 122-140

starting from March 22nd 2020, before a nation-wide lockdown was imposed from March 25th till April 14th. This was further extended till May 3rd, followed by a third phase from May 4th till May 17th. During this third phase, districts were further divided into red, orange and green districts based on the number of reported cases.[7] Summary statistics is reported in Table 1 in the appendix.

I use a district-level event study with staggered treatment adoption (i.e., first reported Covid-19 case in a district) to estimate the dynamic, causal effects of Covid-19 contagion across Indian districts. This research design allows me to investigate the lagged impacts on my dependent variable(s) of interest, i.e. measures of total and sub-types of conflict, up to 6 weeks after contagion. To verify the identifying assumption required for a causal interpretation of the lagged effects, I can also test whether conflict events were already affected during three leading weeks before contagion. The lack of statistically significant differences in pre-treatment trends would support the identification assumption required for a causal interpretation of the treatment effects (Goodman-Bacon, 2018; Athey and Imbens, 2018). The main limitation for this methodology in this application is the potential loss of statistical power for evaluating the statistical significance of the coefficients for lagged time periods.

The estimation equation is given below:

$$\begin{aligned} Conflict_{dst} &= \alpha + \beta FirstCase_{dst} + \sum_{j=-3}^{6} \delta_j D_{ds,t_0+j} + \nu Lockdown_{dst} + \Omega \mathbf{X}_{st} + \\ & \quad \gamma District_d + \theta Date_t + \phi State_s \times Week_t + \epsilon_{dst} \end{aligned} \tag{1}$$

where $Conflict_{dst}$ represents a binary indicator equal to 1 if a conflict event is recorded in district d, state s on date t (0 otherwise). $FirstCase_{dst}$ is my treatment indicator equal to 1 on date t when the first Covid-19 is reported, while D_{ds,t_0+j} equals 1 for $-3 < j < 6$ weeks before and after $FirstCase_{dst}$. $Lockdown_{dst}$ is a vector of binary indicators equal to 1 when district d is under lockdown on date t corresponding to the three phases of the Indian lockdown.[8] X_{st} is a vector of state-level Covid-19 measures including total confirmed cases, deaths and recoveries for state s and date t. I include district and date fixed effects, $District_d$ and $Date_t$, to eliminate

[7] The fourth phase of the lockdown will last till 31 May 2020.

[8] I include the time-varying indicator for Lockdown Phase 1. The indicator for Lockdown Phase 2 is abosrbed by the date fixed effects. In the Lockdown Phase 3 (4-17 May, 2020), each district is designated as either a red, orange or green zone under lockdown. The green zone districts' indicator is treated as the base category and excluded from the regression equation.

Covid Economics 25, 3 June 2020: 122-140

district-specific, time-invariant factors (e.g., transportation connections, population, population density, etc.) as well as country-wide common shocks (e.g., central government Covid-19 security and medical testing policy announcements). $State_s \times Week_t$ fixed effects are also included to control for time-varying state-level factors (e.g. regular updates in state public health policies and implementation guidelines).[9] I estimate robust standard errors ϵ_{dst} which are triple-clustered by district, date and state-week to account for serial correlation in treatment status and intra-cluster correlations in contagion by nation-date and state-week (Bertrand et al., 2004; Cameron and Miller, 2015; Abadie et al., 2017).[10] This linear probability model is estimated using ordinary least squares (OLS).

