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Tanika Chakraborty
Anirban Mukherjee

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Tanika Chakraborty
Indian Institute of Management Calcutta and IZA

Anirban Mukherjee
University of Calcutta

MAY 2021

ABSTRACT

Economic Geography of Contagion: A Study on COVID-19 Outbreak in India*

We propose a regional inequality-based mechanism to explain the heterogeneity in the spread of Covid-19 and test it using data from India. We argue that a core-periphery economic structure is likely to increase the spread of infection because it involves movement of goods and people across the core and peripheral districts. Using nightlights data to measure regional inequality in the degree of economic activity, we find evidence in support of our hypothesis. Further, we find that regions with higher nightlight inequality also experience higher spread of Covid-19 only when lockdown measures have been relaxed and movement of goods and services are near normal. Our findings imply that policy responses to contain Covid-19 contagion needs to be heterogeneous across India, depending on the ex-ante economic structure of a region.

JEL Classification:	I15, I18, R1
Keywords:	COVID-19, contagion, core-periphery, nightlight, industrial-heterogeneity

Corresponding author:
Tanika Chakraborty
Indian Institute of Technology
FB 626
Kanpur, UP 208016
India
E-mail: tanika@iitk.ac.in

1. Introduction

The Covid-19 epidemic that started from China in the month of November, 2019 has already created a havoc worldwide. With 113 million confirmed cases and 2.5 million deaths as of February 27, 2021, Covid-19 is being labelled as the worst epidemic since Spanish Flu of 1918. One of the striking features of the Covid-19 epidemic is the cross-country variation in terms of the number of infected and deaths; the number of confirmed cases per 1 million population is much higher in Europe and America than in Asia and Africa. For example, while the number of confirmed patients per 1 million population is 87,884 in the USA and 61,222 in United Kingdom, it is only 7989 in India, 3860 in Sri Lanka and 4,178 in Zambia. Such cross-continent comparisons, however, is not always meaningful as underdeveloped countries often do not have enough facilities to carry out more tests and the lower number of cases could just be the result of a smaller number of tests. But the cross-country differences are difficult to miss even if we compare similar type of countries. For example, the number of confirmed patients per 1 million population in Canada, standing at 22,766, is almost one fourth of that in the United States. A similar difference within a continent can also be seen among European nations; the number of confirmed patients per 1 million population is 78,986 in Portugal, 63,172 in Netherlands, 48,140 in Italy and 29,010 in Russia[1].

There could be several factors that explain such cross-country differences; the major candidates being population density, urbanization, available infrastructure to carry out effective quarantine etc. While social and demographic characteristics may partly and significantly explain the variations in the extent of the contagion, we propose a different explanation based on the economic geography of a country. We argue that the contagion depends on certain patterns of regional development. Our argument draws heavily on the economic-geography theory of economic development, pioneered by Paul Krugman (see Krugman, 1991; Krugman and Venables, 1995) which shows that the process of economic development ends up creating a heavily industrialized, small core area, surrounded by a large non-industrial periphery. In the absence of the core-periphery pattern, different regions within a country can operate in autarky and in the event of any outbreak in that country, an infected region can be disconnected from the rest of the country without seriously disrupting the supply of essentials. This becomes more difficult in presence of core-periphery structure where remote regions are all connected with the economic hub and therefore to each other. If any of the hubs get affected -- which is a likely scenario as hubs are densely populated -- the contagion does not only spread within the hub,

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[1] The country specific data come from https://www.worldometers.info/coronavirus/ as of 28 February, 2021

but it spreads to the remote areas as well. Given the heavy dependence of peripheral areas on the core in a core-periphery structure, any attempt to isolate the core will impose a very high burden of economic costs on the peripheries.

In our paper, we propose the hypothesis that the extent of contagion will be higher in areas characterized by higher regional inequality (i.e., core-periphery structure). Even though we motivated our research by giving international examples, doing this analysis using cross country samples hardly makes any sense as difference across countries could be the result of institutional or cultural differences which are difficult to control. We, instead, explain variation in infection rates across regions within India by variations in the potential degree of the core-periphery structure across these regions.

The core-periphery structure essentially embeds regional inequality. For instance, a state showing a stronger core-periphery structure will also have greater intra-state economic inequality. In addition, night time luminosity is a well-established measure to compare economic and industrial development across countries as well as regions within a country (Henderson, Storeygard and Weil, 2012; Prakash *et al.*, 2019). Hence, we construct a regional inequality index based on night time luminosity data, across the districts of India, to measure of the core-periphery structure of a region[2].

The higher the luminosity level of a district, the higher is the level of industrial development in the district. Therefore, a state will have a stronger core-periphery structure if inter-district nightlight inequality in that state is high. We expect that the states with higher intra-state regional inequality will show higher Covid-19 infection rate, after accounting for other factors that vary across states and over time. We follow the growing literature on Covid 19 to identify a range of variables to control for. Most of the hypotheses, that are tested by other researchers, are either some ideas generated from the understanding of contagious diseases in general (e.g. contagion spreads faster in densely populated area) or some heuristics that originated from casual, empirical observations (e.g. COVID 19 spreads less in areas covered by BCG vaccination). The controls we consider, fall in three broad categories: demographic, economic and disease environment. Section 2.2 provides further details on these potential correlates. However, even after including a long list of variables, one obvious issue with using a state level measure of regional inequality is that we cannot account for unobserved state level correlates, of both inequality and contagion; governance, institutions or culture, to name just a few. To address this endogeneity issue, we construct a measure of district-neighbourhood inequality

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[2] We use night time luminosity and nightlights interchangeably in this paper.

which measures regional inequality among a group of neighbouring districts. We use it to explain variations in contagion rate across districts within a state. This allows us to eliminate state specific unobserved heterogeneity.

In addition to the core-periphery framework using nightlight inequality, we also investigate whether the extent of contagion in a district is affected by the industrial heterogeneity of the district. Our measure of industrial heterogeneity captures the extent to which a district's work force is fractionalized across industries. A district with higher heterogeneity would mean that people in that district are employed in a greater number of industries than in a district with lower heterogeneity. While in spirit, industrial heterogeneity of a district is related to the core-periphery structure, this measure is expected to affect the contagion rate in a more complex way than regional inequality. On the one hand, a district with more industries would mean that that district can survive in autarky and therefore, has lower chance of infection. But in such a district, a family would typically have members working in different industries. Hence, if one member's workplace is hit by the contagion, it will infect other members of the family and eventually the industries other members are working in. The net effect of these two countervailing forces is ambiguous.

The mechanism that underlies both of our measures involves movement of people – from core to the periphery or from the household to various industrial clusters. In response to the Covid-19 contagion, the Indian government, in March 2020, announced a lockdown resulting in suspension of usual activities of government offices, business establishments and educational institutions. Subsequently, over different phases of lockdown (and eventually unlocks) different types of activities were allowed. These different phases of lockdown and unlock led to different degree of movements of people and vehicles. Hence, for both regional inequality and industrial heterogeneity, we expect the relative strength of their effects on the contagion to depend on the degree of movement restrictions across different phases of lockdown and unlock. Accordingly, we check how the relationship between Covid-19 infection rate and regional inequality changes across different phases of lockdown and unlock.

Our findings support the hypothesis that the core-periphery economic structure leads to a higher spread of the infection. We find that a higher degree of state level regional inequality in nightlights leads to greater contagion. Our findings are similar when we account for state fixed effects and state level linear time trends using the extent of nightlight inequality in a district's neighborhood. In both cases, the findings remain robust to a staggered inclusion of all the time varying district and state level variables. The heterogeneity analysis by phases of nationwide

lockdown and unlock, as announced by the Central government, shows that the core-periphery structure contributes to the spread of the Covid19 infection when the economy opens up. The results are absent or muted during the lockdown periods and early phases of unlock. Similarly, a district with greater industrial heterogeneity also experiences a higher contagion once the economy opens up. The results from our heterogeneity analysis underscores the channel through which the core-periphery structure or the industrial heterogeneity affects the contagion. Greater movement of people from the core to the peripheral districts or across industries within a district causes greater contagion, after accounting for district level economic development. In a similar vein, we also use unemployment rates as proxy for movement of people (or lack thereof) and investigate its interaction with the core-periphery structure. We find that districts with higher levels of baseline unemployment experience a lower contagion within states with greater regional inequality in nightlights.

The findings in this paper contribute to the section of the literature which looks at the policy response of governments in face of Covid-19. The most common strategy practiced by any government is that of lockdown which is complemented by health policies. Chiplunkar & Das (2020) showed that the nature and extent of such policies vary widely across countries depending on the political system prevailing in those countries. Nevertheless, we have seen that whenever a lockdown was imposed, more often than not it was imposed homogeneously across all the regions of a country. Such a country wide lockdown involves huge economic loss. In the context of India, for example, quite a few papers estimated the negative impact of lockdown policies on economic outcomes (Beyer, Jain and Sinha, 2020; Beyer, Franco-Bedoya and Galdo, 2021). Our paper, on the other hand, provides a road map of selective lockdown that can minimize the economic costs. We argue that a contagion is more severe in areas characterized by higher regional inequality and therefore, lockdown should be imposed more stringently in these areas. The idea of selective lockdown is not completely novel. We have seen that during the unlock phases, Indian government has followed this strategy based on the number of confirmed cases in an area. Essentially, under this policy, the districts were categorized in to various color-coded zones based on the severity of the contagion. The districts with a very high number of cases were labelled as red zone and the most stringent lockdown policy was imposed on them. The orange and green districts had moderate and low number of cases, respectively, and the stringency of the lockdown policies were more relaxed in these districts. But this categorization was done based on the number of confirmed cases, an ex-post realization. The selective lockdown strategy that follows from our work is better than this policy. Unlike the government strategy which uses the ex-post number of confirmed cases, our

strategy is based on an ex-ante measure, regional nightlights inequality, that can determine the severity of the contagion. Therefore, while government strategy only works after an area is severely affected, our approach can be deployed before the contagion spreads and can be used to minimize economic and human loss.

Our paper is structured in the following way: in section 2 we discuss the data and descriptive statistics, in section 3 the empirical strategy, in section 4 the results. In section 5 we conclude.

2.   Data and Descriptive Statistics

2.1 Data on Covid-19 infection: state-wise variation

In this section we outline the various sources from where we collect our data and explain the distribution of Covid-19 infection and death rates across various states during our sample period. One of the serious issues that we face is regarding the quality and availability of data for different states. Since health is a state subject in India, district level information on Covid19 infections in India is provided by each state. States have followed their own templates, in publishing the information related to Covid19 tests and infections, which has also changed over time within each state. While the non-uniform format across all states and over time poses its own challenges, a much bigger constraint is that some states provided district level information, while others have only provided state level information on tests conducted and cases confirmed, active or recovered. Even within each state, sometimes the information published is aggregated and sometimes disaggregated. Since all states are required to pass on the detailed information routinely to the centre, Ministry of Health and Family Welfare also provides the data on confirmed, recovered, active and deaths aggregated at the state level for the current day. However, there is no central database that publishes and updates either patient level information or even district level information on tests and detections for all India on a daily basis. Fortunately, a crowd sourced initiative, *Covid19india* came up in India in the early days of the pandemic which gathered data from various publications of state governments available online, such as twitter feeds of different state's health department, press releases and bulletins. They created a publicly available database of Covid19 infections in India. We obtain all information related to Covid19 from this database available at https://www.COVID19india.org/.

In our paper, we seek to explain inter-state heterogeneity in terms of Covid-19 infection rate. The state governments tried to control the contagion by using the dual strategies of tracing whereabouts of people who came in direct contact with confirmed patients and restricting general movements of the mass through lockdown. While the former took the centre stage in

the first one or two months, eventually the strategy of shutting down economic activities became the spearhead of government's anti-Covid policies. In the early days of the pandemic, the data source we are using was able to collect and create a patient level database on daily basis. The patient level data provides information on the location, gender and age of each patient recorded and even has information regarding the mode of infection, as a result of contact tracing. For instance, the data records whether the infection was likely contracted from a relative or friend, from a public gathering, while travelling by train etc. This means that it most likely points to a possibility of *community infection* in cases where the source could not be traced. Figure 1 plots the fraction of cases that could not be traced across India and how that evolved over time.

Fig 1: 7-Day Average India Fraction of Community Infection vs Total Confirmed

It shows that towards the beginning of the pandemic, up until March 15th, the source of almost all cases could be traced. By March 15th, India had about 114 Covid positive patients. As time evolved and the number of Covid infections started climbing, the extent of contact tracing went down, and the fraction of cases that were untraced went up. The nationwide lockdown in India started from March 22nd. From early April, the source of infection could hardly be ascertained for any case and after the first week of April, by when there were around five thousand cases in India, there was either no attempt to trace the source or the information stopped coming in. With an increase in the number of infections, not only was it more challenging to find information on the source of infection, it became difficult to get information on a case-by-case basis and the individual level data was also discontinued after 26th April. From then, only district level measures are available consistently on the basis of publications by the health departments of each state. In a few cases where the specific state only published state level aggregates, only state level measures are available. Please see appendix table 1 for the details of data availability.

Figure 2: Share of Covid-10 confirmed cases in 10 leading states

Figure 2 shows the distribution of Covid infections across states as of 1st February, 2021. 10 states account for more than 75% of all cases in the country. Hence, for the rest of the descriptive statistics on Covid-19 infection in India, we report expositions based on these 10 states.

