

Chakraborty, Tanika; Mukherjee, Anirban

**Working Paper**

## Economic geography of contagion: A study on Covid-19 outbreak in India

GLO Discussion Paper, No. 1028

**Provided in Cooperation with:**

Global Labor Organization (GLO)

*Suggested Citation:* Chakraborty, Tanika; Mukherjee, Anirban (2022) : Economic geography of contagion: A study on Covid-19 outbreak in India, GLO Discussion Paper, No. 1028, Global Labor Organization (GLO), Essen

This Version is available at:

<https://hdl.handle.net/10419/249201>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# Economic geography of contagion: A study on Covid-19 outbreak in India<sup>\*</sup>

Tanika Chakraborty<sup>+</sup>

Anirban Mukherjee<sup>++</sup>

## Abstract

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 an area characterized by core-periphery economic structure creates regional inequality in which the periphery remains dependent on the core for the supply of jobs, goods and services. Hence, areas arranged in core-periphery structure induce greater degree of mobility which in turn ends up at a higher infection rate than the more homogeneously developed areas at the time of pandemic. 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. Using mobility data, we provide direct evidence in support of our proposed mechanism; that the positive relationship between regional inequality and Covid-19 infection is driven by mobility. Our findings imply that policy responses to contain Covid-19 contagion needs to be heterogeneous across India where the priority areas can be chosen ex-ante based on inequality in economic activity.

JEL Codes: I15; I18; R1

Keywords: Covid-19; contagion; core-periphery; nightlight; mobility

---

<sup>\*</sup> We thank the seminar participants at the Delhi School of Economics and South Asian University for their helpful comments. We are particularly grateful to Robert Carl Michael Beyer for the nightlights data and helpful feedback on the paper. Srutakirti Mukherjee and Vishal Nagwani provided excellent research assistance. Chakraborty acknowledges the financial support provided by IIM Calcutta for this research.

<sup>+</sup> Indian Institute of Management Calcutta, India; Email: tanika@iimcal.ac.in

<sup>++</sup>University of Calcutta, India; Email: ameco@caluniv.ac.in

## 1. Introduction

The Covid-19 epidemic that started from China in the month of November, 2019 has already created a havoc worldwide. One of the striking features of the Covid-19 epidemic is the cross-country variation in terms of the number of infections and deaths; the number of confirmed cases per 1 million population was much higher in Europe and America than in Asia and Africa, during the first year of the pandemic. 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 an artifact 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<sup>1</sup>.

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. The regional inequality created through the core-periphery mechanism captures the fundamental process of economic development not only in the developed part of the world, but in the developing regions as well. 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

---

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

where remote regions (periphery) are all connected with the economic hub (core) 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, but it spreads to the remote areas as well. Given the heavy dependence of peripheral areas on the core in a core-periphery structure, the movements of goods and people are very high between the core and the peripheral regions and any attempt to isolate the core will impose a very high burden of economic costs on the peripheries. In our paper, we argue that the high degree of movements between the core and periphery becomes instrumental in spreading the disease. Hence, the extent of contagion will be higher in areas characterized by a core-periphery structure than in areas consisting of similarly developed sub-regions.

Even though our research is motivated by cross country differences in the spread of infection, conducting the analysis on 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 in economic activity. For instance, a state showing a stronger core-periphery structure will also have greater intra-state regional inequality. Night time luminosity is a well-established measure to compare economic and industrial activity across countries, as well as across regions within a country (Henderson et al., 2012; Prakash et al., 2019). We construct an index of regional inequality in economic activity based on night time luminosity data, across the districts of India, to measure the core-periphery structure of a region; the stronger the core-periphery structure, the higher is the inter-district nightlight inequality in that region.<sup>2</sup> We expect that the regions with higher intra-regional inequality in economic activity will experience higher Covid-19 infection rate, after accounting for factors that covary with the spread of the infection and regional inequality.

In addition to state and time fixed-effects to account for unobserved heterogeneity across states and 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

---

<sup>2</sup> We use night time luminosity and nightlights interchangeably in this paper.

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.

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 is associated with 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 neighbourhood. In both cases, the findings remain robust to a staggered inclusion of a range of control variables.

Movements of people play a key role in our story. The mechanism that underlies our measure involves movement of people from the core to the periphery. We provide evidence on this channel in three ways. First, we use differences in potential mobility over *lockdown* and *unlock* periods, announced by the Indian government, to test whether the relationship between Covid-19 and regional inequality varied across the different lockdown phases. Second, we use mobility data from the *Facebook Data for Good* project to study the mechanism directly. Third, we also use unemployment rates as a proxy for movement of people (or lack thereof) and investigate its interaction with the core-periphery structure.<sup>3</sup> The analysis by the phases of lockdown and unlock shows that the core-periphery structure contributes to the spread of the Covid-19 infection when the economy opens up. The results are absent or muted during the lockdown periods and early phases of unlock. We also find that movement of people, as proxied by the Facebook data, is strongly correlated with our measure of regional inequality and is the main driver of the baseline relationship. Finally, we find that for the same level of intra-state regional inequality in nightlights, districts in states with higher levels of baseline unemployment, experience a lower extent of contagion.

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. In one such paper Bonacini et al.,( 2021) showed how people's expectation formation can mitigate the effect of lockdown policies. Lockdown policies however are seen to effect economies in various, nuanced ways. (Bonacini et al., 2021b) for example, showed that lockdown induced work-from-home practice creates the risk of exacerbating inequality. This can only be mitigated government policies directed at

---

<sup>3</sup> In **Section 5.4.3** we provide evidence that higher unemployment is related to lower mobility in India.

addressing the issues of income inequality. In the pre-vaccine phase of the contagion, the most common strategy practiced by any government was that of lockdown which is complemented by health policies whose implementation and success in curbing the contagion varied across countries (Chiplunkar and Das, 2021; Qiu et al., 2020) . 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 et al., 2020, 2021). In the context Our paper 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 underlying notion of our paper is similar to Milani, 2021, who analysed how social connectedness (captured by Facebook data) across countries explain the cross country similarity in social responses to Covid pandemic.

It is important to note that the policy implication of our paper applies to all possible anti-epidemic measures. After the Covid-19 vaccines were invented, vaccination and lockdown spearheaded the anti-Covid policy measures. Nevertheless, the approach to the use of the policies remains homogenous; they were implemented with similar intensity across the country. We propose an *ex-ante selection criterion*; we predict that the spread of epidemic will be higher in areas characterized by core-periphery structure and therefore, any anti-epidemic policy -- be it creation of special Covid hospitals, lockdown or vaccination -- should be implemented with greater intensity in those areas.

Our paper is structured in the following way: We elaborate our argument and the issues related to our framework in the Section 2. We discuss the data and descriptive statistics in section 3, the empirical strategy in section 4, and the results in section 5. In section 6, we conclude.