3 Results

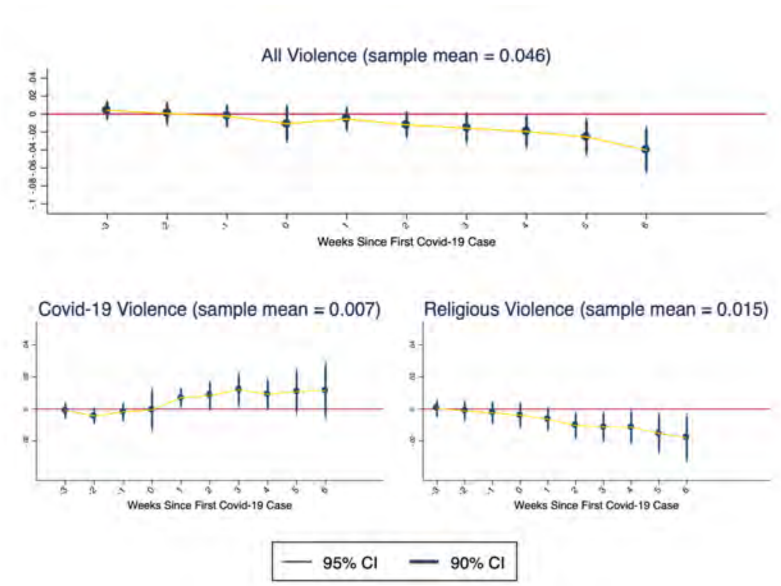


Figure 4: Results - Total Violence, Covid-19 Violence and Religious Violence

My main findings are reported in Figure 4 and Table 2 in the appendix. **First, the results indicate there is a sustained decrease in total violence risk after the first Covid-19 case**

[9]Legislation and implementation of public health policies are a prerogative of the states under the federal structure denoted by the Constitution of India.

[10]Similar research design is used in the emerging impact evaluation literature related to Covid-19 pandemic. See Brzezinski et al. (2020) and Wright et al. (2020).

is reported in a district. The coefficients for the lead weeks are not statistically significant, while the lagged week coefficients indicate a declining trend which is statistically significant after the second week post-contagion. The estimated magnitudes indicate a 1.6 percentage point decline in week 3 (statistically significant at 90% confidence level) and increases to 4.0 percentage points by week 6 (statistically significant at 99% confidence level). The sample mean probability of violence across Indian districts of 0.046 (or 4.6%), therefore these results indicate a large and statistically significant declines in the probability of conflict.

A similar trend is observed in the event probabilities for religious violence which decline in the weeks following contagion. The results indicate a 0.6 percentage point decrease in the week following contagion (statistically significant at 90% confidence internal). The decline increases to 1.8 percentage points by the sixth lagged week (statistically significant at 95%).

There is a statistically significant increase in risk of Covid-19 related violence in the four lagged weeks following contagion. Covid-19 violence risk increases by 0.7 percentage point in the first lagged week which remains statistically significant till the fourth lagged week. The sample mean probability for Covid-19 related violence is 0.7% which indicates a 100% increase in violence related to Covid-19 disease, quarantines and lockdown.