Figure 3 shows the evolution of Covid over time in the top 10 states. As has been well known, Maharashtra led by a big margin, in total number of infections, over the entire period of time from the onset of the pandemic in India to early February, 2021, when our data ends. It was followed by Delhi for a short while. But Delhi was quickly surpassed by Andhra Pradesh, Tamil

Nadu , Karnataka and UP by August. The rest of the states in the top 10, viz. West Bengal, Bihar, Telangana and Assam remained relatively closer to each other and later.

Figure 3 : Time series Share of Covid-19 confirmed cases in 10 leading states

While this graph gives an overall idea about the cross sectional spread of the disease across India, it fails to account for the difference in sizes of these states. For example, comparing the entire state of Maharashtra with Delhi may be not be very informative given the large difference in population and land sizes.

Figure 4: Total confirmed Covid-19 cases per 100 thousand population of the states.

Figure 4 normalizes the total numbers by population sizes of each state. States such as Maharashtra and Tamil Nadu which dominate the Covid-19 scenario in India in terms of total number of patients rank much lower when we consider per capita infection spread. Now, Delhi surpasses all other states by a large margin with the gap starting to show up significantly from early June. Andhra Pradesh, which was much lower down initially, caught up with Delhi by September. Maharashtra and Tamil Nadu are the next in the list which remained much below Delhi but much higher up than other states throughout the period. Like Andhra Pradesh Karnataka too caught up, although at a lower level with Maharashtra and Tamil Nadu, around September. Next in the order are Telangana and Assam, followed by West Bengal. Uttar Pradesh, being the largest state was high up in the list of total infections, but towards the end in the list of top ten, along with Bihar.

Of course, one must also keep in mind that these numbers, observed in isolation, hides more than it reveals. States that tested more and tested more efficiently are more likely to report more cases. While we cannot say much about effectiveness of testing samples and procedures, Figures below present the total number of tests performed by each state over time.

Figure 5a: Pie Chart: Total tests in 10 leading states

Figure 5b: Time series of total tests in 10 leading states

Figure 5c here: State-wise Per capita Tests

Figure 5a and 5b show that there is a wide disparity in the number of tests performed across different states. For instance, while Maharashtra accounted for 21% of India's total case load, it only constituted 6% of all tests conducted. On the other hand, while UP accounted for 6% of the cases, it conducted 13% of tests. However, once again, these numbers are not exactly comparable for a) different states have conducted different shares of RTPCR and RAT tests which are known to have significantly different accuracy (Chakrabarti, 2020)and 2) at the very least test data, just like case load, needs to account for difference in population sizes. Information on the first is available only for a handful of state-date combinations and therefore,

it is difficult to make the comparison. Figure 5c which represents number of tests per 100000 population addresses the second issue. We find that that when normalized by population, Delhi becomes the front runner with 44,122 tests per 1,00,000 population. Uttar Pradesh (UP), on the other hand, which carried out more tests than any other test, ranks low when we compare using this metric. It has carried out 10706 tests for each 1,00,000 population. Maharashtra is very close to UP with 10498 tests.

However, the direction of causality underlying the positive relationship between tests and confirmed patients can run both ways. On one hand, if a state runs less tests, there will be lower number of confirmed patients. But on the other hand, a state that is suffering from lower degree of pandemic, may decide to run less tests and save resources. One way to check which one is correct by looking at test per confirmed patient ratio. This tells us for each Covid positive case how many non-Covid people have been tested.

Figure 6a: Tests per confirmed patients: All India time series

Figure 6b: Tests per confirmed patients: Top 10 states bar chart as of 1 Feb, 2021

Figure 6a shows the variation in this number for India over time – from 31 March, 2020 to 31 January, 2021. We find that in the month of April, 2020 this ratio hovered around 25 which means for each positive patient tested, there were around 24 non infected persons tested. However, beginning May, the ratio fell below 25 and remained so until October 2020. From then the ratio picked up and towards the end of the year 2020, it came close to the 100 mark. From figure 6b, we see wide variation in this ratio across states. In this case, the ratio has been calculated taking the cumulative test and confirmed case figure for the entire period (January 31, 2020-January 31, 2021) into account. For Maharashtra and Kerala, this ratio is really low (22.44 and 9.33 respectively). But it is very high for Uttar Pradesh (542.74) and Delhi (around 433.54). Among other states, Andhra Pradesh, Odisha and Rajasthan come somewhere in the middle which tested around 200-300 non-infected people to get 1 confirmed case. On the other hand, the ratio is around the 100 mark for states such as Karnataka, West Bengal and Tamil Nadu.

Finally, in addition to total infections what also matters, to understand the extent of the pandemic, is the death rate. Figure 6 plots the *case fatality rate* across the top 10 states.

Figure 7: State-wise case fatality rate in 10 leading states

To be sure, the case fatality rate, although a ratio, is also not directly comparable across states without accounting for differences in testing numbers. This is made clear when we look at the numbers for West Bengal which stands out with an extremely high *case fatality rate* towards the early part of the pandemic. However, the fatality rate fell equally sharply for West Bengal

by end of June, also a time when test rates in Bengal started climbing up (see Figure 7). However, as all states increased their testing rates by July, the case fatality rate fell and finally we notice a convergence in fatality rates across states. However, as in the case of Covid-19 infections, there are inconsistencies in the data on deaths particularly during the early part of the pandemic. Moreover, most states did not consistently publish death data at the district level. Hence, we restrict our analysis to the spread of the disease from May 4, 2020, onwards, when the third phase of nationwide lockdown started in India.

There are two reasons why we choose this date cut-off. First, the district level database of Covid19india.org starts from this date possibly because the quality of data gets better from this period as different state governments start reporting data in a consistent fashion. Second, our theory is relevant when there are some movements of goods and people. In the first month of lockdown (lockdown 1 and 2) very stringent restrictions were imposed on business and vehicles. From 4 May 2020, the nationwide lockdown was eased for the first time with several relaxations. Further, we include the following major states in our sample[3]. Andhra Pradesh, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, Uttarakhand, West Bengal. As of February 1, 2021, the last date for our data, these states together account for around 84% of our data.

While our empirical specification accounts for state fixed effects, we try to account for time invariant district level covariates and time varying state or district level covariates using existing information on correlates of Covid-19 contagion. However, given the novelty of COVID 19, our choice of correlates is not grounded in any theory. Most of the hypotheses, that are tested by other researchers, are either some ideas generated from our understanding of contagious diseases in general (e.g., contagion spreads faster in densely populated area) or some heuristics that originated from casual, empirical observations (e.g., COVID 19 spreads less in areas covered by BCG vaccination). For instance, the hypotheses regarding the Bacillus Calmette-Guérin (BCG) childhood vaccination has been tested by Miller et al. (2020) and they found that countries without universal BCG vaccination such as Italy, Nederland and USA had been more severely affected by COVID 19 than the countries with universal BCG program, at least at the time they wrote the paper. There has been quite a few papers looking at the

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[3] Our estimation sample includes 19 major states. It excludes among others Delhi and other Union Territories. Since Union Territories are not divided in to districts, we cannot calculate nightlight inequality. Also, for Delhi, the Covid data is reported for Delhi as a whole. Consequently, there is no district level variation within Delhi. And nightlight inequality does vary over time. Hence it will mean a single nightlight inequality measure will explain variations in Covid over time.

correlation between temperature and COVID infection which has been found to be negative (less contagion in high temperature area) (Bannister-Tyrrell *et al.*, 2020; Wang *et al.*, 2020, Sajadi et al. 2020). However, there are papers which dispute this claim of negative relationship between temperature and COVID infection. In one such paper, Zhu & Xie (2020) looking at the COVID situation 122 cities across China, did not find any consistent negative relation between temperature and COVID infection.

Taking cue from the existing literature and ideas we use a rich set of covariates consisting of demographic, weather, economic and disease environment related variables. Under the demographic variables we consider population density. We control for weather variations using temperature, rainfall, latitude and longitude. The variables that are considered under the economic category include levels of nightlight and unemployment. The disease environment variables include general immunization rate, BCG immunization rate and historical Malaria index.

We combine the Covid-19 database with information on these demographic, health, social, economic, geographic and meteorological indicators from multiple sources for our analysis. While some of these indicators, including the information on Covid-19, are available at the district level, a few of our measures could only be obtained at the state level. Therefore, for the testing of our hypotheses we use the district level aggregated information where data is available. In some cases, where we are restricted to state level data, we use state level aggregation.

Below we provide a detailed outline of all the supplementary data sources, summarising each variable used in our analysis in Table 1.

Table 1: Summary Statistics here

2.2 Data on Demographic variables:

The demographic variables that we use, include the population of the district and population density. However, the data come from 2011 census. In case of those districts that were created after 2011, we use the total population for the original district from the 2011 census and then distribute it in proportion to land area among the newly formed districts. The average population in a district is roughly 2.1 million. The average population per square km of a district is 601, with a standard deviation more than double the value. We use the total population in a district to calculate our dependent variable, per capital infection rate in a district.

2.3 Data on Weather variables:

The temperature and rainfall variables are obtained from the Indian Meteorological Department. Both variables are measured at the district level on a daily basis. Hence, we are only able to use data from 2019 since updating the Covid data on a daily basis would also require real time weather data for 2020, which is not freely available. The average temperature remains around 34 degree Celsius. Mean rainfall is about 6.6 mm but with a very high variance.

2.4 Data on Health variables:

We have discussed earlier that there are studies trying to link between the extent of BCG vaccination program and spread of COVID 19 outbreak, claiming that the relationship between these two variables is negative. To allow for such variation in the spread of Covid19 across India, we have included the extent of BCG vaccination in Indian districts measured by the fraction of children in a district who have been given BCG vaccination, as of 2007-2008, the earliest year for which we could find district level information on BCG vaccination. The data comes from District Level Household Survey (DLHS)-3, a nationally representative sample survey covering 720,000 households, that was conducted in 2007-08. There is another potential correlate that have been discussed in popular media – malaria prevalence. It was observed that COVID 19 infection is negatively related to malaria prevalence. Hence, we include information on prevalence of malaria across the districts of India, from the colonial period, as one of the independent variables in our regression framework. The data comes from Cutler et al. (2010). This data provides a classification of districts according to its malaria intensity. There are 6 categories in total – categories 1 and 2 for non-malarious, 3 and 4 for potential epidemic, while 5 and 6 are classified as malarious.

2.5 Measures of the Core-Periphery structure:
2.5.1 Nightlight inequality – state level

Finally, we turn to our main variable of interest. We use nightlight data that measures the luminosity of night time lights using the satellite images. Typically, nightlights data is widely used as a proxy for economic activity. We use the district level measure of luminosity in 2019 to create a state level inequality of luminosity. Specifically, we use the ratio of the highest 90% to the lowest 10% from the distribution of luminosity across districts within a state. We argue that the state level dispersion captures the degree of conglomeration in a state. In addition to the inequality measure, we also control for the level of nightlights in a district as a proxy for overall economic development.

2..5.2 Nightlight inequality – district-neighbourhood level

We use this measure to solve the problem of unobserved heterogeneity at the state level. We call two districts neighbour if they share boundaries. This way for each district there exists a cluster of districts which form its neighbourhood. We calculate the nightlight inequality for this neighbourhood. The neighbourhoods typically consist of 3-4 districts and therefore, our original measure of inequality – ratio of 90th and 10th percentile does not make much sense. Instead, we measure nightlight inequality in the following way:

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$$\eta_d = 1 - \frac{\mu_{Min}^d}{\mu_{Max}^d} \tag{2}$$

In the above expression η_d measures the neighbourhood nightlight inequality for district d, μ_{Min}^d measures the minimum nightlight in the neighbourhood of district d while μ_{Max}^d the maximum value in the neighbourhood. This expression essentially becomes R_d/μ_{Max}^d where R_d refers to range (Max-Min) of nightlights in the neighbouring districts. Range captures the degree of dispersion and therefore, higher the value of η_d, higher will be the value of neighbourhood inequality.

2.5.3 Industrial Heterogeneity Index:

We argued that states with greater inter district inequality is more likely to suffer from greater degree of infection. We reasoned that a state characterised by greater intra-state regional inequality is likely to experience more inter district movements of goods and services between districts causing the disease spread at a faster rate. In this subsection we test the hypothesis in a different way. Here, we calculate the industry mix present in a district and argue that a district with greater industrial heterogeneity will suffer from less degree of contagion as it depends less on other districts for supplies.

We calculate industrial heterogeneity using the following formula:

$$H_d = 1 - \sum_i s_{id}^2 \tag{2}$$

Where H_d is the district level heterogeneity index and s_{id} is the share of labor force in industry i and district d.

2.6 Correlation between Covid-19 infection and explanatory variables

Figure 7 shows the bivariate relationship between the spread of Covid and the various factors that we discuss above. We find a positive correlation between nightlights inequality and the total number of infections reported in a state, with most states huddling up around the mean relationship. However, Andhra Pradesh seems to have a much higher level of covid infection compared to what is predicted by its level of nightlight inequality. Uttar Pradesh, on the other hand, seems to have a much lower level of Covid 19 infection compared to what is predicted by its level of nightlight inequality. These other factors that potentially predict the spread of the infection are shown in the rest of the panels.

Figure 8: Correspondence of Total Confirmed Covid19 cases per 100,000 people with various potential determinants of the spread of the infection.

As expected, the intensity of infection is higher in states with higher population density. However, contrary to what has been noted based on cross country evidence, we find a positive correlation between the spread of Covid19 and the penetration of BCG vaccination in a state. Since poorer health infrastructure could predict both the extent of BCG vaccination and Covid19 spread, we also used the overall level of immunization. Once again, we find a positive relationship between the prevalence of immunization in children in 2007-08 and Covid19 spread. With respect to the intensity of malaria we find that states with higher historic prevalence of malaria have experienced a lower spread of Covid19. Finally, we find that states with industrial heterogeneity also experienced a higher spread of the infection. While bivariate relationships are useful to see the comparative position of states on each factor and the resultant spread of Covid in the state, it is important to purge the effect of each of these variables to get closer to the true relationship between nightlights inequality and the spread of covid 19. We do that in the next section.