## **2. Conceptual Framework**

In this paper, we explore the relationship between regional inequality in economic activity and Covid-19 infection. There are two key concepts that need to be explained before we discuss the empirical analysis. The first one concerns the mechanism underlying our hypothesis and the second one is related to the measurement of regional inequality in economic activity. The core-periphery model (also known as the centre-periphery model) of development postulates

that the process of economic development organizes an economy in the geographical structure of core-periphery where most of the economic activities are carried out in an industrialized core which supplies goods and services to less industrially active peripheral areas. The alternative to this structure will be that of regional autarky where a region consists of a few similarly developed sub-regions consisting of both industrial and agricultural sectors. The creation of the core-periphery structures is embedded in the process of development and both developed and less developed countries across the globe show such a locational pattern of economic activities. In fact, the more developed a region gets, the greater the degree of sub-regional inequality; this becomes evident from the studies on Africa (Mveyange, 2015) and India (Singhal et al., 2020). One implication of the creation of the core-periphery structure is increased movements of commodity and people between core and periphery; goods and services move from the core to the periphery while labor moves from the periphery to the core. On the other hand, if a country consists of a few autarkic regions, we expect less movements between such regions. Therefore, we expect greater movements of people and, consequently, higher degree of contagion at the time of epidemic in regions characterised by core-periphery structure. This argument forms the basis of our empirical strategy. We use regional inequality in economic activity as a proxy for such movements and hypothesize that higher regional inequality will be associated with greater degree of Covid-19 infection. One major reason for using the measures of inequality instead of mobility itself is the availability of data. The nightlight-based inequality measures are more readily available than measures of mobility. There are two important criteria that Facebook use restricts the availability of the Facebook mobility data. It can only collect data from people who has a smartphone with GPS turned on and the Facebook app. Moreover, it does not include data from a geographical unit if there are less than 10 movements in a day. Consequently, not all the districts are covered in the Facebook database.

The second concept that deserves discussion is the measurement of the core-periphery structure. How can we measure the degree of ‘*core-periphery-ness*’ of a region? The use of nightlights to find spatial patterns of economic clusters is not an entirely novel approach. However, the exploratory spatial data analysis, also called ESDA techniques, applied in the literature are commonly used to capture spatial spill-over (Rodríguez-Pose et al., 2013; Rodríguez-Pose and Tselios, 2011; Tselios and Stathakis, 2020) and are not suitable for answering our research question. We instead measure ‘*core-periphery-ness*’ of a region using measures of regional inequality in economic activity.

Covid-19 data in India is available at the district level. To match this data structure, in our framework, we treat districts as the unit of observation whose level of economic activity is measured by the level of nightlight. To test our hypothesis, we need to measure inequality across districts which must be measured at a *supra-district* level. The natural choice of such supra-district level is state. In this case, we rank the districts of each state according to their respective nightlights and then measure the ratio of nightlights at the 90<sup>th</sup> and 10<sup>th</sup> percentile (P90/P10 ratio). The use of the P90/P10 as the measure of inequality is now widely being used in the literature on economic inequality (Burkhauser et al., 2009; Kijima, 2006; Piketty, 2014). Unlike other measures such as Standard Deviation and Gini Coefficient which take into account all intermediate income groups, this ratio makes a direct comparison between the most active and the least active districts and therefore, brings out the sharpness of inequality. In our case, this measures the economic distance between the core (the most active) and the periphery (the least active). We argue that greater the distance between the core and the periphery in terms of economic development (as measured by nightlight), the greater is the dependence of the periphery on the core for jobs and necessary supplies. This in turn entails greater movements of goods and people between the core and the periphery and higher rate of Covid 19 infection.

However, a measure of regional inequality at the state level renders regression with state fixed effects infeasible. Inter-state comparisons are difficult to rely on given that most policies, especially health policies are decided and implemented at the state level. Hence even though we use state level measure of regional inequality in our baseline regression, for most of our empirical exercises, we use regional inequality measured at the district neighbourhood level where the neighbourhood of a district  $i$  is defined as the cluster of districts that share borders with the district  $i$ . However, for each district there are at most 4-5 neighbouring districts and calculating the P90/P10 for such a small group is not meaningful. We, therefore calculate the ratio between the minimum and maximum nightlight in the district-neighbourhood and subtract it from 1. The resulting measure becomes a function of the difference between the maximum and minimum nightlight in the neighbourhood. We formally introduce this measure in section 3.2.4. In essence, both the measures capture the distance between the most economically active and the least economically active district in the region which in our case can be interpreted as the distance between the core and the periphery.



### 3. Data and Descriptive Statistics

#### 3.1 Covid-19 infection: state-wise variation

In this paper we offer an economic-geography based hypothesis that explains regional variation in Covid-19 infection in India in terms of regional inequality captured by luminosity data. In this section, we provide a cursory look at the inter-state variation of Covid-19 infection.

Before proceeding further, let us give a brief description of the administrative boundaries within India. India is divided in 28 states and 8 union territories. The states and union territories are further divided in districts. At the time of the last census in India in 2011 there were 640 districts in India. The number of districts has increased over time as they have sometimes been bifurcated for administrative ease. As of 2021, there are 740 districts. The districts are further subdivided into sub-districts and sub-districts into blocks. The Covid-19 that we use is reported at the district level.

Since health is under the jurisdiction of state governments in India, district level information on Covid19 infections in India is provided by each state. But there was a significant heterogeneity in terms of data publication format across the state which made the data work all the more challenging. During our study period (January, 2020-January,2021), there was 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 the appendix, we provide a table which details the issue of heterogeneity across state regarding data availability.

In this paper, the issues pertaining to data availability made us 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 i.e. from March, 25, 2020 to May 3, 2020) very

stringent restrictions were imposed on business and vehicles. From 4<sup>th</sup> May, 2020, the nationwide lockdown was eased for the first time with several relaxations. Further, we include the following major states in our sample<sup>4</sup>. Andhra Pradesh, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh (U.P), Uttarakhand, West Bengal. As of February 1, 2021, the last date for our data, these states together account for around 84% of our data.

In the following figures, we present a broad picture of inter-state variation in terms of the number of Covid-19 patients. Figure 1 shows the distribution of Covid infections across states as of 1<sup>st</sup> 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 1: Share of Covid-10 confirmed cases in 10 leading states**

Figure 2 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 Uttar Pradesh 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 2 : Time series 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 not be very informative given the large difference in population and land sizes.

### **Figure 3: Total confirmed Covid-19 cases per 100 thousand population of the states**

Figure 3 depicts a map representation of the number of Covid-19 patients normalized 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

---

<sup>4</sup> Our estimation sample includes 19 major states. It excludes among others Delhi and other Union Territories. Since Union Territories are not divided into 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.

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 ranked low initially, almost 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 the other states throughout the period. Around September, 2020 Karnataka made a big jump and almost caught up with Maharashtra and Tamil Nadu. 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.