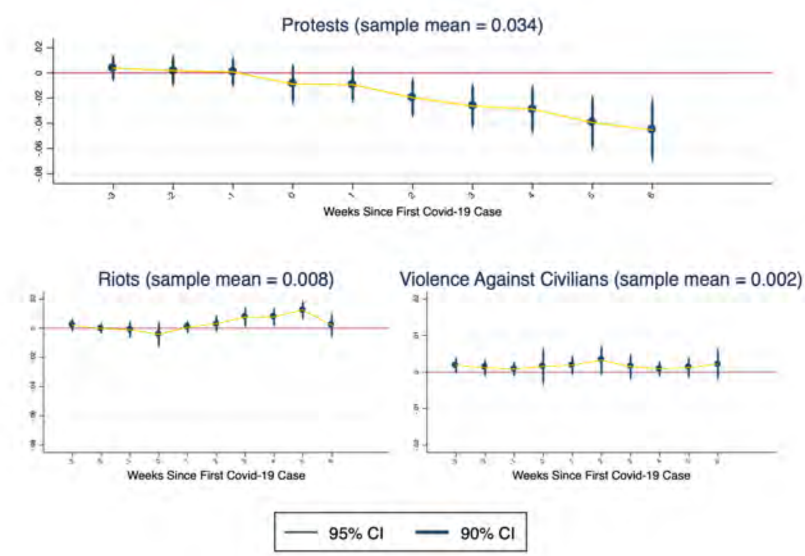


Figure 5: Results - Sub-types of Violence

Covid Economics 25, 3 June 2020: 122-140

CEPR PRESS

Finally, I report the results for disaggregated sub-types of conflict events in Figure 5 and Table 5 in the appendix. These findings indicate that the decline in total violence is driven predominantly by a large and statistically significant decline in the probability of public protests equal to 2 percentage points in the second lagged week which increases to 4.5 percentage point decline by lagged week 6 (statistically significant at 90%). However, I also find a statistically significant, countervailing increase in event probabilities for riots by 0.7 - 1.3 percentage points between lagged weeks three and five.

3.1 Sub-sample Results

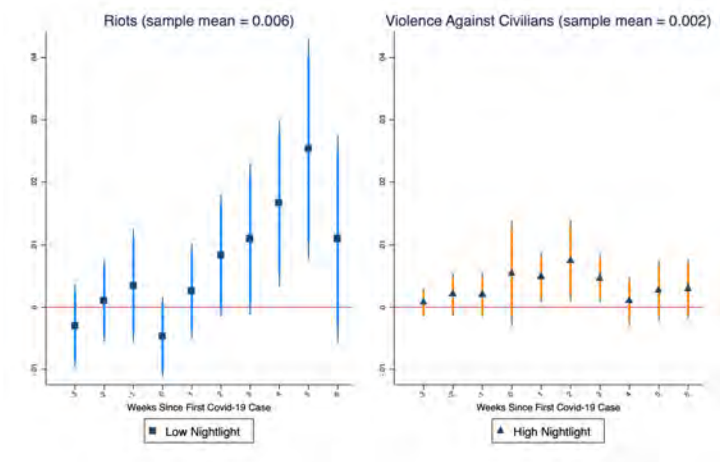


Figure 6: Results - High and Low Nighlight Districts

I conduct sub-sample analysis to explore whether district-level characteristics are associated with any diverging trends in violence. First, I test the hypothesis that district-level wealth predicts post-contagion violence due to the asymmetric economic costs imposed by the Covid-19 pandemic and associated restrictions on non-essential public movement. Nightlight intensity is used as a proxy for wealth and districts below the national median level are referred to as poor districts, while those above the median are designated as rich districts. The results are reported in Figure 6 and Table 5 in the appendix. The estimated coefficients for poor districts indicate an increase in riots in poor districts (up to 2.5 percentage points in lagged week 5, statistically significant at 99% confidence level). On the other hand, there is a short-term increase in violence against civilians in

Covid Economics 25, 3 June 2020: 122-140

Covid Economics 25, 3 June 2020: 122-140

rich districts. This increase is indicative of security forces' actions against internal migrants who aim to return to their places of origin after losing their employment in rich districts.

Finally, I explore whether district-level medical infrastructure capacity predicts post-contagion violence as a result of public panic and backlash against poor state infrastructure. I construct a measure of high capacity districts as those with total hospital and clinic beds above median and vice versa for low capacity districts. The results are reported in Figure 7 and Table 4 in the appendix. I find that total violence declines from the second lagged week onward in high health capacity districts. In low capacity districts, on the other hand, there is a delayed and short-term increase in probability of riots (up to 3.4 percentage points in lagged week 5 which corresponds to an approximately 380% increase above the sample mean).