3. Empirical Model

In our empirical section we perform two major exercises – estimate how the core-periphery structure of the economy along with the demographic, economic factors, weather and disease environment influence the COVID 19 infection. We test this with the district level information. The specific model we estimate for this purpose is the following:

$$y_{dst} = \beta_0 + \beta_1 X'_{1dst} + \beta_2 T_t + \beta_3 NLI_s + \varepsilon_{dst} \tag{1}$$

In the equation above, y_{dst} captures the measure of contagion (number of confirmed Covid-19 cases per 1000 population) in district d, state s and time t. Time is measured as number of days.

NLI$_s$ represents nightlight inequality in state, s (the construction of this variable is discussed in section 2.5), X$_{1dst}$ represents district, district-time and state-time varying controls. In our analysis we have only two variables that vary at district-time level – temperature and rainfall. Most variables, such as latitude, population density, BCG vaccination, historical malaria intensity, nightlights, are all recorded at the district level and does not vary with the days of 2020. We also include the extent of Covid tests conducted. It varies across states and with the days of 2020. β_3 is our parameter of interest. The variable T measures the day of the year. We assign a value of 1 to the 1st day of January 2020 and cumulatively calculate the number of days for each date in the 2020 calendar.

4. Results

4.1 Baseline Results

In Table 2 we report the estimates from equation (1), our baseline specification. Our main variable of interest is nightlight inequality and from our hypothesis, we expect that the effect of nightlight inequality on confirmed cases to be positive – the more unequal a state, the greater will be the movement between the core and the peripheral regions and higher will be the degree of Covid-19 contagion. In column 1, we regress total confirmed cases per 1 million population in a district on nightlight inequality at the state level. As expected, the coefficient for nightlight inequality is positive and significant.

Table 2: Baseline Regression

In column (2) we add factors that determine the number of confirmed cases mechanically. First, since the rate of infection is likely to vary over time, we include controls for time elapsed as days since January 1, 2020. Second, the number of Covid-19 tests performed has also varied significantly across the states. We include daily Covid-19 tests performed. Finally, the extent of urbanity or development of an area determines where the infection started spreading first. Hence, we include average nightlight of a district before Covid-19 started, from 2019. In columns 3-7 we include additional district level characteristics which are potential predictors of the number of cases per capita. In column (3) we add population density of the district, in column (4) we add a district's monthly temperature and rainfall information, in column (5) we add the extent of BCG and overall immunization, which includes tuberculosis, influenza etc., cover in a district, in column (6) we add malaria intensity from historical data during the colonial period, and finally in column (7) we add controls for district's latitude and longitude.

We see that the coefficients for nightlight inequality are positive and significant across specifications implying that a state characterized by a stronger core-periphery structure, necessitating movement of goods and people from the core to the periphery, experience a greater rate of Covid-19 infection per capita. The number of tests conducted seems to be negatively correlated with the number of infections in columns 2 through 4. This could simply reflect that states with worse health investments have more cases and conduct fewer tests. Indeed, as a wider range of a state's health indicators are accounted for in columns 5-7, we find a positive correlation between Covid-19 tests and cases, as is likely to be the case mechanically since more tests will result in more detected cases.

The negative coefficients on number of days elapsed since the beginning of the pandemic suggests that the average number of infections per capita fell over time. One reason this could happen is that after the initial first wave, there has been a secular decline in the Covid cases till 1st February 2021, the end date in our data, and the sub-periods of decline are dominating the aggregate situation. This idea becomes clearer when we show phase-wise results.

As expected, the coefficients for district level nightlights are also positive and significant across specifications implying that greater urbanization or economic development is correlated with a higher rate of infection. One counter-intuitive finding is that the population density is negatively related with the total confirmed cases per 1000 population. One possible reason could be that richer areas usually attract more people and therefore, more densely populated and richer areas could be the ones which are better managed in terms of contact tracing and disease prevention. In line with the popular belief, we find that daily infections rise with fall in temperature. The relationship between infection and rainfall, however, is positive. Contrary to the popular beliefs, daily infections are higher in districts with greater level of vaccination (BCG and overall). The correlation between infection and malaria intensity is negative initially but after accounting for a district's latitude and longitude, turns positive. This points to the fact that the spread of malaria, at least during the colonial period, was limited to certain geographies. Within similar geographic areas, in terms of latitude and longitude, the regions that are historically more prone to malaria infection are also more prone to Covid-19 spread.

Our results show that there exists a strong correlation between state level nightlight inequality and Covid-19 daily infection. However, identification remains a critical issue here as there are many unobserved heterogeneities at the state level that we could not take control of as our main variable of interest – nightlight inequality – is time invariant and also measured at the state level. These unaccounted-for unobserved heterogeneities could also be the reason behind variability in the coefficients of the control variables across all the 7 specifications.

In order to solve the problem, we use regional inequality measured at the district-neighbourhood level. The idea behind this measure is that a state might have multiple core regions and the movement of goods and people to various regions depends on which core serves which periphery. In other words, the extent of movement of people and goods might vary even within a state depending on the relative inequality of districts with respect to their neighbouring districts. We report the results from this estimation in Table 3.

Table 3 Baseline regression with neighbourhood inequality

In column 1, we regress total confirmed cases per 1 million population on neighbourhood nightlight inequality with state fixed effect. The coefficient is positive and significant. From column 2 onwards, we keep adding controls like we did in the baseline regression. For all the controls, the coefficients are similar to what we observed in Table 2. However, unlike in Table 2, after accounting for unobserved heterogeneity, the correlation between each of the control variables and confirmed cases remains the same across all specifications. In column 7 we account for state level linear time trends considering that different states experienced the first Covid-19 wave and their peak infection rates at different times. The effect of nightlight inequality remains unchanged with the staggered inclusion of all these covariates. We present the rest of our results in this paper on the basis of the full specification in column 7,

4.2 Heterogeneity Analysis

In response to the COVID 19 pandemic, the government of India announced shutting down of all business and government services except those related to the supply of essential goods and services.[4] This set of policies, popularly known as lockdown, varied in their intensity over time – they were relaxed or tightened depending on the Covid-19 situation in India. The details of the lockdown and unlock phases are given in Table 4.

Table 4 Phases of lockdown

Our hypothesis, that the core-periphery structure of the economy can affect the rate of infection transmission, rests on the premise that it involves movement of people from/to the core to/from the periphery. Hence, the effects are likely to depend on the restrictions imposed on the movement of goods and people in the first place.

The results for lockdown 3 and 4, when stringent initial restrictions on movements of goods and people were beginning to be relaxed, are given in Table 6a. Subsequently, the relaxations

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[4] The list of essential goods was defined at the beginning of the Lockdown in March. Appendix Table A2 and A3 provides details on the various restrictions across lockdown and unlock phases and the essential goods, respectively.

were increases in a phased manner between unlock 1-8. The results for these unlock phases are given in Table 6b.

Table 5a Neighbourhood inequality and Covid infection rate across lockdown phases

Table 5b Neighbourhood inequality and Covid infection rate across unlock phases

We find that nightlight inequality in a district's neighborhood has no effect on the spread of the disease during Lockdown 3 when the stringent movement restrictions were just beginning to be relaxed. During Lockdown 3, districts were categorized in to red, orange and green zones on the basis of the severity in the spread of infection and some relaxations were allowed in districts that had lowest severity (i.e. green zone) at that time. During Lockdown 4, we find that district level regional inequality has a negative effect on disease spread. Unlike in the previous lockdown phases, during Lockdown 4, states were given a larger say in the demarcation of districts in to red, orange and green zones. With better local information state level administrations are likely to better identify districts that are potentially at a higher risk of contagion. For instance, local governments are better able to identify regions that are economically more active. Knowing that economic development of a region and infection rates are directly proportional, it is possible that state governments grant fewer lockdown relaxations to the more economically active districts (the core), within a state, than the less economically active districts (the periphery). This would make movement from the core district to the peripheral districts, within a state, more difficult. Indeed, this is evident from the negative significant coefficient on the average nightlight in a district in column 4. A district with higher levels of nightlights, indicating more development, also have fewer cases during lockdown. Now consider two distinct cluster of districts within a state. For example, in the state of West Bengal suppose cluster 1 has Kolkata as the core district and cluster 2 has Siliguri as the core district. Now since Kolkata is economically much more active than Siliguri, the restrictions are likely to be much higher in Kolkata than in Siliguri. In other words, lockdown stringency, administered by the states, is likely to be higher for core districts than for peripheral districts and for more active 'core' districts than for less active 'core' districts. This in turn means that the disease would spread faster in cluster 2, where the economic distance between the core (Siliguri) and the periphery is lower, than in cluster 1, where the distance between the core (Kolkata) and the periphery is higher and lockdown restriction higher. This could potentially explain the negative coefficient on the neighborhood inequality measure during the Lockdown periods.

Table 5b shows the results for the Unlock phases. During Unlock 1, the central government continued to impose lockdown restrictions but only in 'containment zones' with severe case

load, while activities were to be permitted in other zones in a phased manner. During Unlock 1, night curfews were still in effect from 9 p.m. to 5 a.m. across the country and state governments were allowed to impose additional restrictions on all activities depending on the local situation. Taken together, the situation was similar to Lockdown 4. With the economy just opening up from 3 months of Lockdown activities were possibly still moving slowly. Hence, we continue to find a negative effect of neighborhood nightlight inequality on the spread of Covid-19. During Unlock 2, night curfews were still in place, but some more relaxations were allowed. During Unlock 3, further relaxations were allowed and night curfews were also stopped. However, several states, particularly the ones with metropolitan cities, like Maharashtra, Tamil Nadu and West Bengal, continued with Lockdowns on all or a few days of the week. Restrictions on public transportation continued in most states. Our estimates continue to show no significant effect of regional inequality on Covid-19 spread. And simultaneously the correlation between economic development and the contagion changes from negative to zero to positive and then increases as economic activities open up.

From Unlock 4 onwards, with further relaxation in movement, we see a positive significant effect of regional inequality on the spread of Covid-19. This effect remains steady and even goes up over time until Unlock 7. Since then, overall Covid-19 cases fell consistently in India until March 2021. It could be this reason why the size of the effect of regional inequality on the spread of the disease also dampens during Unlock 8 although it still remains positive and significant.

4.3 Unemployment

In understanding the effect of nightlight inequality on Covid-19 infection, we argued that the underlying mechanism is the mobility of goods and people. If all the business establishments and transportation are shut down, there should not be much of a difference between equal and unequal regions in terms of the spread of the disease. To understand the mobility mechanism, we examined the effect of nightlight inequality on the contagion over different phases of the Lockdown and Unlock periods. In this section, we examine the same idea using a different empirical strategy. Rather than using phases of lockdown and unlock to represent mobility, we use state-level daily unemployment rates as a proxy for mobility.[5] Higher levels of unemployment would imply lower levels of mobility. Hence, we expect that when

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[5] We interpolate the daily unemployment rate using the monthly unemployment rate published by Centre for Monitoring Indian Economy (CMIE)

unemployment rate is high, the effect of nightlight inequality on Covid infection rate will be low. In other words, the interaction effect of nightlight inequality and unemployment rate is expected to be negative. We present the regressions with interaction effect in Table 6.

Table 6 Interaction between unemployment and nightlight and its effect on Covid infection rate.

The specification that we use is comparable to column (7) of Table 2 except that now we introduce daily unemployment rate and the interaction of state-nightlight inequality with unemployment rate. Column (1) presents the iteration without any state FE. We find that the nightlight inequality has a positive effect on contagion, as before. Also, states with higher unemployment rate have lower levels of contagion, after accounting for economic development proxied by average levels of nightlight. The interaction between nightlight inequality and unemployment is also negative. This means that the positive effect of the inequality on infection is partially mitigated in states whenever the movements are less (i.e. unemployment is high). These results remain similar across the four different specifications. In column 2 we introduce state level linear time trends. In column (3) we account for unobserved heterogeneity at the state level and in column (4) we introduce both state fixed effects and state level linear time trends – the interaction effect remains unaltered.

4.3 Robustness check

In this section, we explore an alternative measure to capture the mobility of people. We use a measure of district level industrial heterogeneity. Our measure of industrial heterogeneity uses the share of labor force in different industries (see Section 2.5 for details). Hence, in a district with high value of the heterogeneity index, the chances are very high that people from one family work in different industries. In such a district, if a person gets the infection from his workplace there is a high chance that the contagion spreads to the workers of other industries through his family members who work there. Let us call this mechanism the *network effect*. We expect that districts with greater industrial heterogeneity will experience higher degree of contagion through the *network effect*. Since industrial heterogeneity is measured at the district level, we account for state fixed effects. In addition, since the network effect due to industrial heterogeneity will depend on whether an industry is open or under lockdown, we estimate the effect of industrial heterogeneity on Covid-19 infection rate separately for different phases of lockdown and unlock. The results are reported in Tables 7a and 7b.

Table 7a: Robustness check with industrial heterogeneity index during lockdown

Table 7b: Robustness check with industrial heterogeneity index during unlock phases

The results in columns 1 and 2 of Table 7a show that industrial heterogeneity has no effect on the contagion during the Lockdown phases when most restrictions were still active. This is however, not very surprising as during these phases of lockdown most of the industries were closed and the *network effect* is less likely to work.