In this next two figures we present the all-India level variation in average Covid-19 infection and nightlight variation – the two variables that our paper is trying to link.

#### **Figure 4: A district level map of daily confirmed cases of Covid-19**

Figure 4 presents the number of Covid infection at the district level averaged over days until 31<sup>st</sup> January, 2021. In the map darker shades indicate more cases while the lighter shades represents less cases. We see a wide variation in the number of Covid-19 cases across India with more cases in more industrialized Southern states.

### **3.2 Variables and data sources**

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.(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 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). However, there are papers which dispute this claim of a negative relationship between temperature and COVID infection. In one such paper, Zhu & Xie (Zhu

and Xie, 2020) looking at the COVID situation in 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, and summarize each variable used in our analysis in Table 1.

**Table 1: Summary Statistics here**

**3.2.1 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.

**3.2.2 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.

### **3.2.3 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.

### **3.2.4 Measures of the Core-Periphery structure:**

#### **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. Specifically, we use the data from (Beyer et al., 2020). They extract the district level nighttime light data from the VIIRS-DNB Cloud Free Monthly Composites (version 1) provided by the Earth Observation Group at Colorado School of Mines. While the monthly data would have allowed us to exploit more variation, the monthly nightlight data has significant amount of noise (Beyer et al., 2020). Hence, we use the noise and outlier corrected lights averaged over time, and standardized by area at the district level used by (Beyer et al., 2021). The nightlights data is widely used as a proxy for economic activity (Prakash et al., 2019). 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.

### **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 90<sup>th</sup> and 10<sup>th</sup> percentile does not make much sense. Instead, we measure nightlight inequality in the following way:

$$\eta_d = 1 - \frac{\mu_{Min}^d}{\mu_{Max}^d} \quad (2)$$

In the above expression  $\eta_d$  measures the neighbourhood nightlight inequality for district d,  $\mu_{Min}^d$  measures the minimum nightlight in the neighbourhood of district d while  $\mu_{Max}^d$  the maximum value in the neighbourhood. This expression essentially becomes  $R_d/\mu_{Max}^d$  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  $\eta_d$ , higher will be the value of neighbourhood inequality.

In Figure 5 we present the variation in nightlight across the districts of India. In this map darker shades represent higher nightlight (or core) while the lighter spots represent low nightlight (or periphery).<sup>5</sup> The map reveals the structure of the core-periphery all across the country. In all parts of India we see dark shaded core areas being surrounded by the light shaded periphery regions.

**Figure 5: A district level map of District-Neighborhood Nightlight-Inequality**

---

<sup>5</sup> The bottom 10 percentile of the nightlight distribution is represented by the lightest shade. The top 10 percentile is represented by the 2 darkest shades.

#### 4. 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:

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

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.  $\beta_1$  is our parameter of interest. The variable  $T$  measures the day of the year. We assign a value of 1 to the 1<sup>st</sup> day of January 2020 and cumulatively calculate the number of days for each date in the 2020 calendar. This is our baseline specification. However, in section 5.2 we use district-neighborhood level of regional inequality along with state fixed effect.

#### 5. Results

##### 5.1 State Level Regional Inequality and Covid-19 infection

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: State Level Nightlight Inequality and Covid-19 infection**

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 those 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 explanation of this counter-intuitive result could be the more stringent lockdown measures that were implemented in densely populated areas. More densely populated areas are more susceptible to Covid-19 outbreak and governments usually more impose stricter restriction there. Population density is however related to various other things such as economic prosperity as



well. But in our full specification, when we control for all other factors population density probably captures the intensity of lockdown measures imposed by the governments and therefore, the sign of the coefficient is negative.<sup>6</sup>

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). This result however, is possibly driven by confounding variables. The BCG and other vaccination drive was possibly taken more vigorously in districts where the chance of epidemic is high due to several demographic and socio-economic variables. When a pandemic such as Covid-19 hits the country, these districts are more likely to be affected more. Therefore, the positive association between the rate of vaccination (BCG and other) in the past and Covid-19 infection rate in the present could be driven by those confounding variables. 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. Before moving to the next section, let us compare our results with Tan et al. (2021) who also found positive association between county level income inequality and Covid-19 infection and death in the United States. The nature of inequality and the mechanism discussed there however, are different from our analysis. They found that the association between income inequality and Covid-19 infection nearly peaked during summer. They hypothesized that this was driven by

---

<sup>6</sup> The results from the heterogeneity analysis in **Section 5.3** also point towards this possibility. During the strict lockdown phase, that was imposed country wide, the coefficient for population density is positive (**Table 5a**). However, as the economy opened up gradually during the unlock period, the coefficient on population density turned negative possibly due to stricter enforcement of 'micro-containment' zones in more dense regions (**Table 5b**).

poor people working in high risk, contact prone sectors such as hotels, restaurants and entertainment venues. Our results on the other hand, is driven by regional inequality where the mobility between the core and the periphery assumes the critical role. It is somewhat difficult to directly compare these two results. Nevertheless, our story can be mapped to that paper if could show that most of people working in contact prone sectors in the core comes from the periphery and phases of lockdown and unlock which affected these sectors the most forced these workers to move back and forth between their workplaces in the core and homes in the periphery. However, because of data issue we cannot make such claims.

## 5.2 Nightlight Inequality at District Neighborhood Level and Covid-19 infection

In order to solve the identification problem in Table 2, 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. Equation 2 shows the estimation specification corresponding to Table 3, where  $\beta_1$  is the coefficient of interest.

$$\begin{aligned} y_{dst} = & \beta_0 + \beta_1 NLI_d + \beta_2 Days_t + \beta_3 NL_d + \beta_4 Test_{st} + \beta_5 Density_d + \\ & \beta_6 Temperature_{dt} + \beta_7 Rainfall_{dt} + \beta_8 BCG_d + \beta_9 Vaccine_d + \beta_{10} Malaria_d + \\ & \beta_{11} Latitude_d + \beta_{12} Longitude_d + Dummy_s + Dummy_s * Days_t + \varepsilon_{dst} \end{aligned} \quad (2)$$

### Table 3 Baseline regression with neighbourhood inequality

In column 1, we regress total confirmed cases per 1million 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 8 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 8.<sup>7</sup>

### 5.3 Heterogeneity Analysis

In response to the COVID 19 pandemic, the government of India, in March 2020, announced a lockdown resulting in suspension of usual activities of government offices, business establishments and educational institutions, except those related to the supply of essential goods and services.<sup>8</sup> Subsequently, over different phases of lockdown (and eventually unlocks), different types of activities were allowed. 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

These different phases of lockdown and unlock led to different degree of movements of people and vehicles. Hence, we expect that the effect of the core-periphery structure (as measured by regional inequality of nightlights) on the contagion would 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 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 5a. Subsequently, the relaxations were increases in a phased manner between unlock 1-8. The results for these unlock phases are given in Table 5b.