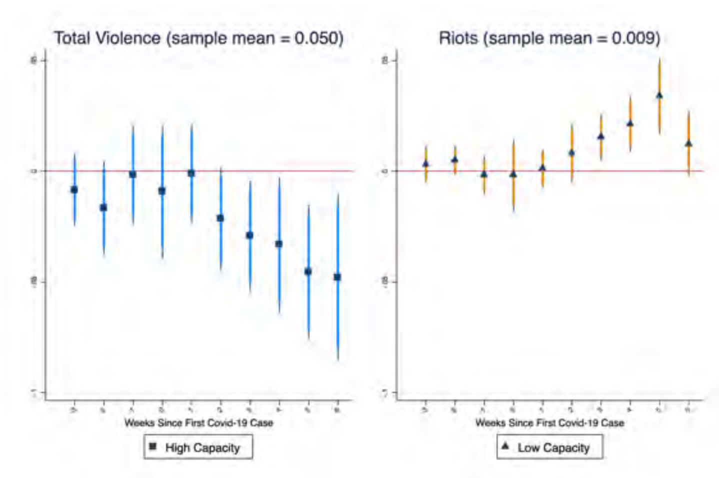


Figure 7: Results - High and Low Medical Capacity Districts

4 Conclusion

This paper provides early and real-time evidence of the impact of Covid-19 pandemic on conflict across Indian districts. Using detailed micro-data aggregated up to the district level, I use an event study design to identify the causal impacts of Covid-19 contagion on the probability of overall conflict, as well as disaggregated measures for civilians protests, riots and violence against civilians. Two novel measures of Covid-19 related violence and religious violence are also generated to distinguish between different trends in conflict. The results align with emerging cross-country evidence on the dampening effects of the pandemic and associated lockdowns on overall conflict (Berman et al., 2020). Moreover, this paper also provides new evidence on an increase in Covid-19 related conflict which is especially concentrated in poor and low-health capacity regions.

In conclusion, these findings should be treated as early evidence of short-term impacts of the pandemic on conflict based on preliminary data from an ongoing phenomenon. As more data emerges and the Covid-19 contagion spreads further across India, the estimations will get more precise and the findings more generalizable. However, the security implications of the pandemic indeed represent an urgent concern for India where the security impacts from the resulting economic crisis, internal migrant crisis and religious polarization have yet to manifest.

Covid Economics 25, 3 June 2020: 122-140

Covid Economics 25, 3 June 2020: 122-140

References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. (2017). When should you adjust standard errors for clustering? Working Paper 24003, National Bureau of Economic Research.

ACLED (2019). Armed Conflict Location and Event Data Project Codebook. Technical report, Armed Conflict Location and Event Data Project.

Asher, S., Lunt, T., Matsuura, R., and Novosad, P. (2019). The Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG). Working paper.

Athey, S. and Imbens, G. W. (2018). Design-based Analysis in Difference-In-Differences Settings with Staggered Adoption. Working Paper 24963, National Bureau of Economic Research. Series: Working Paper Series.

Baldwin, R. (2020). Remobilising the workforce: A two-imperatives approach. Library Catalog: VoxEU.

Becker, G. S. (2000). Crime and Punishment: an Economic Approach. In Fielding, N. G., Clarke, A., and Witt, R., editors, *The Economic Dimensions of Crime*, pages 13–68. Palgrave Macmillan UK, London.

Bergholt, D. and Lujala, P. (2012). Climate-related natural disasters, economic growth, and armed civil conflict. *Journal of Peace Research*.

Berman, N., Couttenier, M., Monnet, N., and Ticku, R. (2020). Shutdown Policies and Worldwide Conflict. *ESI Working Papers*.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics*, 119(1):249–275. Publisher: Oxford Academic.

Brzezinski, A., Kecht, V., Van Dijcke, D., and Wright, A. L. (2020). Belief in Science Influences Physical Distancing in Response to COVID-19 Lockdown Policies. SSRN Scholarly Paper ID 3587990, Social Science Research Network, Rochester, NY.

Cameron, A. C. and Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, 50(2):317–372. Publisher: University of Wisconsin Press.

Dal Bó, E. and Dal Bó, P. (2011). Workers, Warriors, and Criminals: Social Conflict in General Equilibrium. *Journal of the European Economic Association*, 9(4):646–677. Publisher: Oxford Academic.

De Juan, A., Pierskalla, J., and Schwarz, E. (2020). Natural disasters, aid distribution, and social conflict: A Micro-level evidence from the 2015 earthquake in Nepal. *World Development*, 126:104715.