The results for the Unlock phases are shown in Table 7b. As in the case of nightlight inequality, once again we find that during the early phases of Unlock when the relaxations to the strict lockdown rules were just beginning and night time lockdowns were still in place, the effect of a district's industrial heterogeneity on the spread of the contagion is negative. As discussed before, this is possible if richer areas, that have more industries, are the ones that are better able to track and contain the disease. However, once the industries open up in these regions, and mobility increases, the spread is faster than the regions with fewer industries. Unlock phase 3 onwards, we find a positive effect of industrial heterogeneity on the spread of Covid-19. The difference across the different phases of unlock can be explained by the mechanism of *network effect*. Across the unlock phases, different industries were allowed to operate in a phased manner. Consequently, the *network effect* grew stronger in the later phases when more industries were open. Let us illustrate our argument with an example. Suppose, in a district there are three industries X, Y and Z. Also suppose industry X were allowed to open up in unlock 5, while Y and Z were allowed to operate in unlock 6. The members of a typical family work in all three industry. Now if industry X is hit by the contagion, through the family network it cannot spread to the workers of Y and Z during unlock 5; this will only happen in unlock 6 when these sectors are kept open.

5. Conclusion

The growing literature studying the factors that contribute to Covid-19 spread focuses on demographic, social, weather, health related indicators. We provide an additional explanation based on the economic organization of markets. Using data from the first wave of the Covid-19 contagion across the various districts of India we find that Covid-19 spreads more in regions characterized by a stronger core-periphery economic structure. We measure core-periphery structure using inequality in the incidence of nightlights across districts. We argue that a core-periphery economic structure is likely to increase the spread of infection because it involves movement of goods and people across the core and peripheral districts. Indeed, when we conduct the exercise over different phases of lockdown and unlock, imposed by the Government of India, we find that regions with higher nightlight inequality also experience higher spread of Covid-19 only when lockdown measures have been relaxed and movement of

goods and services are near normal. Our findings are similar when we use industrial composition of districts instead of nightlight inequality. Higher industrial heterogeneity leads to a higher spread of Covid-19. Higher industrial heterogeneity makes it more likely for different members of the same family to work in different industries which in turn means that if one family member gets sick it quickly spreads to the workers of other industries through the family network. As should be the case, we find that lockdown breaks this channel of spread and the relationship exists only when industries open up after lockdown.

Our finding has critical policy implication. The policy responses to Covid-19 contagion that we have seen in India, be it the lockdown strategy or the vaccination strategy, are quite homogeneous in nature --- prescribe one policy for the entire nation. We have seen some variation across states in terms of the announcement of red, orange and green zones – different categories of containment zones with different degrees of mobility restriction. But all these heterogenous policies were ex-post as they were announced after observing the Covid-19 condition in different areas. The heterogeneous policy responses our paper prescribes on the other hand, are ex-ante in nature – it calls for stronger policies in more unequal regions, and more industrially-diverse districts, even before the contagion reaches an alarming level and therefore, it may play a more effective role in the prevention of the contagion.

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Figures:
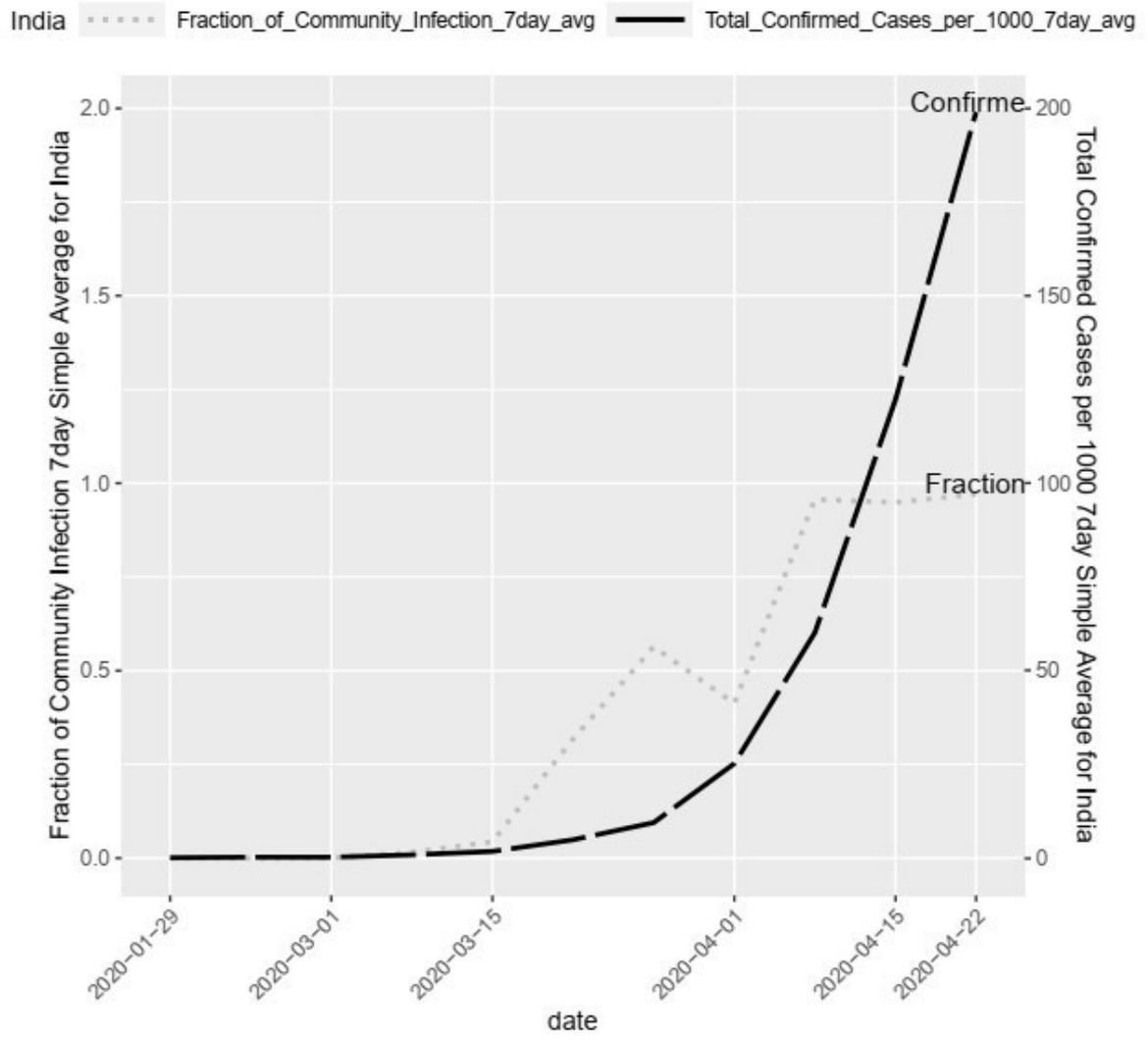
Fig 1: 7-Day Average India Fraction of Community Infection vs Total Confirmed
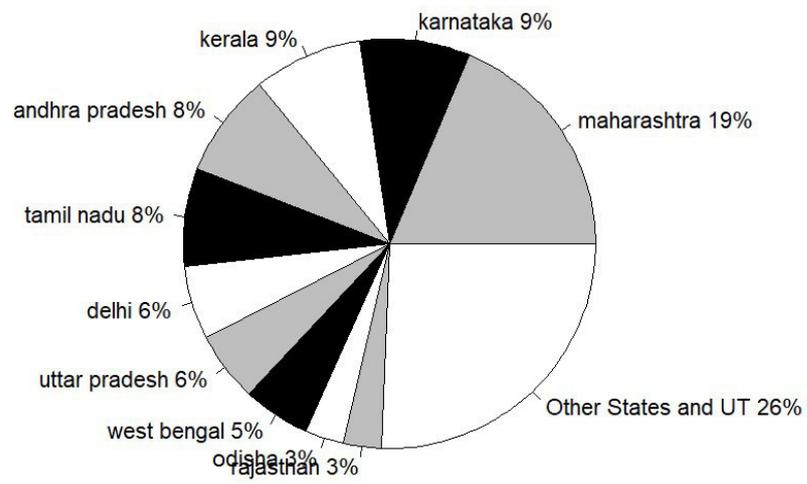
Figure 2: Share of Covid-10 confirmed cases in 10 leading states
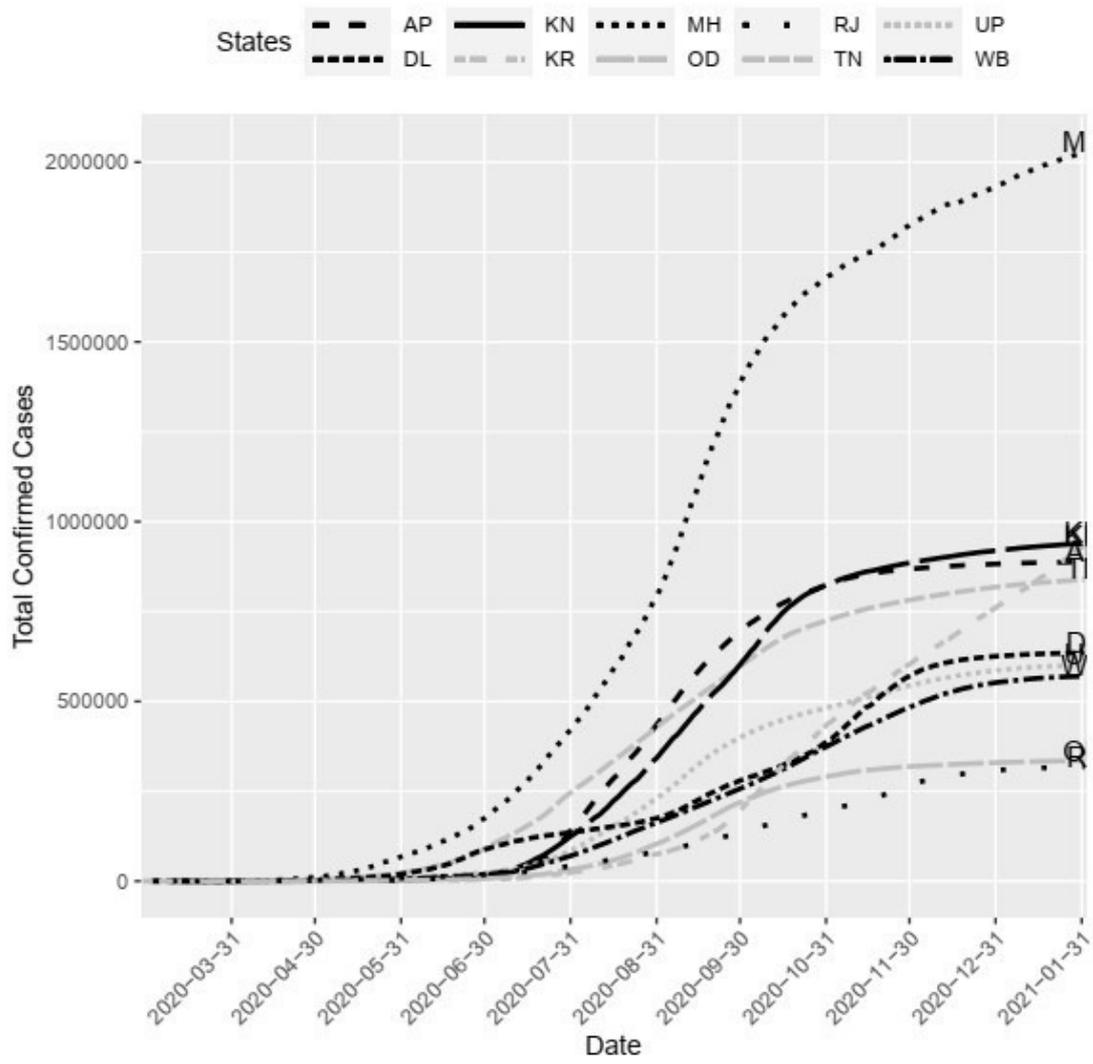
Figure 3: Time series Share of Covid-10 confirmed cases in 10 leading states
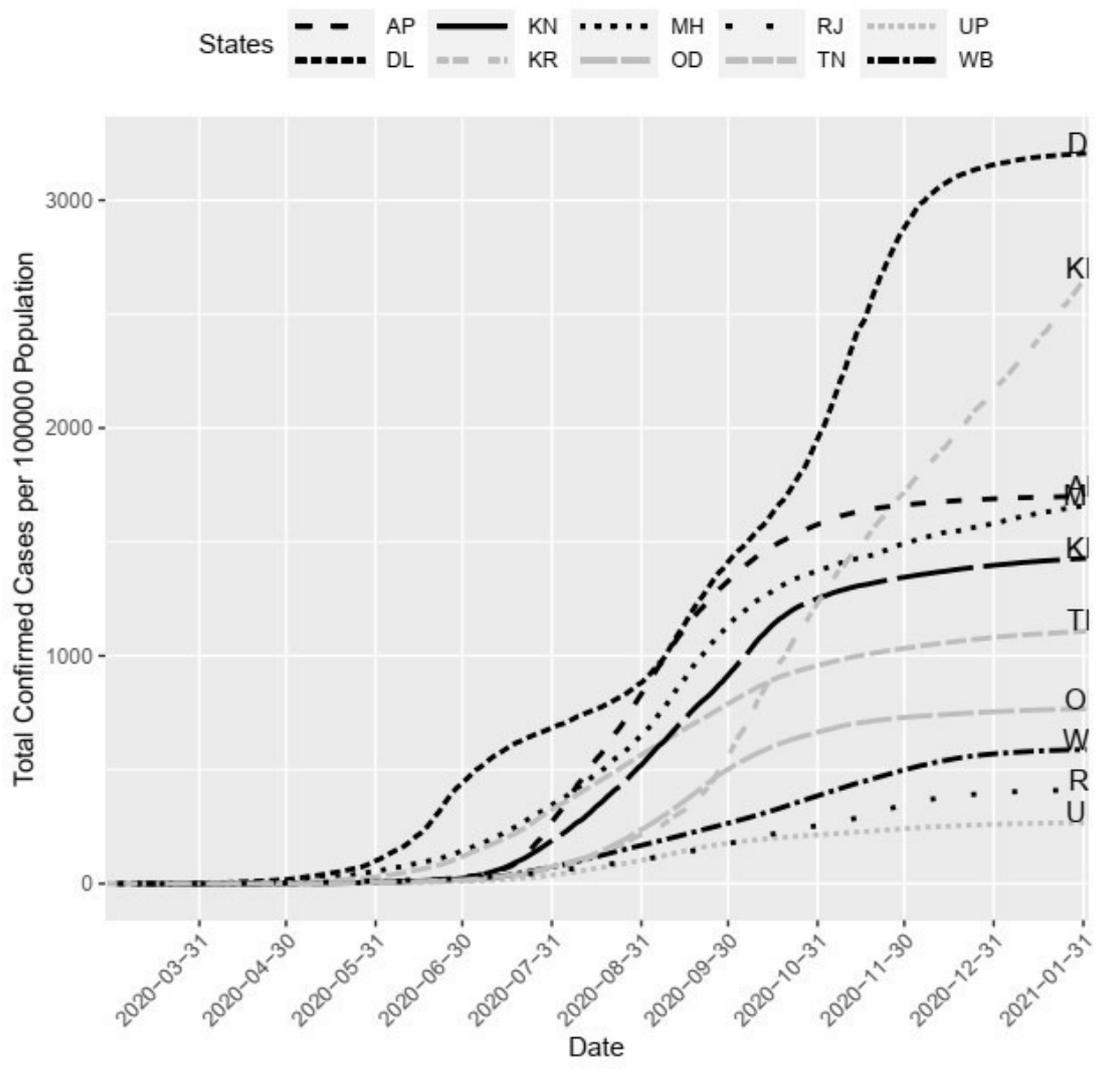
Figure 4: Total confirmed Covid-19 cases per 100 thousand population of the states
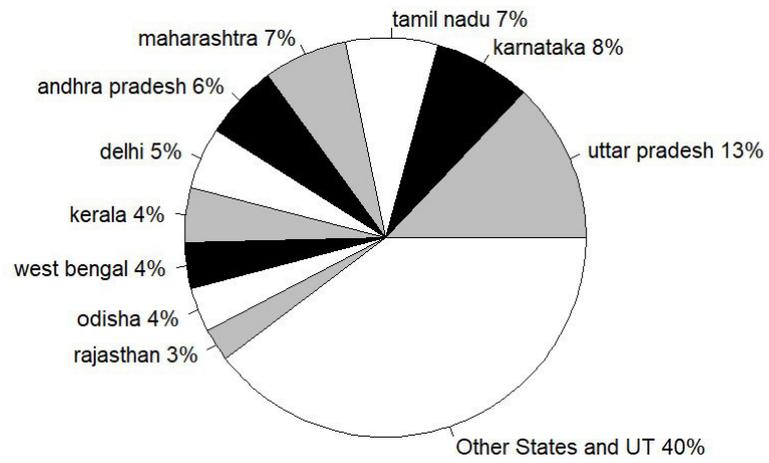
Figure 5a: Total tests in 10 leading states