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

---

<sup>7</sup> As observed in Figures 2 and 3, confirmed cases evolve non-linearly over time. To account for this, we introduced non-linear time effects in our model. The results, presented in **Appendix Table A5**, remain unchanged.

<sup>8</sup> 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.

### **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 eased. 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.

Let us consider two distinct cluster of districts (Southern cluster and Northern Cluster) within a state. For example, consider the state of West Bengal Southern cluster has Kolkata (West Bengal's capital and one of the biggest cities in India) as the core district and Northern cluster has Siliguri (the biggest city in the Northern part of the state) as the core district. Since Kolkata is economically 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 nighttime 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.

## **5.4 Mechanism and Robustness**

### **5.4.1 Nighttime Inequality and Mobility**

In understanding the effect of nighttime 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. In the previous section, we provided indirect evidence of this mechanism by using the lockdown-unlock phases. In this section we provide more direct evidence using mobility information from Facebook Data for Good<sup>9</sup>. The data from Facebook includes the mobility data of people with smartphone with Facebook app which keeps their GPS turned on. Therefore, the data represents the mobility of a small fraction

---

<sup>9</sup> We access this data from “Facebook Data for Good” (<https://dataforgood.facebook.com/>).

of population. Nevertheless, it corresponds with migration reported in the Census data and hence provides a useful proxy of the overall mobility (Chadha and Raghu, 2021). We argue that unequal regions are characterized by greater mobility which in turn leads to greater Covid infection. In Table 6 we present the results from a regression where we regress daily movement data from Facebook on neighbourhood inequality. In column (1) we regress daily movement on neighbourhood inequality without any control and find that the coefficient is positive and significant, implying that higher nightlight inequality in the neighborhood of a district reflects greater degree of movement to and from that district. From column (2) to (5), we keep adding controls similar to the ones used in the baseline regression in Table 3. In column (2) we account for the average nightlight of a district to capture the overall level of activity. The strong positive coefficient confirms our prior that a high level of economic activity is associated with a high degree of mobility. In addition, the negative coefficients on the number of days since start of covid and on the number of daily covid tests indicate that overall mobility has gone down as covid cases went up. The effect-size of neighborhood inequality on mobility remains unaltered by addition of further controls in columns (3) through (5). Overall, we find that nightlight inequality remains a strong predictor of mobility measured from the Facebook data.

**Table 6: Nightlight inequality and mobility [here](#)**

#### 5.4.2 Mobility as the underlying mechanism

While the results in Table 6 shows the first-stage relationship that we implicitly assumed in Table 3, we turn to a direct investigation of the extent to which the relationship between neighborhood nightlight inequality and spread of the contagion is indeed driven by mobility across districts. Specifically, if mobility is the main channel through which nightlight inequality is driving the spread of Covid, then controlling for mobility in Table 3 should temper the effect of nightlight inequality on Covid-19 spread.<sup>10</sup> In Table 7, we provide the evidence

---

<sup>10</sup> In an alternative analysis we also use district level industrial heterogeneity to proxy for mobility of and higher social interaction among people. Our measure of industrial heterogeneity ( $h_d$ ) uses the share of labor force in different industries ( $h_d = 1 - \sum_i s_{id}^2$ , where  $s_{id}$  is the share of work force in industry  $i$  in district  $d$ ). The underlying thought is that, in a district with higher industrial heterogeneity people from the same family are more likely to work in different industries. Hence if a person gets infected from her workplace, there is a higher chance of spread to other industries through her family members who work there. Since industrial heterogeneity is measured at the district level, we account for state fixed effects in these specifications. The estimates are in line with our main findings. Industrial heterogeneity has no effect on the contagion during the Lockdown phases. However, as the industries open up and mobility increases, we find a positive effect of industrial heterogeneity on the spread of Covid-19. These results are reported in Appendix Tables A6 and A7. However, we due to data limitations, we are unable to establish our claim to the mechanism that higher industrial heterogeneity reflects greater diversity in employment within the same household. Hence, we cannot be sure that industrial heterogeneity

on this potential mechanism. In columns (1) and (3) of this table we report the baseline results corresponding to columns 1 and 8 of Table 3 for the estimation sample in columns 2 and 4 of Table 7 respectively.<sup>11</sup> In column (2) we report the baseline relationship between Covid infection and Nightlight inequality (analogous to Column 1 of Table 3) after controlling for mobility. In column 4 we estimate the full baseline specification (analogous to Column 8 of Table 3) along with a control for mobility. Comparison of columns (1) and (2) reveals that inclusion of mobility leads to a large reduction in the magnitude of the coefficient on nightlight inequality and mobility itself is an important predictor of the contagion. In column (4), we present the results for the regression with full specification along with mobility as an independent variable. Comparison between column (3) and (4) provide stronger support in favor of our hypothesis. In column (4), after inclusion of the mobility data, the coefficient of the nightlight inequality becomes insignificant while the coefficient for mobility remains positive and significant. This means that inequality affects Covid inequality through the mobility channel as we predicted in our conceptual framework. These results together provide direct evidence in favour of our hypothesis and the underlying mechanism.

**Table 7: Effect of nightlight inequality on Covid 19 infection with and without mobility control here**

### 5.4.3 Unemployment and mobility

While the evidence in Table 7 strongly indicates that the effect of nightlight inequality on the contagion works through mobility, there are limitations of the Facebook Mobility data in terms of its representativeness. Hence, in this section, we further investigate the mechanism using state-level daily unemployment rates as a proxy for mobility.<sup>12</sup> We argue that traveling to work depends on employment status. Specifically, mobility is driven by the employed and regions with higher level of unemployment would experience lower levels of mobility. Indeed, we see this relationship in our data. Appendix Table A4 shows the relationship between state-level daily unemployment rates and mobility patterns. We conduct this analysis for the unlock phases (beginning with May 2020 till the end of our data) considering that mobility was restricted due to government regulations during the lockdown period. The negative estimates imply that both

---

is indeed capturing greater extent of social interactions. Hence, we refrain from reporting these findings as part of our main analysis.

<sup>11</sup> Facebook data reports mobility from one region to another when at least 10 people move across these regions. Hence, not all districts-days are available in the Facebook mobility data.

<sup>12</sup> We interpolate the daily unemployment rate using the monthly unemployment rate published by Centre for Monitoring Indian Economy (CMIE)



inter-district and within-district mobility were significantly low in states with high unemployment rates. Hence, we expect that when unemployment rate is high, the effect of nightlight inequality on Covid infection rate will be low, since the mobility effect will be muted. Accordingly, we regress district level daily per capita infection spread on the interaction of state level nightlight inequality and state level daily unemployment rate. In contrast to Table 2, this specification also allows us to introduce state fixed effects and state level time trends to account for all other state level factors that might affect the spread of Covid-19, that are either fixed over time or varies linearly over time. The specification that we use is comparable to Table 2 except that now we introduce daily unemployment rate and the interaction of state-nightlight inequality with unemployment rate. We expect, the interaction effect of nightlight inequality and unemployment rate to be negative. Between two states with different levels of nightlight inequality, the spread of Covid-19 is expected to be lower in the state with higher levels of unemployment. We present the results in Table 8.