Fearon, J. D. and Laitin, D. D. (2003). Ethnicity, Insurgency, and Civil War. *American Political Science Review*, 97(1):75–90. Publisher: Cambridge University Press.

Goodman-Bacon, A. (2018). Difference-in-Differences with Variation in Treatment Timing. Working Paper 25018, National Bureau of Economic Research. Series: Working Paper Series.

Grossman, H. I. (1991). A General Equilibrium Model of Insurrections. *The American Economic Review*, 81(4):912–921. Publisher: American Economic Association.

Schleussner, C.-F., Donges, J. F., Donner, R. V., and Schellnhuber, H. J. (2016). Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries. *Proceedings of the National Academy of Sciences*, 113(33):9216–9221. Publisher: National Academy of Sciences Section: Physical Sciences.

Wright, A. L., Sonin, K., Driscoll, J., and Wilson, J. (2020). Poverty and Economic Dislocation Reduce Compliance with COVID-19 Shelter-in-Place Protocols. Technical Report ID 3573637, Social Science Research Network.

Covid Economics 25, 3 June 2020: 122-140

Covid Economics 25, 3 June 2020: 122-140

Appendix: Tables

Table 1: Summary Statistics

	Obs.	Mean	S.D.	Min	Max
Covid19India Data					
Reported Covid-19 Cases (district, #)	93,210	0.35	5.12	0	402
Lockdown Phase 1 (binary indicator)	93,210	0.33	0.47	0	1
Lockdown Phase 2 (binary indicator)	93,210	0.15	0.35	0	1
Lockdown Phase 3: Red Zone (binary indicator)	93,210	0.007	0.086	0	1
Lockdown Phase 3: Orange Zone (binary indicator)	93,210	0.017	0.129	0	1
Lockdown Phase 3: Green Zone (binary indicator)	93,210	0.022	0.147	0	1
Daily Total Reported Covid-19 Cases (state, #)	93,210	219.501	668.401	0	6,696
Daily Total Cured Covid-19 Cases (state, #)	93,210	60.447	250.457	0	3,470
Daily Total Covid-19 Deaths (state, #)	93,210	9.863	49.299	0	731
ACLED Violence Data					
Total Violence (district, #)	93,210	0.10	1.08	0	121
Protests (district, #)	93,210	0.07	0.92	0	121
Covid-19 Violence (district, #)	93,210	0.01	0.20	0	36
Religious Violence (district, #)	93,210	0.04	0.80	0	121
Battles (district, #)	93,210	0.01	0.45	0	72
Explosions (district, #)	93,210	0.001	0.053	0	12
Riots (district, #)	93,210	0.01	0.18	0	16
Strategic Violence (district, #)	93,210	0.001	0.044	0	4
Violence Against Civilians (district, #)	93,210	0.003	0.091	0	15
Total Violence (Binary indicator)	93,210	0.05	0.21	0	1
Protests (binary indicator)	93,210	0.03	0.18	0	1
Covid-19 Violence (binary indicator)	93,210	0.01	0.09	0	1
Religious Violence (binary indicator)	93,210	0.02	0.12	0	1
Battles (binary indicator)	93,210	0.003	0.051	0	1
Explosion (binary indicator)	93,210	0.0005	0.0220	0	1
Riots (binary indicator)	93,210	0.008	0.088	0	1
Strategic Violence (binary indicator)	93,210	0.001	0.031	0	1
Violence again civilians (binary indicator)	93,210	0.002	0.047	0	1
District Characteristics					
High Medical Capacity (binary indicator)	93,210	0.618	0.486	0	1
High Nightlight Intensity (binary indicator)	93,210	0.566	0.496	0	1

Notes: Data sources are as follows - Covid-19 data is acquired from Covid19india.org (https://api.covid19india.org/), Violence data is acquired from Armed Conflict Location & Event Data Project (ACLED, acleddata.com), and finally the district and state-level characteristics are acquired from the Indian Population Census (2011). Data on majority political parties in state governments is acquired from the Election Commission of India, while the notification of Naxal-violence affected districts is acquired from the Ministry of Home Affairs, Government of India.