Figure 5b: Time series of total tests in 10 leading states

Total Tested per 100000 Population for 1st Jan 2021
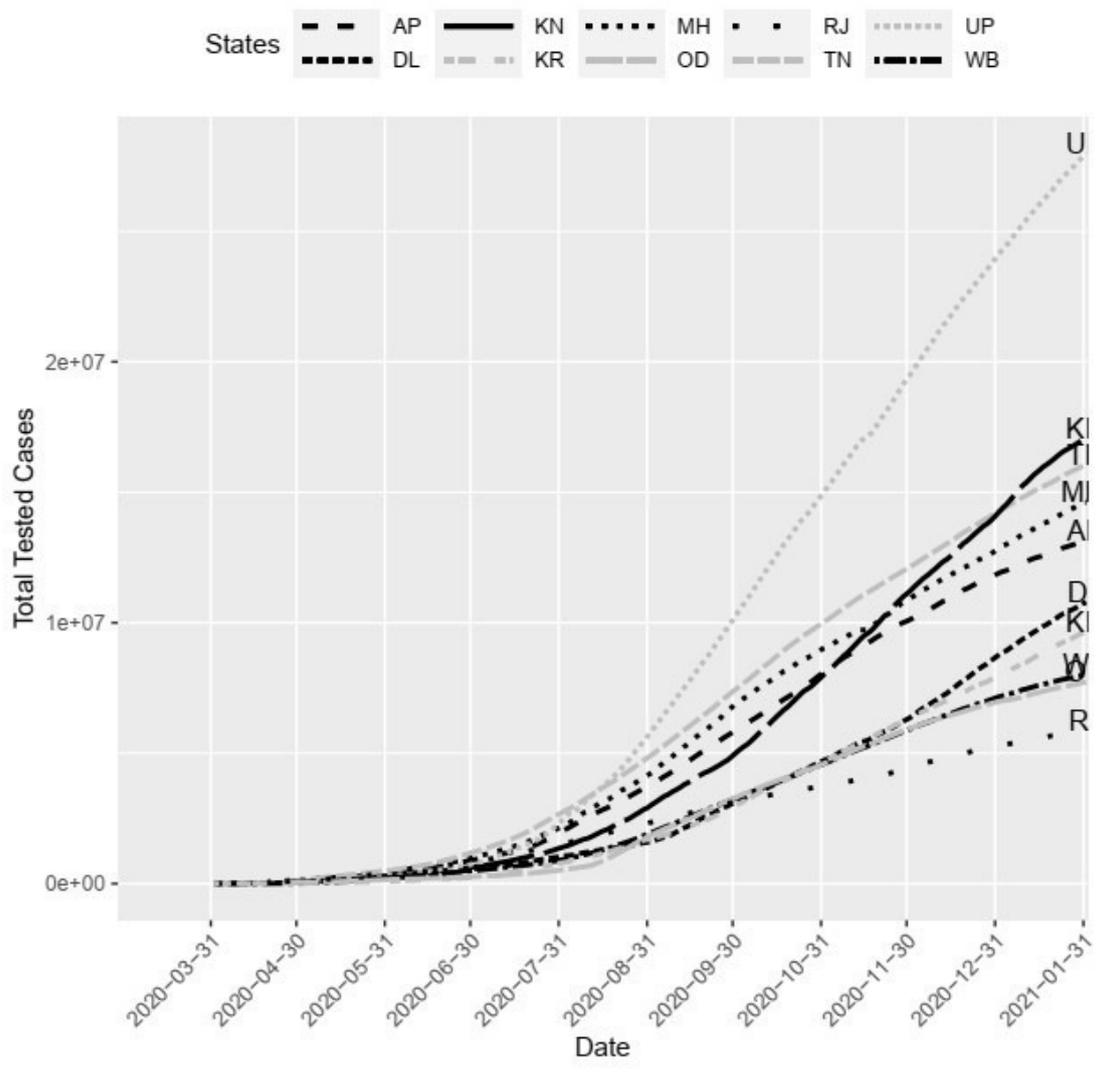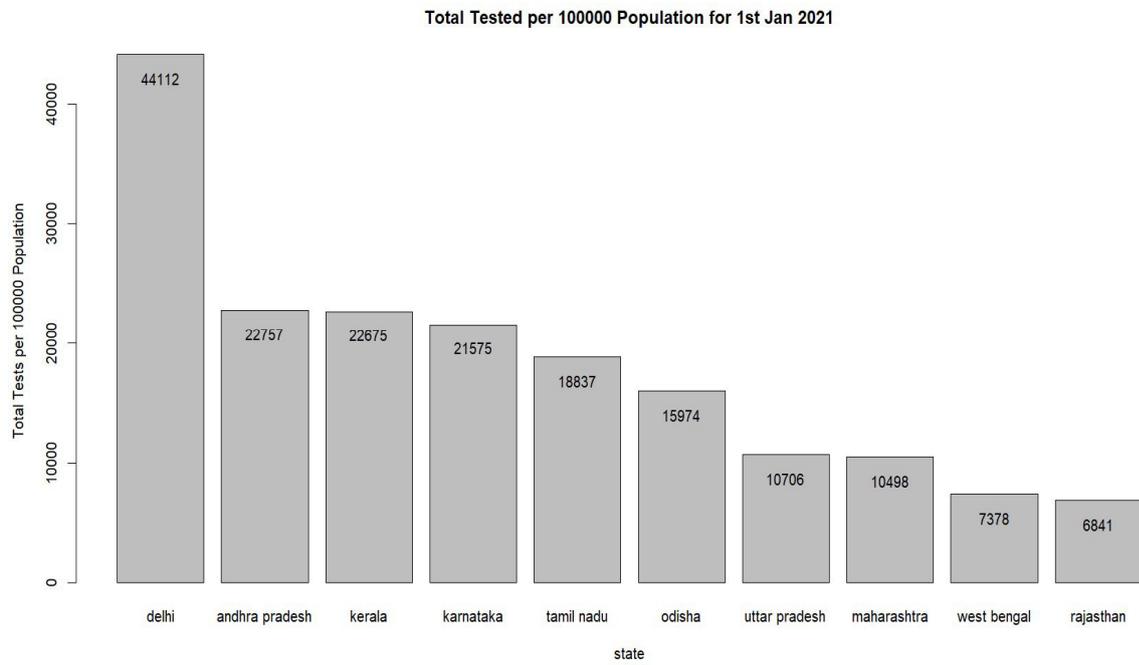
Figure 5c: State-wise Per capita Tests
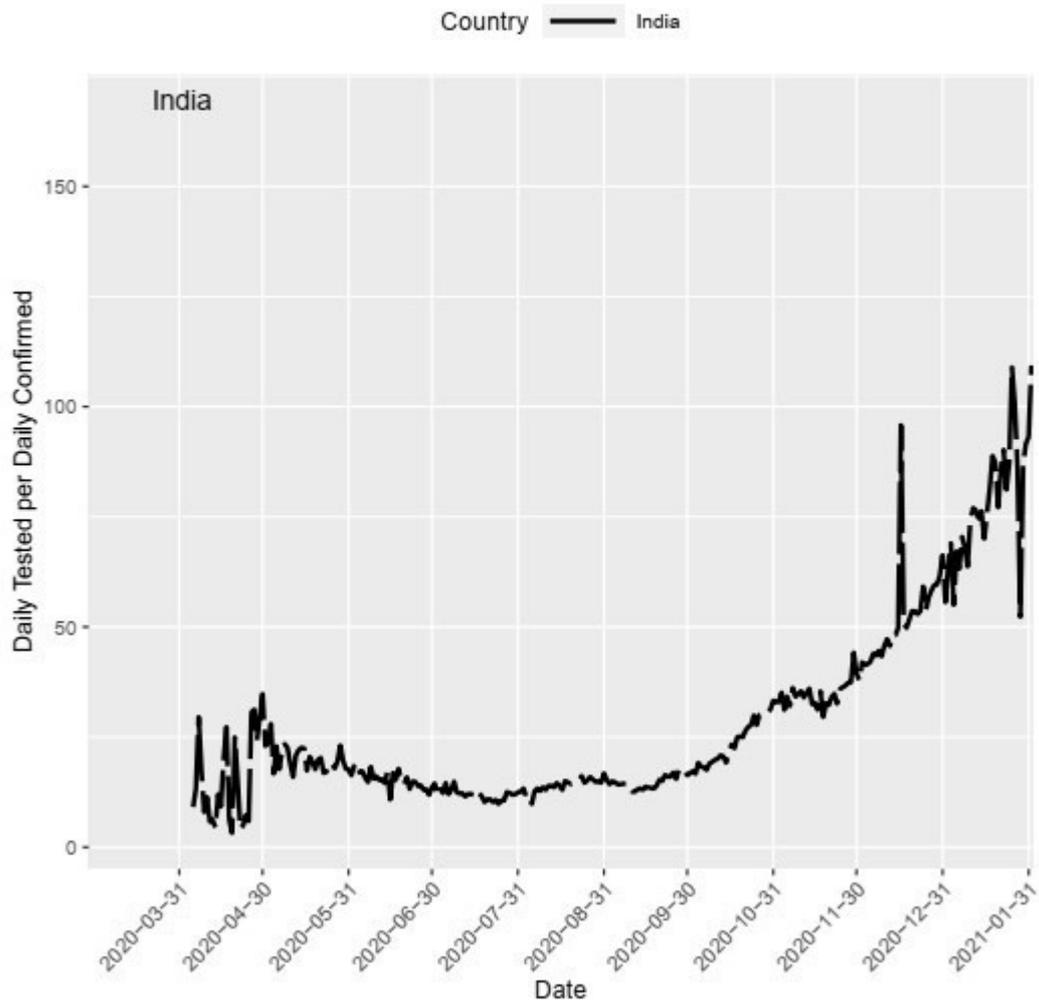
Figure 6a: Tests per confirmed patients - all India time series