**Table 8 Interaction between unemployment and Nightlight Inequality and its effect on Covid infection rate.**

Column (1) presents the iteration-specification without any fixed effects. We find that 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 significantly negative. Together these results imply 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.

**Appendix Table 6: Migration and Unemployment during unlock phases**

## 6. 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 geographical organization of markets. Using data from the first year (March, 2020-January, 2021) 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 people across the core and peripheral districts. 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. Further, using mobility data, we provide direct evidence that much of the effect of nightlight inequality on the spread of Covid is explained by movement of people.

Our finding has a 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. However, such stringent lockdown came at a very high cost. We have seen a handful of academic papers along with numerous reports in newspapers and policy documents which detailed the economic loss during lockdown. An estimate published in April, 2021 by State Bank of India show that total economic loss is in the range of INR 1.5 Trillion<sup>13</sup> (approximately 20 Billion USD). Besides the figures of economic loss, the first two phases of lockdown in India saw an unprecedented humanitarian crisis in the plight of the migrant workers<sup>14</sup>. A large part of this crisis had its root in the initial stringent lockdown which was imposed uniformly across India.

One critical implication of our research is selective policy implementation based on regional inequality; more intense implementation of the policy instrument in areas characterised by more regional inequality. The idea of selective policy implementation is not entirely novel when it comes to lockdown strategies. We have seen that during the unlock phases, the Indian government has followed this strategy based on the number of confirmed cases in an area. Essentially, under this policy, the districts were categorized into 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

---

<sup>13</sup> [https://www.business-standard.com/article/economy-policy/economic-cost-of-mobility-curbs-lockdowns-at-rs-1-5-trillion-sbi-report-121042300326\\_1.html](https://www.business-standard.com/article/economy-policy/economic-cost-of-mobility-curbs-lockdowns-at-rs-1-5-trillion-sbi-report-121042300326_1.html)

<sup>14</sup> <https://www.bbc.com/news/av/world-asia-52776442>

the lockdown policies were more relaxed in these districts. But this categorization was done based on the number of confirmed cases which was revealed ex-post. The selective lockdown strategy that follows from our research 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 predict the prospective severity of the contagion in different regions. 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.

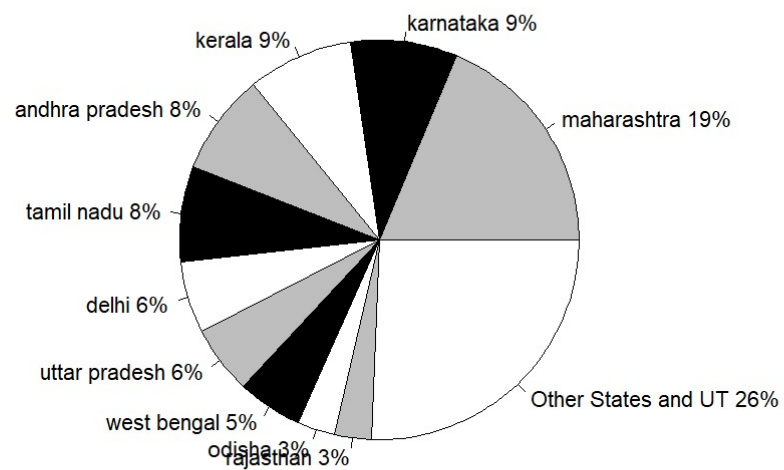
However, there is one important caveat of this policy suggestion. Stringent lockdown in unequal regions may have severe negative impact on the poor if the poor are more likely to live in more unequal regions. However, previous research shows that districts with a stronger core-periphery structure, i.e., more unequal districts, are not necessarily the poorer ones. In fact, more developed regions are generally characterized by greater degree of sub-regional inequality (Mveyange, 2015; Singhal et al., 2020). Hence, in the event of a stringent lockdown we can think of a redistributive policy which would transfer resources from the rich core to the poor periphery to support the poor people in the peripheries. Second, the alternative to our selective lockdown is the blanket lockdown which has been practised in India. The blanket lockdown did impact both equal and unequal regions alike and therefore, is Pareto inferior to the policy of selective lockdown. Moreover, it is important to note that the policy implication of our paper is not restricted to lockdown policies. Now, with vaccine's inclusion to the array of anti-Covid policy instruments, we can apply the basic principle of our policy suggestion and prioritize areas for vaccination drive based on the core-periphery structure.