CEPR PRESS

Covid Economics 25, 3 June 2020: 122-140

Table 2: Event Study: Types of Violence

	Total Violence (1)	Covid19 Violence (2)	Religious Violence (3)
First Covid-19 Case	-0.0108	-0.0005	-0.0039
	(0.0111)	(0.0069)	(0.0043)
Lockdown Phase 1	-0.0087	-0.0034	-0.0018
	(0.0114)	(0.0046)	(0.0061)
Lockdown Phase 3 - Red zone	-0.0069	0.0354***	-0.0228***
	(0.0142)	(0.0088)	(0.0053)
Lockdown Phase 3 - Orange zone	0.0162**	0.0036	0.0065**
	(0.0071)	(0.0047)	(0.0029)
Total Covid-19 Cases	0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
Cured Covid-19 Cases	-0.0000	0.0000	-0.0000**
	(0.0000)	(0.0000)	(0.0000)
Deaths from Covid-19	0.0001	-0.0000	0.0001
	(0.0002)	(0.0001)	(0.0001)
Lead Week 3	0.0041	-0.0009	0.0003
	(0.0056)	(0.0027)	(0.0029)
Lead Week 2	0.0006	-0.0043	-0.0012
	(0.0068)	(0.0026)	(0.0034)
Lead Week 1	-0.0024	-0.0019	-0.0025
	(0.0067)	(0.0031)	(0.0038)
Lag Week 1	-0.0056	0.0071**	-0.0064*
	(0.0071)	(0.0032)	(0.0038)
Lag Week 2	-0.0121	0.0084*	-0.0104**
	(0.0078)	(0.0048)	(0.0045)
Lag Week 3	-0.0158*	0.0120**	-0.0112**
	(0.0089)	(0.0055)	(0.0050)
Lag Week 4	-0.0195**	0.0092*	-0.0114**
	(0.0098)	(0.0051)	(0.0056)
Lag Week 5	-0.0256**	0.0108	-0.0152**
	(0.0109)	(0.0076)	(0.0067)
Lag Week 6	-0.0402***	0.0116	-0.0180**
	(0.0136)	(0.0094)	(0.0078)
Observations	93,210	93,210	93,210
R^2	0.16	0.06	0.13
District FEs	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes
State x Week FEs	Yes	Yes	Yes

Notes: The dependent variables are binary indicators equal to 1 (0 otherwise) if any violence is reported (column 1), any Covid-19 related violence is reported (column 2), and any religious violence is reported (column 3). The treatment variable is First Covid-19 Case, which is a binary indicator equal to 1 when the first covid-19 case is reported on a particular date in a district (0 otherwise). The independent variables of interest include three lead week indicators equal to 1 in the respective weeks before First Covid-19 case, and six lag weeks indicators equal to 1 in the respective weeks following First Covid-19 Case (0 otherwise). Covariates include district-level binary indicators equal to 1 for Lockdown Phase 1 (different starting dates across districts between March 22-25 up to April 14, 2020), phase 3-red zone and phase 3-orange zone (after May 4, 2020). Lockdown Phase 2 is excluded due to lack of variation across districts and phase 3 - green zone indicator is excluded as the omitted category. Finally, state-level measures of reported Covid-19 infections, cured and deaths are included. All columns include district, date and state-week fixed effects. Robust standard errors triple-clustered by district, date and state-week are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Event Study: Types of Violence