Daily Tested per Daily Confirmed for 31st Jan 2021
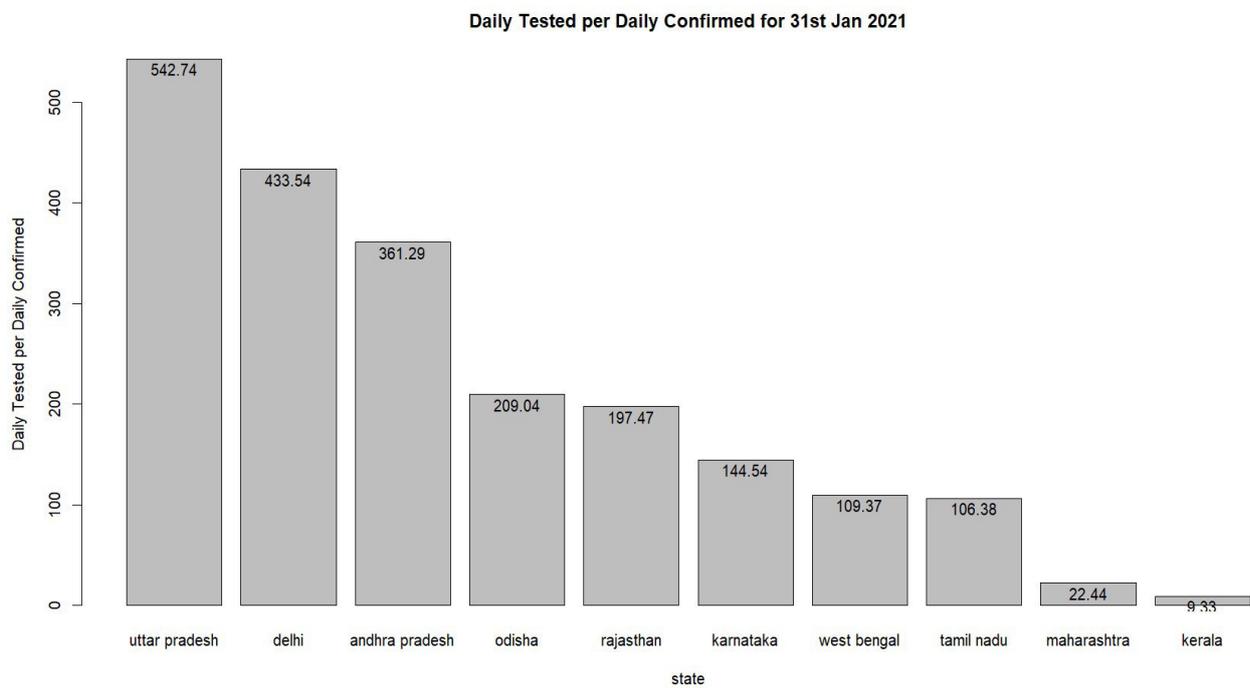
Figure 6b: Tests per confirmed patients: Top 10 states bar chart as of 1 Feb, 2021
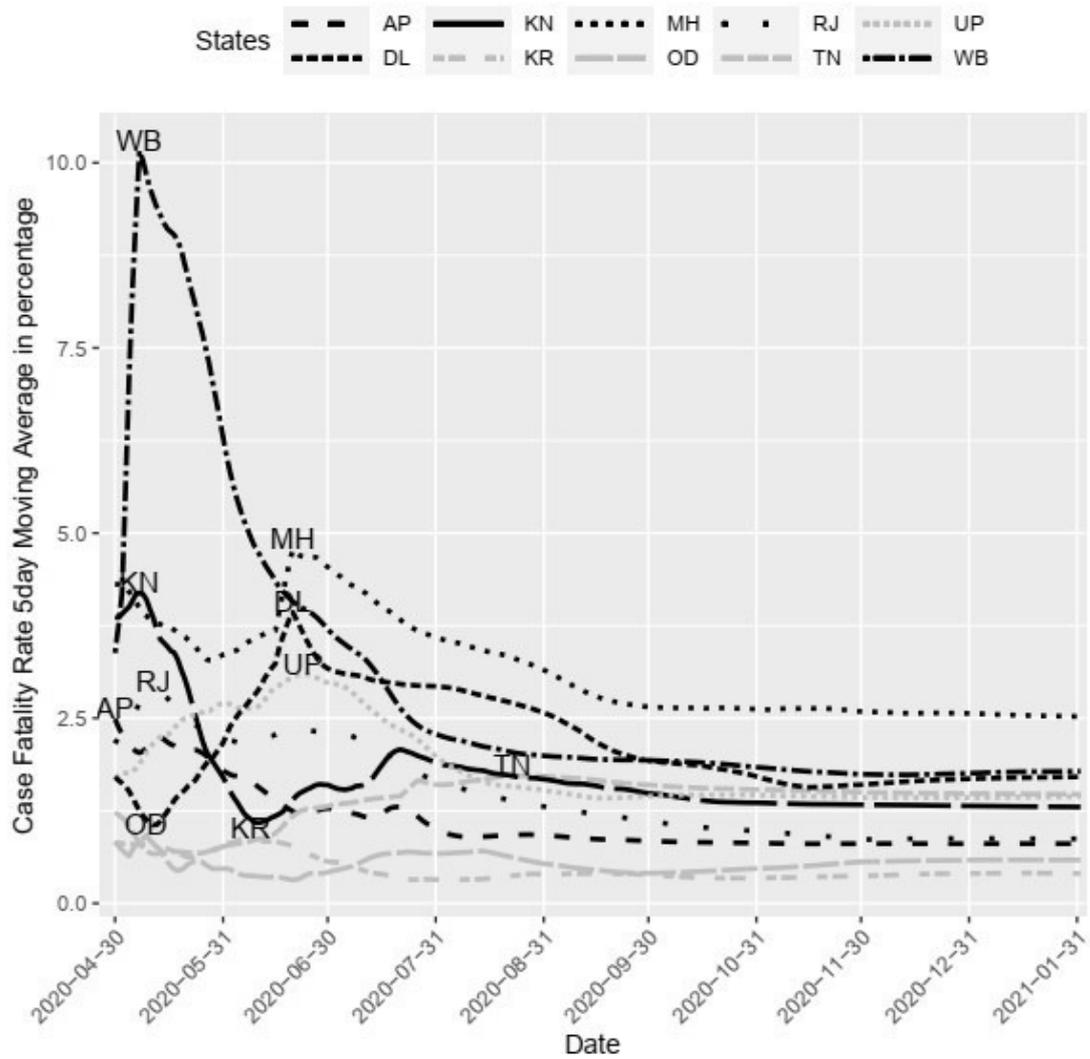
Figure 7: State-wise case fatality rate in 10 leading states

Tables:

Variables	Mean	SD
Confirmed per million	8127.79	4914.1
District Population (million)	2.14	1.5
Nightlight (avg over districts)	4.44	1.055284
Nightlight Inequality [p90/p10]	2.38	1.1
District Population Density, 2019	578.08	1218.4
Temperature (Celsius)	31.00	6.3
Rainfall (mm)	4.21	13.3
Malaria	4.80	1.3
Latitude (N)	24.32	4.7
Longitude (E)	79.23	4.6
% BCG Vaccination, 2007	87.76	11.2
% Fully Immunized, 2007	56.08	21.4
Industrial Heterogeneity Index	0.87	0.1
Observations	126261.00	126261.0

Table 1: Summary Statistics

Dependent Variable: Total Confirmed Covid19 per million population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nightlight Inequality	6.528***	6.012***	6.000***	5.648***	3.347***	3.452***	3.755***
	(0.177)	(0.178)	(0.178)	(0.180)	(0.180)	(0.183)	(0.182)
Days since Jan1. 2020		-0.012***	-0.013***	-0.038***	-0.071***	-0.074***	-0.084***
		(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Nightlight (average)		0.476***	0.598***	0.611***	0.567***	0.575***	0.614***
		(0.012)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Daily tested		-0.000***	-0.000***	-0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density			-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature				-0.529***	-0.570***	-0.540***	-0.750***
				(0.047)	(0.046)	(0.046)	(0.048)
Rainfall				0.332***	0.281***	0.263***	0.241***
				(0.014)	(0.014)	(0.014)	(0.014)
BCG vaccination					0.695***	0.684***	0.565***
					(0.029)	(0.030)	(0.030)
Total vaccination					0.258***	0.265***	0.213***
					(0.016)	(0.016)	(0.016)
Colonial malaria						-0.620***	0.663***
						(0.145)	(0.165)
Latitude							-0.604***
							(0.034)
Longitude							-1.013***
							(0.046)
Constant	18.177***	21.518***	21.532***	43.638***	-20.383***	-18.917***	91.007***
	(0.469)	(0.756)	(0.755)	(2.389)	(2.990)	(3.012)	(4.828)
Observations	148,737	147,875	147,875	147,473	145,640	139,309	139,309
Adjusted R-squared	0.009	0.021	0.021	0.025	0.052	0.053	0.059

Table 2: Baseline with Nightlight Inequality varying at the state level. Average nightlight, population density, latitude, longitude, BCG vaccination(in 2017), total vaccination(in 2017) and colonial malaria vary at the district level. Covid19 daily tested varies by state-day. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Dependent Variable: Total Confirmed Covid19 per million population								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nightlight Inequality	1.310***	0.690***	0.645***	0.604***	0.436***	0.618***	0.584***	0.476***
	(0.138)	(0.138)	(0.138)	(0.138)	(0.137)	(0.142)	(0.142)	(0.139)
Days since Jan1. 2020		-0.010***	-0.010***	-0.010***	-0.011***	-0.011***	-0.011***	-0.008***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Nightlight (average)		0.054***	0.071***	0.072***	0.072***	0.071***	0.071***	0.072***
		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Daily tested		0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density			-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature				0.000	-0.014***	-0.010**	-0.011**	-0.094***
				(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Rainfall				0.026***	0.026***	0.024***	0.024***	0.020***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BCG vaccination					0.004	0.006**	0.007**	0.007**
					(0.003)	(0.003)	(0.003)	(0.003)
Total vaccination					0.014***	0.011***	0.009***	0.009***
					(0.002)	(0.002)	(0.002)	(0.002)
Colonial malaria						-0.152***	-0.137***	-0.142***
						(0.017)	(0.018)	(0.017)
Latitude							-0.058***	-0.071***
							(0.015)	(0.015)
Longitude							-0.058***	-0.053***
							(0.012)	(0.012)
Constant	2.286***	3.832***	3.863***	3.617***	3.346***	3.611***	9.487***	13.799***
	(0.121)	(0.133)	(0.132)	(0.274)	(0.349)	(0.355)	(1.037)	(1.024)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trend	No	No	No	No	No	No	No	Yes
Observations	148,737	147,875	147,875	147,473	145,640	139,309	139,309	139,309
Adjusted R-squared	0.086	0.114	0.115	0.115	0.116	0.118	0.119	0.157

Table 3: Baseline with neighbourhood inequality and state fixed effect. Nightlight Inequality, Average nightlight, population density, latitude, longitude, BCG vaccination (in 2017), total vaccination (in 2017) and colonial malaria vary at the district level. Covid19 daily tested varies by state-day. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

	Phase	Dates	Number of days	Confirmed per million
1	Pre-Lockdown	1 Jan, 2020-24 Mar, 2020	84	0.41
2	Lockdown 1	25 Mar, 2020 – 14 April, 2020	21	7.93
3	Lockdown 2	15 Apr, 2020 – 3 May, 2020	19	22.86
4	Lockdown 3	4 May, 2020 -- 17 May, 2020	14	38.38
5	Lockdown 4	18 May, 2020 – 31 May, 2020	14	64.01
6	Unlock 1	1 June, 2020 – 30 June, 2020	30	279.00
7	Unlock 2	1 July, 2020 – 31 July, 2020	31	784.46
8	Unlock 3	1 Aug, 2020 – 31 Aug, 2020	31	1407.29
9	Unlock 4	1 Sept, 2020 – 30 Sept, 2020	30	1974.05
10	Unlock 5	1 Oct, 2020 – 31 Oct, 2020	31	1412.30
11	Unlock 6	1 Nov, 2020 – 30 Nov, 2020	30	950.53
12	Unlock 7	1 Dec, 2020 – 31 Dec, 2020	31	605.82
13	Unlock 8	1 Jan, 2021 – 31 Jan, 2021	31	347.07

Table 4: Phases of India-wide Lockdown and subsequent Unlock as stipulated by the Government of India. Information gathered from various official notifications by the Ministry of Home Affairs, GOI, and media reports.