## References:

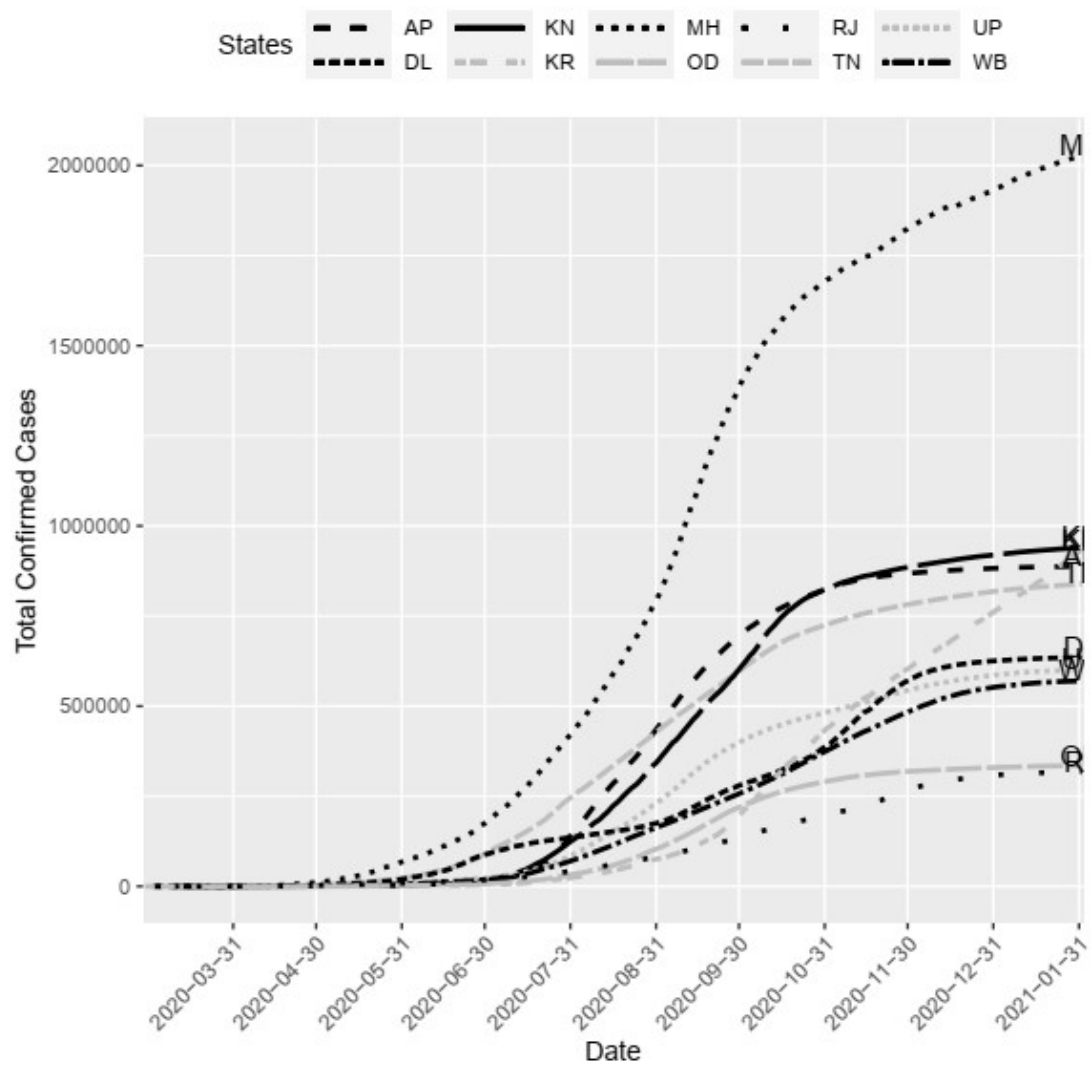
- Bannister-Tyrrell, M., Meyer, A., Faverjon, C., Cameron, A., 2020. Preliminary evidence that higher temperatures are associated with lower incidence of COVID-19, for cases reported globally up to 29th February 2020. medRxiv.
- Beyer, R., Jain, T., Sinha, S., 2020. Lights Out? COVID-19 Containment Policies and Economic Activity.
- Beyer, R.C.M., Franco-Bedoya, S., Galdo, V., 2021. Examining the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity. *World Development* 140, 105287.
- Bonacini, L., Gallo, G., Patriarca, F., 2021a. Identifying policy challenges of COVID-19 in hardly reliable data and judging the success of lockdown measures. *Journal of Population Economics* 34, 275–301.
- Bonacini, L., Gallo, G., Scicchitano, S., 2021b. Working from home and income inequality: risks of a ‘new normal’ with COVID-19. *Journal of Population Economics* 34, 303–360. <https://doi.org/10.1007/s00148-020-00800-7>
- Burkhauser, R.V., Feng, S., Jenkins, S.P., 2009. Using the P90/P10 Index to Measure U.s. Inequality Trends with Current Population Survey Data: A View from Inside the Census Bureau Vaults. *Review of Income and Wealth* 55, 166–185. <https://doi.org/10.1111/j.1475-4991.2008.00305.x>
- Chadha, N., Raghu, S., 2021. Measuring migration-related movements from daily mobility data (No. 2021/1), India Development Foundation Working Paper.
- Chiplunkar, G., Das, S., 2021. Political institutions and policy responses during a crisis. *Journal of Economic Behavior & Organization* 185, 647–670. <https://doi.org/10.1016/j.jebo.2021.03.018>
- Cutler, D., Fung, W., Kremer, M., Singhal, M., Vogl, T., 2010. Early-life malaria exposure and adult outcomes: Evidence from malaria eradication in india. *American Economic Journal: Applied Economics* 2, 72–94. <https://doi.org/10.1257/app.2.2.72>
- Henderson, J.V., Storeygard, A., Weil, D.N., 2012. Measuring economic growth from outer space. *American economic review* 102, 994–1028.
- Kijima, Y., 2006. Why did wage inequality increase? Evidence from urban India 1983–99. *Journal of Development Economics* 81, 97–117. <https://doi.org/10.1016/j.jdeveco.2005.04.008>
- Milani, F., 2021. COVID-19 outbreak, social response, and early economic effects: a global VAR analysis of cross-country interdependencies. *Journal of population economics* 34, 223–252.
- Miller, A., Reandelar, M.J., Fasciglione, K., Roumenova, V., Li, Y., Otazu, G.H., 2020. Correlation between universal BCG vaccination policy and reduced morbidity and mortality for COVID-19: an epidemiological study. MedRxiv.
- Mveyange, A., 2015. Night lights and regional income inequality in Africa. WIDER Working Paper.
- Piketty, T., 2014. Capital in the twenty-first century. Cambridge Massachusetts : The Belknap Press of Harvard University Press, 2014.
- Prakash, A., Shukla, A.K., Bhowmick, C., Beyer, R.C.M., 2019. Night-time luminosity: Does it brighten understanding of economic activity in India. Reserve Bank of India Occasional Papers 40.
- Qiu, Y., Chen, X., Shi, W., 2020. Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics* 33, 1127–1172.

- Rodríguez-Pose, A., Tselios, V., 2011. Mapping the European regional educational distribution. *European Urban and Regional Studies* 18, 358–374.  
<https://doi.org/10.1177/0969776411399345>
- Rodríguez-Pose, A., Tselios, V., Winkler, D., Farole, T., 2013. Geography and the Determinants of Firm Exports in Indonesia. *World Development* 44, 225–240.  
<https://doi.org/10.1016/j.worlddev.2012.12.002>
- Singhal, A., Sahu, S., Chattopadhyay, S., Mukherjee, A., Bhanja, S.N., 2020. Using night time lights to find regional inequality in India and its relationship with economic development. *PloS one* 15, e0241907.
- Tan, A.X., Hinman, J.A., Abdel Magid, H.S., Nelson, L.M., Odden, M.C., 2021. Association Between Income Inequality and County-Level COVID-19 Cases and Deaths in the US. *JAMA Network Open* 4, e218799.  
<https://doi.org/10.1001/jamanetworkopen.2021.8799>
- Tselios, V., Stathakis, D., 2020. Exploring regional and urban clusters and patterns in Europe using satellite observed lighting. *Environment and Planning B: Urban Analytics and City Science* 47, 553–568. <https://doi.org/10.1177/2399808318788567>
- Wang, J., Tang, K., Feng, K., Lv, W., 2020. High temperature and high humidity reduce the transmission of COVID-19. Available at SSRN 3551767.
- Zhu, Y., Xie, J., 2020. Association between ambient temperature and COVID-19 infection in 122 cities from China. *Science of the Total Environment* 138201.