	Protests	Riots	Violence Against Civilians
	(1)	(2)	(3)
First Covid-19 Case	-0.0089	-0.0043	0.0015
	(0.0083)	(0.0046)	(0.0027)
Lockdown Phase 1	-0.0113	-0.0040	-0.0023
	(0.0097)	(0.0029)	(0.0026)
Lockdown Phase 3 - Red zone	-0.0055	0.0033	-0.0010
	(0.0113)	(0.0071)	(0.0017)
Lockdown Phase 3 - Orange zone	0.0147***	-0.0039	0.0019*
	(0.0047)	(0.0031)	(0.0011)
Total Covid-19 Cases	0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
Cured Covid-19 Cases	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Deaths from Covid-19	0.0001	0.0001*	-0.0000
	(0.0002)	(0.0000)	(0.0000)
Lead Week 3	0.0039	0.0021	0.0018
	(0.0053)	(0.0023)	(0.0011)
Lead Week 2	0.0018	-0.0003	0.0012
	(0.0065)	(0.0018)	(0.0012)
Lead Week 1	0.0007	-0.0011	0.0008
	(0.0062)	(0.0029)	(0.0010)
Lag Week 1	-0.0093	0.0006	0.0019
	(0.0073)	(0.0022)	(0.0014)
Lag Week 2	-0.0196**	0.0031	0.0032
	(0.0081)	(0.0029)	(0.0021)
Lag Week 3	-0.0263***	0.0076**	0.0014
	(0.0091)	(0.0036)	(0.0019)
Lag Week 4	-0.0289***	0.0078**	0.0009
	(0.0099)	(0.0033)	(0.0011)
Lag Week 5	-0.0394***	0.0125***	0.0012
	(0.0112)	(0.0034)	(0.0015)
Lag Week 6	-0.0453***	0.0020	0.0022
	(0.0130)	(0.0043)	(0.0023)
Observations	93,210	93,210	93,210
R^2	0.17	0.03	0.02
District FEs	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes
State x Week FEs	Yes	Yes	Yes

Notes: The dependent variables are binary indicators equal to 1 (0 otherwise) if any protests are reported (column 1), any riots are reported (column 2), and any violence against civilians is reported (column 3). Independent variables are described in Table 2. All columns include district, date and state-week fixed effects. Robust standard errors triple-clustered by district, date and state-week are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Covid Economics 25, 3 June 2020: 122-140

Covid Economics 25, 3 June 2020: 122-140

Table 4: High vs Low Medical Capacity Districts

	Total Violence		Riots	
	Low Capacity (1)	High Capacity (2)	Low Capacity (3)	High Capacity (4)
First Covid-19 Case	-0.0288**	-0.0093	-0.0017	-0.0065
	(0.0135)	(0.0151)	(0.0082)	(0.0046)
Lockdown Phase 1	-0.0156	-0.0005	0.0002	-0.0041
	(0.0157)	(0.0117)	(0.0059)	(0.0026)
Lockdown Phase 3 - Red zone	-0.0135	0.0307*	-0.0145	0.0165
	(0.0200)	(0.0164)	(0.0138)	(0.0110)
Lockdown Phase 3 - Orange zone	0.0056	0.0309***	-0.0033	0.0028
	(0.0113)	(0.0106)	(0.0089)	(0.0049)
Total Covid-19 Cases (state)	-0.0000	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cured Covid-19 Cases	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Deaths from Covid-19	0.0001	0.0001	0.0001	0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Lead Week 3	-0.0067	-0.0085	0.0030	0.0009
	(0.0092)	(0.0083)	(0.0043)	(0.0038)
Lead Week 2	0.0001	-0.0166	0.0048	-0.0046
	(0.0094)	(0.0107)	(0.0034)	(0.0029)
Lead Week 1	-0.0235***	-0.0018	-0.0018	-0.0016
	(0.0087)	(0.0113)	(0.0043)	(0.0053)
Lag Week 1	-0.0178*	-0.0012	0.0010	0.0009
	(0.0100)	(0.0113)	(0.0045)	(0.0035)
Lag Week 2	-0.0207*	-0.0217*	0.0080	0.0007
	(0.0119)	(0.0117)	(0.0067)	(0.0042)
Lag Week 3	-0.0157	-0.0292**	0.0154***	0.0082
	(0.0134)	(0.0126)	(0.0053)	(0.0062)
Lag Week 4	-0.0147	-0.0332**	0.0213***	0.0090*
	(0.0134)	(0.0154)	(0.0063)	(0.0049)
Lag Week 5	-0.0078	-0.0455***	0.0340***	0.0116
	(0.0176)	(0.0153)	(0.0088)	(0.0072)
Lag Week 6	-0.0210	-0.0479**	0.0123	-0.0055
	(0.0197)	(0.0190)	(0.0074)	(0.0069)
Observations	35,620	57,590	35,620	57,590
R^2	0.20	0.29	0.14	0.14
District FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
State x Week FEs	Yes	Yes	Yes	Yes