Dependent Variable: Total Confirmed Covid19 per million population

	(1)	(2)
	Lockdown 3	Lockdown 4
Nightlight Inequality	3.177	-7.603**
	(2.834)	(3.404)
Days since Jan1. 2020	0.018	0.155
	(0.452)	(0.503)
Nightlight (average)	-0.006	-0.135***
	(0.031)	(0.040)
Daily tested	0.000	0.000
	(0.000)	(0.000)
Population density	0.001***	0.002***
	(0.000)	(0.000)
Temperature	-0.750***	-0.074
	(0.165)	(0.184)
Rainfall	-0.190	-0.009
	(0.122)	(0.101)
BCG vaccination	0.221***	0.069
	(0.060)	(0.076)
Total vaccination	-0.123***	-0.034
	(0.038)	(0.046)
Colonial malaria	-2.345***	-1.813***
	(0.349)	(0.434)
Latitude	0.860***	-0.405
	(0.290)	(0.359)
Longitude	-0.609**	-1.059***
	(0.237)	(0.293)
Constant	38.124	98.519***
	(23.447)	(28.406)
State FE	Yes	Yes
State Trend	Yes	Yes
Observations	6,133	6,948
Adjusted R-squared	0.154	0.117

Table 5a: Regression with neighbourhood inequality for lockdown phases 3 and 4. Nightlight Inequality, Average nightlight, population density, latitude, longitude, BCG vaccination (in 2017), total vaccination (in 2017) and colonial malaria vary at the district level. Covid19 daily tested varies by state-day. Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Dependent Variable: Total Confirmed Covid19 per million population								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unlock-1	Unlock-2	Unlock-3	Unlock-4	Unlock-5	Unlock-6	Unlock-7	Unlock-8
Nightlight Inequality	-27.87***	-5.23	-6.16	16.04***	24.86***	22.83***	17.68***	6.09***
	(4.079)	(5.658)	(6.382)	(3.217)	(2.420)	(3.652)	(1.694)	(1.560)
Days since Jan1. 2020	0.77***	0.18	-0.32	0.02	0.03	-0.48**	-0.85***	-0.14
	(0.271)	(0.365)	(0.410)	(0.215)	(0.156)	(0.239)	(0.110)	(0.088)
Nightlight (average)	0.03	0.73***	0.90***	1.45***	1.33***	1.31***	0.71***	0.22***
	(0.049)	(0.068)	(0.076)	(0.039)	(0.029)	(0.043)	(0.019)	(0.017)
Daily tested	-0.00	0.00	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.01	-0.46	-1.48***	-0.82***	-1.08***	-2.18***	-0.40***	-0.54***
	(0.198)	(0.307)	(0.460)	(0.238)	(0.176)	(0.323)	(0.102)	(0.096)
Rainfall	0.28***	0.07*	-0.03	0.00	0.01	-0.06	-0.03	-0.11*
	(0.048)	(0.040)	(0.040)	(0.024)	(0.034)	(0.074)	(0.051)	(0.067)
BCG vaccination	-0.17*	-0.05	0.19	0.08	0.00	0.17**	0.03	0.02
	(0.091)	(0.126)	(0.142)	(0.072)	(0.054)	(0.081)	(0.038)	(0.036)
Total vaccination	0.08	-0.03	-0.18**	0.47***	0.32***	0.10**	0.22***	0.12***
	(0.055)	(0.076)	(0.085)	(0.043)	(0.033)	(0.049)	(0.022)	(0.021)
Colonial malaria	1.10**	-1.06	0.55	2.82***	-2.49***	-7.57***	-1.70***	-0.28
	(0.511)	(0.701)	(0.794)	(0.401)	(0.301)	(0.447)	(0.203)	(0.192)
Latitude	-1.00**	-2.22***	-2.18***	-0.46	-0.78***	0.02	0.54***	-0.44**
	(0.430)	(0.594)	(0.673)	(0.339)	(0.255)	(0.404)	(0.189)	(0.171)
Longitude	-1.24***	-2.50***	-1.40**	-1.74***	0.32	1.82***	0.29**	0.12
	(0.348)	(0.481)	(0.547)	(0.273)	(0.206)	(0.310)	(0.141)	(0.130)
Constant	93.02***	201.56***	414.09***	215.92***	267.60***	41.19	121.31***	36.47**
	(32.564)	(46.190)	(51.584)	(28.642)	(23.068)	(37.819)	(19.637)	(15.170)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,555	16,121	15,947	15,507	15,926	15,154	14,908	13,946
Adjusted R-squared	0.064	0.093	0.136	0.490	0.568	0.330	0.571	0.578

Table 5b: Regression with neighbourhood inequality for Unlock phases 1-8. Nightlight Inequality, Average nightlight, population density, latitude, longitude, BCG vaccination (in 2017), total vaccination (in 2017) and colonial malaria vary at the district level. Covid19 daily tested varies by state-day. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Dependent Variable: Total Confirmed Covid19 per million population				
	(1)	(2)	(3)	(4)
	No FE	State-Trend	State-FE	State-Trend+FE
Nightlight Inequality	4.457***	14.790***		
	(0.284)	(0.844)		
Unemployment	-0.098*	0.267***	-0.256***	-0.367***
	(0.058)	(0.077)	(0.072)	(0.094)
Nightlight Inequality* Unemployment	-0.070***	-0.318***	-0.178***	-0.293***
	(0.020)	(0.027)	(0.024)	(0.033)
Days since Jan1. 2020	-0.094***	-0.223***	-0.136***	-0.090***
	(0.004)	(0.006)	(0.004)	(0.010)
Nightlight (average)	0.624***	0.730***	0.719***	0.725***
	(0.017)	(0.016)	(0.017)	(0.016)
Daily tested	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Population density	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	-0.746***	-0.477***	-0.176***	-0.736***
	(0.048)	(0.054)	(0.050)	(0.057)
Rainfall	0.221***	0.162***	0.196***	0.161***
	(0.014)	(0.013)	(0.013)	(0.013)
BCG vaccination	0.515***	0.083***	0.072**	0.073**
	(0.030)	(0.031)	(0.032)	(0.031)
Total vaccination	0.229***	0.060***	0.099***	0.099***
	(0.016)	(0.018)	(0.019)	(0.019)
Colonial malaria	0.531***	-1.181***	-1.288***	-1.309***
	(0.166)	(0.171)	(0.174)	(0.170)
Latitude	-0.544***	0.221**	-0.620***	-0.702***
	(0.034)	(0.088)	(0.148)	(0.145)
Longitude	-0.960***	-0.086	-0.570***	-0.550***
	(0.047)	(0.093)	(0.120)	(0.117)
Constant	93.860***	39.418***	118.980***	157.303***
	(4.835)	(8.031)	(10.295)	(10.132)
State FE	No	No	Yes	Yes
State Trend	No	Yes	No	Yes
Observations	139,309	139,309	139,309	139,309
Adjusted R-squared	0.060	0.141	0.123	0.163

Table 6: Interaction between unemployment and nightlight and its effect on Covid infection rate. Nightlight Inequality, Average nightlight, population density, latitude, longitude, BCG vaccination (in 2017), total vaccination (in 2017) and colonial malaria vary at the district level. Covid19 daily tested varies by state-day. Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Dependent Variable: Total Confirmed Covid19 per million population		
	(1)	(2)
	Lockdown 3	Lockdown 4
Industrial Heterogeneity	3.997	-9.727
	(5.205)	(6.001)
Days since Jan1. 2020	0.023	0.168
	(0.453)	(0.504)
Nightlight (average)	0.020	-0.223***
	(0.062)	(0.082)
Daily tested	-0.000	0.000
	(0.000)	(0.000)
Population density	0.000	0.003***
	(0.001)	(0.001)
Temperature	-0.765***	-0.050
	(0.165)	(0.184)
Rainfall	-0.193	0.004
	(0.123)	(0.101)
BCG vaccination	0.216***	0.082
	(0.061)	(0.077)
Total vaccination	-0.121***	-0.038
	(0.038)	(0.046)
Colonial malaria	-2.334***	-1.878***
	(0.349)	(0.434)
Latitude	0.850***	-0.353
	(0.292)	(0.360)
Longitude	-0.561**	-1.181***
	(0.243)	(0.299)
Constant	35.780	107.397***
	(24.643)	(29.556)
State FE	Yes	Yes
State Trend	Yes	Yes
Observations	6,105	6,920
Adjusted R-squared	0.146	0.104

Table 7a: Regression with industrial heterogeneity index. Column 1 includes the full sample. Columns 2 and 3 are for Lockdown phases 3 and 4, respectively. Average nightlight, population density, latitude, longitude, BCG vaccination (in 2017), total vaccination (in 2017) and colonial malaria vary at the district level. Covid19 daily tested varies by state-day. Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Dependent Variable: Total Confirmed Covid19 per million population								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unlock-1	Unlock-2	Unlock-3	Unlock-4	Unlock-5	Unlock-6	Unlock-7	Unlock-8
Industrial Heterogeneity	-47.586***	-61.526***	18.548*	93.785***	14.053***	5.833	19.651***	19.081***
	(7.078)	(9.714)	(10.958)	(5.369)	(4.105)	(6.262)	(2.863)	(2.693)
Days since Jan1. 2020	0.768***	0.178	-0.320	-0.029	-0.000	-0.488**	-0.863***	-0.142
	(0.271)	(0.364)	(0.410)	(0.207)	(0.153)	(0.237)	(0.109)	(0.088)
Nightlight (average)	0.375***	1.715***	1.545***	3.169***	2.684***	2.604***	1.224***	0.442***
	(0.098)	(0.136)	(0.152)	(0.074)	(0.057)	(0.085)	(0.039)	(0.034)
Daily tested	-0.000	0.000	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	-0.003***	-0.013***	-0.010***	-0.026***	-0.019***	-0.019***	-0.008***	-0.003***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Temperature	0.058	-0.468	-1.510***	-1.269***	-1.342***	-2.377***	-0.453***	-0.564***
	(0.199)	(0.306)	(0.457)	(0.229)	(0.172)	(0.318)	(0.101)	(0.096)
Rainfall	0.294***	0.076*	-0.027	-0.019	-0.002	-0.058	-0.036	-0.108
	(0.049)	(0.040)	(0.040)	(0.024)	(0.033)	(0.074)	(0.051)	(0.067)
BCG vaccination	-0.133	-0.028	0.148	-0.095	-0.075	0.104	-0.006	-0.014
	(0.092)	(0.127)	(0.143)	(0.070)	(0.053)	(0.081)	(0.037)	(0.036)
Total vaccination	0.075	0.004	-0.171**	0.482***	0.351***	0.138***	0.236***	0.121***
	(0.055)	(0.076)	(0.085)	(0.042)	(0.032)	(0.048)	(0.022)	(0.021)
Colonial malaria	0.958*	-0.731	0.341	2.636***	-2.140***	-7.206***	-1.533***	-0.260
	(0.510)	(0.699)	(0.793)	(0.386)	(0.294)	(0.443)	(0.201)	(0.191)
Latitude	-0.889**	-2.346***	-2.129***	-0.785**	-1.187***	-0.435	0.304	-0.514***
	(0.431)	(0.595)	(0.675)	(0.327)	(0.250)	(0.399)	(0.187)	(0.170)
Longitude	-1.550***	-2.699***	-1.029*	-0.202	0.979***	2.404***	0.662***	0.379***
	(0.355)	(0.490)	(0.558)	(0.269)	(0.205)	(0.313)	(0.143)	(0.133)
Constant	128.119***	266.552***	368.544***	80.060***	255.917***	39.426	103.813***	11.134
	(33.955)	(47.870)	(53.611)	(28.360)	(23.103)	(38.179)	(19.819)	(15.528)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,496	16,059	15,890	15,461	15,883	15,121	14,870	13,903
Adjusted R-squared	0.062	0.098	0.138	0.524	0.583	0.342	0.576	0.581

Table 7b: Regression with industrial heterogeneity index for Unlock phases 1-8. Average nightlight, population density, latitude, longitude, BCG vaccination (in 2017), total vaccination (in 2017) and colonial malaria vary at the district level. Covid19 daily tested varies by state-day. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1: Data availability

State Name	Variable Name	Avaiability	Date Range for Variable Availability
Andaman and Nicobar Islands	Total confirmed	Partial districts, no missing date	4 days in Mar'20 | 10 days in Apr'20
	Daily confirmed	Partial districts, no missing date	4 days in Mar'20 | 10 days in Apr'20
	Covid Tests (Daily)	Partial districts, missing dates interpolated	3 days in Mar'20 | 10 days in Apr'20
Andhra Pradesh	Total confirmed	All districts, but missing dates	13 days in Mar'20 | 1st Apr'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	13 days in Mar'20 | 1st Apr'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	9 days in Mar'20 | 1st Apr'20 - 31st Jan'21
Arunachal Pradesh	Total confirmed	All districts, but missing dates	6 days in Apr'20 | 1st May'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	6 days in Apr'20 | 1st May'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	5 days in Apr'20 | 1st May'20 - 31st Jan'21
Assam	Total confirmed	All districts, but missing dates	31st Mar'20 - 19th Aug'20
	Daily confirmed	All districts, but missing dates	31st Mar'20 - 19th Aug'20
	Covid Tests (Daily)	All districts, but missing dates	3rd Apr'20 - 19th Aug'20
Bihar	Total confirmed	All districts, but missing dates	22nd Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	22nd Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	23rd Mar'20 - 31st Jan'21
Chandigarh	Total confirmed	All districts, no missing dates	19th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, no missing dates	20th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, no missing dates	20th Mar'20 - 31st Jan'21
Chhattisgarh	Total confirmed	All districts, but missing dates	19th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	19th Mar'20 - 31st Jan'21

	Covid Tests (Daily)	All districts, but missing dates	25th Mar'20 - 31st Jan'21
Daman diu and dadra nagar haveli	Total confirmed	All districts, but missing dates	5th May'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	5th May'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	6th May'20 - 31st Jan'21
Delhi	Total confirmed	State level, no missing dates	2nd Mar'20 - 31st Jan'21
	Daily confirmed	State level, no missing dates	3rd Mar'20 - 31st Jan'21
	Covid Tests (Daily)	State level, no missing dates	3rd Mar'20 - 31st Jan'21
Goa	Total confirmed	All districts, no missing dates	25th Mar'20 | 4th Apr'20 | 26th Apr'20 - 19th Aug'20
	Daily confirmed	All districts, no missing dates	25th Mar'20 | 4th Apr'20 | 26th Apr'20 - 19th Aug'20
	Covid Tests (Daily)	All districts, but missing dates	25th Mar'20 | 4th Apr'20 | 26th Apr'20 - 19th Aug'20
Gujarat	Total confirmed	All districts, but missing dates	19th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	19th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	21st Mar'20 - 31st Jan'21
Haryana	Total confirmed	All districts, but missing dates	17th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	17th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	18th Mar'20 - 31st Jan'21
Himachal Pradesh	Total confirmed	All districts, but missing dates	20th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	23rd Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	23rd Mar'20 - 31st Jan'21
Jammu and Kashmir	Total confirmed	All districts, but missing dates	9th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	9th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	13th Mar'20 - 31st Jan'21
Jharkhand	Total confirmed	All districts, but missing dates	31st Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	6th Apr'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	6th Apr'20 - 31st Jan'21
Karnataka	Total confirmed	Partial districts, no missing date	9th Mar'20 - 31st Jan'21