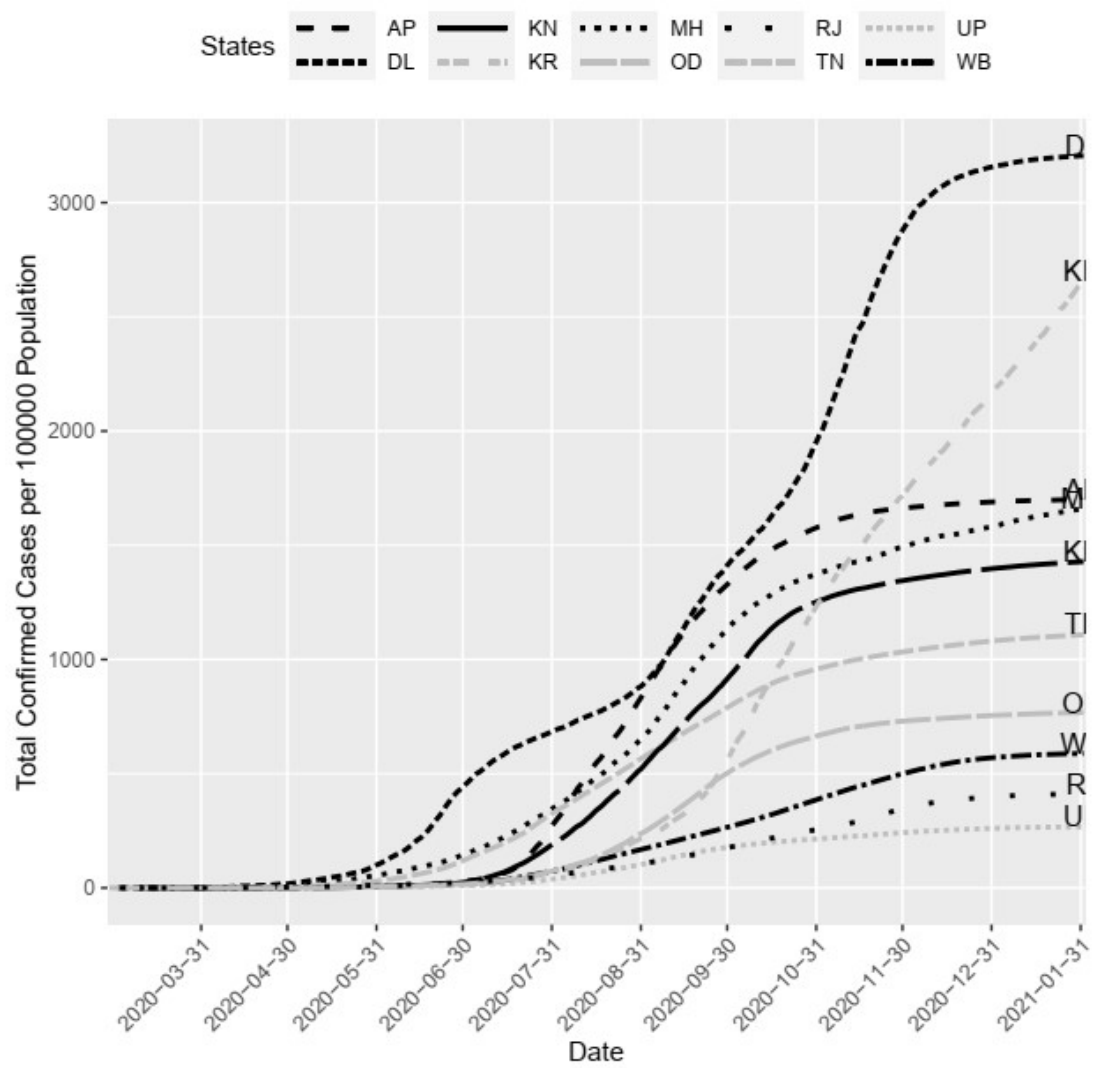
## Figures:



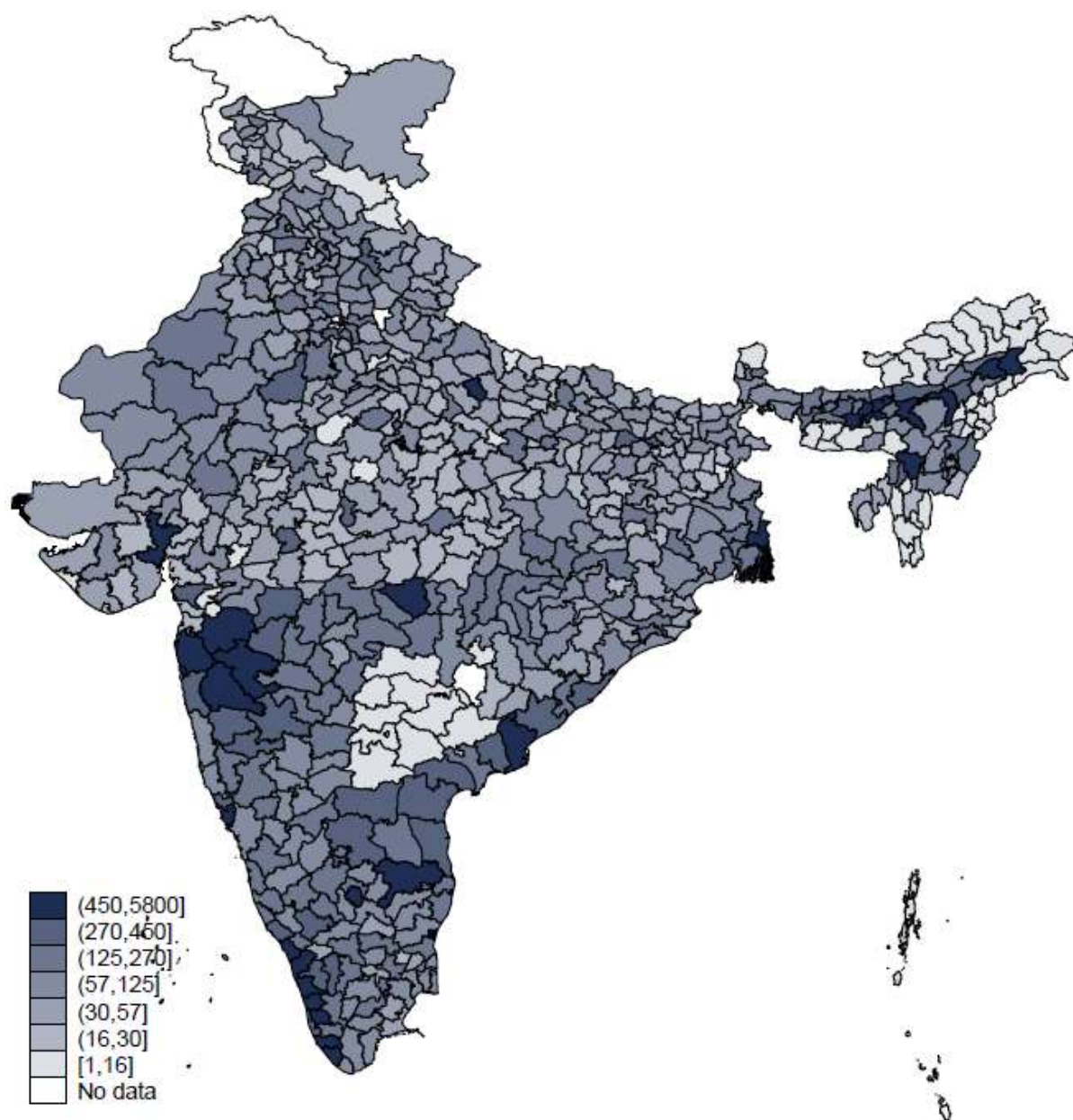
**Figure 1: Share of Covid-10 confirmed cases in 10 leading states**