Notes: The dependent variables are binary indicators equal to 1 (0 otherwise) if any violence is reported (columns 1 and 2) and any riots are reported (columns 3 and 4). Independent variables are described in Table 2. All columns include district, date and state-week fixed effects. Robust standard errors triple-clustered by district, date and state-week are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: High vs Low Nightlight Districts

	Violence Against Civilians		Riots	
	Low Nightlight	High Nightlight	Low Nightlight	High Nightlight
	(1)	(2)	(3)	(4)
First Covid-19 Case	-0.0048**	0.0054	-0.0047	-0.0050
	(0.0023)	(0.0042)	(0.0033)	(0.0072)
Lockdown Phase 1	-0.0077	0.0020	-0.0057*	0.0036
	(0.0071)	(0.0022)	(0.0033)	(0.0045)
Lockdown Phase 3 - Red zone	-0.0001	0.0048	-0.0179*	0.0092
	(0.0027)	(0.0037)	(0.0096)	(0.0086)
Lockdown Phase 3 - Orange zone	0.0007	0.0070**	-0.0060	0.0036
	(0.0023)	(0.0033)	(0.0061)	(0.0038)
Total Covid-19 Cases	0.0000	0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cured Covid-19 Cases	0.0000	0.0000***	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Deaths from Covid-19	-0.0001	-0.0000***	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Lead Week 3	0.0003	0.0007	-0.0030	0.0035
	(0.0026)	(0.0012)	(0.0034)	(0.0036)
Lead Week 2	0.0010	0.0020	0.0010	-0.0009
	(0.0028)	(0.0017)	(0.0033)	(0.0028)
Lead Week 1	-0.0028	0.0020	0.0034	-0.0043
	(0.0022)	(0.0018)	(0.0046)	(0.0043)
Lag Week 1	-0.0011	0.0048**	0.0025	-0.0025
	(0.0024)	(0.0020)	(0.0039)	(0.0046)
Lag Week 2	0.0024	0.0074**	0.0082*	-0.0012
	(0.0045)	(0.0033)	(0.0050)	(0.0056)
Lag Week 3	-0.0005	0.0046**	0.0109*	0.0085
	(0.0034)	(0.0020)	(0.0061)	(0.0057)
Lag Week 4	-0.0008	0.0009	0.0166**	0.0095*
	(0.0023)	(0.0020)	(0.0067)	(0.0050)
Lag Week 5	-0.0061	0.0026	0.0253***	0.0141*
	(0.0038)	(0.0025)	(0.0089)	(0.0071)
Lag Week 6	0.0013	0.0029	0.0109	-0.0029
	(0.0031)	(0.0024)	(0.0084)	(0.0063)
Observations	40,430	52,780	40,430	52,780
R^2	0.13	0.13	0.15	0.13
District FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
State x Week FEs	Yes	Yes	Yes	Yes

Notes: The dependent variables are binary indicators equal to 1 (0 otherwise) if any violence against civilians is reported (columns 1 and 2) and any riots are reported (columns 3 and 4). Independent variables are described in Table 2. All columns include district, date and state-week fixed effects. Robust standard errors triple-clustered by district, date and state-week are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Covid Economics 25, 3 June 2020: 122-140