	Daily confirmed	Partial districts, missing dates interpolated	10th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	Partial districts, missing dates interpolated	10th Mar'20 - 31st Jan'21
Kerala	Total confirmed	All districts, but missing dates	30th Jan'20 | 2nd - 3rd Feb'20 | 8th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	30th Jan'20 | 2nd - 3rd Feb'20 | 8th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	10th Mar'20 - 31st Jan'21
Ladakh	Total confirmed	All districts, but missing dates	7th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	11th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	11th Mar'20 - 31st Jan'21
Lakshadweep	Total confirmed	All districts, but missing dates	18th - 31st Jan'21
	Daily confirmed	All districts, but missing dates	19th - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	19th - 31st Jan'21
Madhya Pradesh	Total confirmed	All districts, but missing dates	20th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	22nd Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	22nd Mar'20 - 31st Jan'21
Maharashtra	Total confirmed	All districts, but missing dates	9th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	9th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	10th Mar'20 - 31st Jan'21
Manipur	Total confirmed	All districts, but missing dates	24th Mar'20 | 2nd Apr'20 | 26th Apr'20 - 19th Aug'20
	Daily confirmed	All districts, but missing dates	24th Mar'20 | 2nd Apr'20 | 26th Apr'20 - 19th Aug'20
	Covid Tests (Daily)	All districts, but missing dates	26th Apr'20 - 19th Aug'20
Meghalaya	Total confirmed	All districts, but missing dates	13th Apr'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	15th Apr'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	15th Apr'20 - 31st Jan'21
Mizoram	Total confirmed	All districts, but missing dates	25th Mar'20 | 26th Apr'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	26th Apr'20 - 31st Jan'21

	Covid Tests (Daily)	All districts, but missing dates	26th Apr'20 - 31st Jan'21
Nagaland	Total confirmed	All districts, but missing dates	19th May'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	20th May'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	20th May'20 - 31st Jan'21
Odisha	Total confirmed	All districts, but missing dates	16th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	19th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	19th Mar'20 - 31st Jan'21
Puducherry	Total confirmed	All districts, but missing dates	17th Mar'20 | 1st - 2nd Apr'20 | 10th Apr'20 | 25th Apr'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	2nd Apr'20 | 10th Apr'20 | 25th Apr'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	2nd Apr'20 | 10th Apr'20 | 25th Apr'20 - 31st Jan'21
Punjab	Total confirmed	All districts, but missing dates	9th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	21st Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	21st Mar'20 - 31st Jan'21
Rajasthan	Total confirmed	All districts, but missing dates	10th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	14th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	14th Mar'20 - 31st Jan'21
Sikkim	Total confirmed	All districts, but missing dates	23rd May'20 - 19th Aug'20
	Daily confirmed	All districts, but missing dates	23rd May'20 - 19th Aug'20
	Covid Tests (Daily)	All districts, but missing dates	24th May'20 - 19th Aug'20
Tamil Nadu	Total confirmed	Partial districts and missing dates	7th Mar'20 - 31st Jan'21
	Daily confirmed	Partial districts and missing dates	19th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	Partial districts and missing dates	19th Mar'20 - 31st Jan'21
Telangana	Total confirmed	Partial districts and missing dates	2nd Mar'20 | 14th Mar'20 - 26th Apr'20
	Daily confirmed	Partial districts and missing dates	2nd Mar'20 | 14th Mar'20 - 26th Apr'20
	Covid Tests (Daily)	Partial districts and missing dates	14th Mar'20 - 26th Apr'20

Tripura	Total confirmed	All districts, but missing dates	6th Apr'20 | 10th Apr'20 | 26th Apr'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	26th Apr'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	26th Apr'20 - 31st Jan'21
Uttar Pradesh	Total confirmed	All districts, but missing dates	4th - 5th Mar'20 | 9th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	9th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	9th Mar'20 - 31st Jan'21
Uttarakhand	Total confirmed	All districts, but missing dates	15th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	19th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	19th Mar'20 - 31st Jan'21
West Bengal	Total confirmed	All districts, but missing dates	17th Mar'20 - 31st Jan'21
	Daily confirmed	All districts, but missing dates	17th Mar'20 - 31st Jan'21
	Covid Tests (Daily)	All districts, but missing dates	20th Mar'20 - 31st Jan'21

Table A2: Lockdown Phases and Restrictions

Phase	Dates	Number of days	Regulations	Source
Pre-Lockdown	1 Jan, 2020- 24 Mar, 2020	84	Business as Usual	
Lockdown 1	25 Mar, 2020 – 14 April, 2020	21	All services and factories, except essential, were suspended. Arrests across the states were made for violating norms of lockdown such as venturing out for no emergency, opening businesses and also home quarantine violations. The national rail network has maintained its freight operations during the lockdown, to transport essential goods. On 29 March, the Indian Railways announced that it would start services for special parcel trains to transport essential goods, in addition to the regular freight service. As the end of the initial lockdown period came near, many state governments expressed their decision to extend it till the end of April. Among them were Odisha, Punjab, Maharashtra, Karnataka with some relaxations, West Bengal and Telangana.	https://www.mha.gov.in/sites/default/files/Guidelines_0.pdf
Lockdown 2	15 Apr, 2020 – 3 May, 2020	19	On 14 April, the nationwide lockdown was extended till 3 May, with a conditional relaxation promised after 20 April for the regions where the spread had been contained by then. Every police station area were to be evaluated to see if it had contained the spread. The areas that were able to do so would be released from the lockdown on 20 April. If any new cases emerged in those areas, lockdown could be reimposed. On 16 April, lockdown areas were classified as "red zone", indicating the presence of infection hotspots, "orange zone" indicating some infection, and "green zone" with no infections in the past 21 days. The government also announced certain relaxations from 20 April, allowing agricultural businesses, including dairy, aquaculture, and plantations, as well as shops selling farming supplies, to open. Public works programmes were also allowed to reopen with instructions to maintain social distancing. Cargo vehicles, including trucks, trains, and planes, would run. Banks and government centres distributing benefits would open as well with limited timings. On 25 April, small retail shops were allowed to open with half the staff. Again, social distancing norms were to be followed. On 29 April, The Ministry of Home Affairs issued guidelines for the states to allow inter-state movement of the stranded persons. States have been asked to designate nodal authorities and form protocols to receive and send such persons.	https://www.businesstoday.in/current/economy-politics/new-coronavirus-lockdown-guidelines-issued-check-full-list-of-relaxations-lockdown-rules-by-mha/story/401030.html https://www.dnaindia.com/india/report-centre-issues-fresh-set-of-guidelines-for-coronavir

				us-lockdown-20-relaxation-for-some-areas-from-april-20-2821074
Lockdown 3	4 May, 2020 -- 17 May, 2020	14	On 1 May, the Government of India (GOI) further extended the lockdown period to two weeks beyond 4 May, with some relaxations. Movement is permitted within green zones with buses limited to 50 percent capacity. Orange zones would allow only private and hired vehicles but no public transportation. The red zones would remain under complete lockdown. The zone classification would be revised once a week.	https://www.mha.gov.in/sites/default/files/MHA%20Order%20Dt.%201.5.2020%20to%20extend%20Lockdown%20period%20for%202%20weeks%20w.e.f.%204.5.2020%20with%20new%20guidelines.pdf
Lockdown 4	18 May, 2020 – 31 May, 2020	14	On 17 May, GOI extended the lockdown for a period for two weeks from 18 May, with additional relaxations. Unlike the previous extensions, states were given a larger say in the demarcation of Green, Orange and Red zones. Red zones were further divided into containment and buffer zones. The local bodies were given the authority to demarcate containment and buffer zones.	https://www.thehindu.com/news/resources/article31608347.ece/binary/MHAOrderdatedMay17-GuidelinesofLockdownextension.pdf

Unlock 1	1 June, 2020 – 30 June, 2020	30	The MHA issued fresh guidelines for June, stating that the phases of reopening would "have an economic focus". Lockdown restrictions were only to be imposed in containment zones, while activities were permitted in other zones in a phased manner. This first phase of reopening was termed "Unlock 1.0" and permitted shopping malls, religious places, hotels, and restaurants to reopen from 8 June. Restrictions on interstate travel was relaxed. However, large gatherings were still banned and night curfews were in effect from 9 p.m. to 5 a.m. in all areas and state governments were allowed to impose additional restrictions on all activities.	https://www.mha.gov.in/sites/default/files/MHAOrderDt_30052020.pdf
Unlock 2	1 July, 2020 – 31 July, 2020	31	Phase II of Unlock began on 1 July. Lockdown measures were only imposed in containment zones. In all other areas, most activities were permitted. However, large gatherings were still prohibited and night curfews were in effect from 10 p.m. to 5 a.m. in all areas. State governments were allowed to put additional restrictions on all activities, but state borders had to be opened for Inter- and intra-state travel. Limited international travel was permitted as part of the Vande Bharat Mission. Shops were permitted to allow more than five persons at a time. Educational institutions, metro railway, recreational activities remained closed till 31 July. Only essential activities were permitted in containment zones.	https://www.mha.gov.in/sites/default/files/MHAOrder_29062020.pdf
Unlock 3	1 Aug, 2020 – 31 Aug, 2020	31	Unlock 3.0 for August 2020 removed night curfews and permitted gymnasiums and yoga centres to reopen after 5 August. Educational institutions remained closed till 31 August. All inter-and intrastate travel and transportation are permitted. Independence Day celebrations are permitted with social distancing. Maharashtra and Tamil Nadu imposed a lockdown for the whole month, while West Bengal imposed lockdowns twice a week. On 30 August the Delhi Metro started its operations with two metro lines	https://www.mha.gov.in/sites/default/files/DOLrDt_29072020.pdf
Unlock 4	1 Sept, 2020 – 30 Sept, 2020	30	On 29 August 2020, the GOI issued guidelines for activities permitted in Unlock 4.0. Lockdown remained in force in the Containment Zones till 30th September 2020. Outside the containment zone, however, additional activities were given permission. Metro Rail was allowed to be reopened in a graded manner from 7 September. Marriage functions with gatherings of up to 50 people and funereal/last rites ceremonies with up to 20 people were permitted. Religious, entertainment, political, sports, academic functions and gatherings of up to 100 people were allowed.	https://www.mha.gov.in/sites/default/files/MHAOrder_Unlock4_29082020.pdf

| Unlock 5 | 1 Oct, 2020 – 31 Oct, 2020 | 31 | On 30 September 2020, the Ministry of Home Affairs issued guidelines for activities permitted in Unlock 5.0.

For schools it was recommended to teach online as far as possible, but States and Union Territories were allowed to make those decisions from 15 October, in a graded manner.

Lockdown shall remain in force strictly in the Containment Zones till 30 November 2020.

Also, swimming pools being used for training of sportsperson would be allowed to open.

Cinema halls, that had remained close all this while, could be opened from 15 October 2020, with a 50% of their seating capacity.

On 3 November the Government of Kerala opened its tourism sector by reopening hill stations, beaches, national park, and inter-state public transport movement. | https://www.mha.gov.in/sites/default/files/MHAOrderDt_30092020.pdf |
| Unlock 6 | 1 Nov, 2020 – 30 Nov, 2020 | 30 | On 27 October 2020, the GOI issued guidelines for activities permitted in Unlock 6.0. No new changes were made to the existing Unlock 5.0 guidelines and notified that Unlock 5 guidelines were to be in the month of November 2020.

Also, a handful of states allowed opening up of more activities outside containment zones and announced partial reopening of schools. Lockdown was enforced time and again in spite of attempts to permanently move towards an unlock phase.

The GOI extended the ban on scheduled international passenger flights till January 31. | https://www.india.com/news/india/mha-issues-unlock-6-guidelines-check-here-whats-allowed-whats-not-in-november-4187769/ |

Table A3: List of essential goods

	List of Essential Items as of 30th March 2020
1	Fruits & Vegetables
2	Rice, wheat flour, other cereals and pulses
3	Sugar and salt, spices and masalas
4	Bakery and dairy (milk, milk products)
5	Tea and coffee
6	Eggs, meat and fish
7	Food grains, oil, masala and food ingredients
8	Packaged food and beverages
9	Health supplements, nutraceuticals, food for special dietary use and food for special medical purpose
10	Infant/baby food
11	Animal feed/pet food
12	Food delivery services and e-commerce for above mentioned products
13	Cold storage and warehousing of food products
14	Fuel such as coal, rice husk, diesel/furnace oil and others necessary to run manufacturing plants and factories
15	All raw materials, intermediaries, packaging materials needed to support the above list of products
16	Sanitary napkins
17	Diapers
18	Soaps and detergents
19	Surface cleaners and disinfectants
20	Body wash and shampoos
21	Tissue papers
22	Toothpaste/ other oral care products
23	Battery cells, chargers

Source: https://www.bloombergquint.com/business/government-expands-list-of-essential-items-to-include-hygiene-products and https://seednet.gov.in/PDFFILES/Essential_Commodity_Act_1955(No_10_of_1955).pdf