**Figure 2: Covid-10 confirmed cases in 10 leading states**

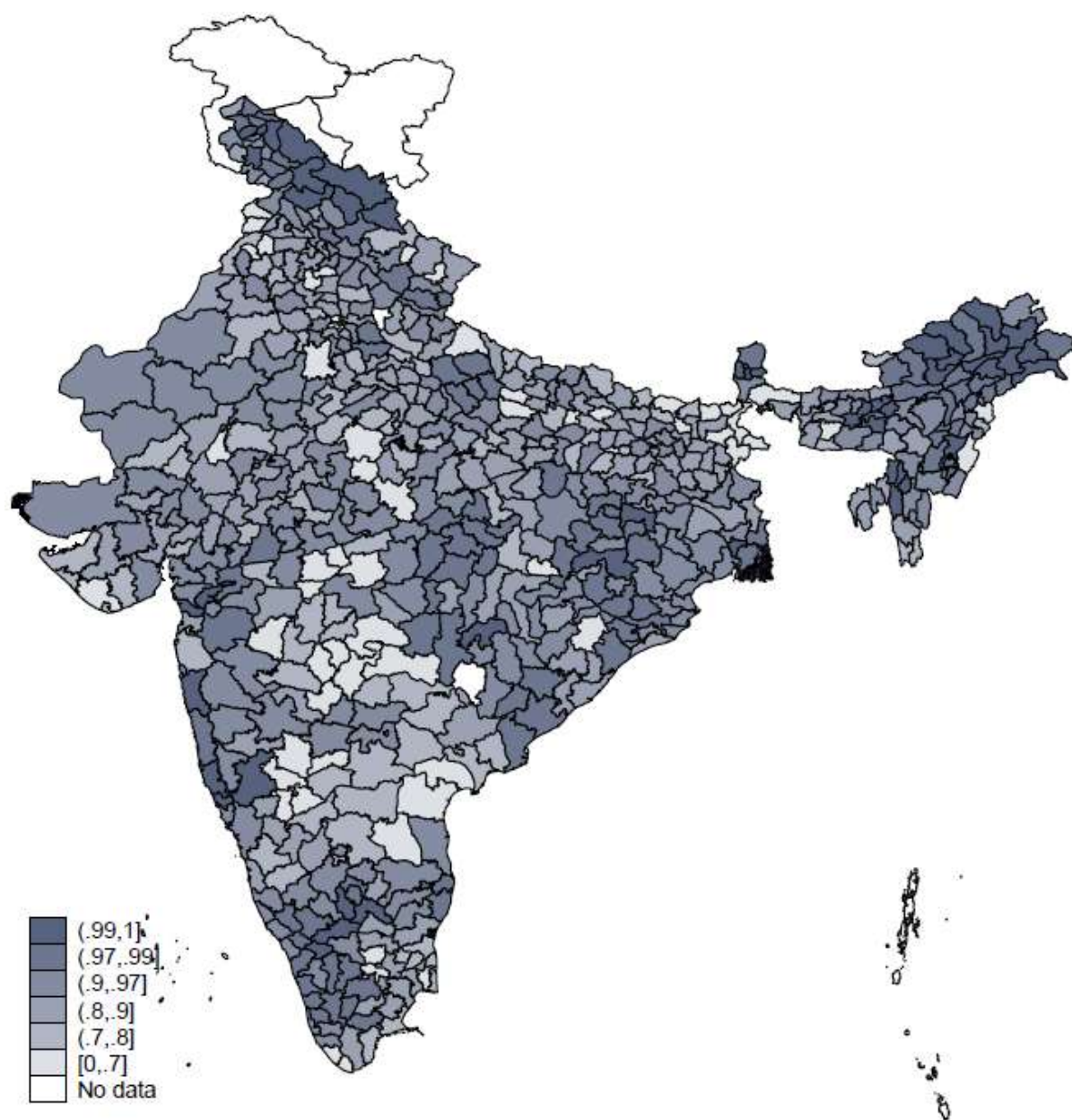


**Figure 3: Covid-10 confirmed cases per 100 thousand population in 10 leading states**



**Figure 4: A district level map of daily confirmed cases**





**Figure 5: A district level map of District-Neighborhood Nightlight-Inequality**

**Tables:**

Variables	Mean	SD	10 Percentile	90 Percentile
Confirmed per million	8857	5570	3154	17049
District Population (million)	2.15	1.53	0.67	4.05
Nightlight (district level)	4.62	14.13	0.49	8.65
Nightlight Inequality [p90/p10]	2.44	1.02	1.03	3.89
District Population Density, 2019	735	3680	157	1099
Temperature (Celsius)	31.08	6.07	23.79	38.91
Rainfall (mm)	4.34	13.48	0.00	12.56
Malaria	4.86	1.26	3.00	6.00
Latitude (N)	23.04	5.98	12.81	30.28
Longitude (E)	79.09	4.44	74.12	85.99
% BCG Vaccination, 2007	87.76	11.20	72.30	98.90
% Fully Immunized, 2007	56.08	21.44	25.60	83.60
Observations	139309	139309	139309	139309

**Table 1:** Summary Statistics, Regression Sample

Dependent Variable: Total Confirmed Covid19 per million population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nightlight Inequality	6.528*** (0.177)	6.012*** (0.178)	6.000*** (0.178)	5.648*** (0.180)	3.347*** (0.180)	3.452*** (0.183)	3.755*** (0.182)
Days since Jan1. 2020		-0.012*** (0.003)	-0.013*** (0.003)	-0.038*** (0.004)	-0.071*** (0.004)	-0.074*** (0.004)	-0.084*** (0.004)
Nightlight		0.476*** (0.012)	0.598*** (0.017)	0.611*** (0.017)	0.567*** (0.017)	0.575*** (0.017)	0.614*** (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*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Temperature				-0.529*** (0.047)	-0.570*** (0.046)	-0.540*** (0.046)	-0.750*** (0.048)
Rainfall				0.332*** (0.014)	0.281*** (0.014)	0.263*** (0.014)	0.241*** (0.014)
BCG vaccination					0.695*** (0.029)	0.684*** (0.030)	0.565*** (0.030)
Total vaccination					0.258*** (0.016)	0.265*** (0.016)	0.213*** (0.016)
Colonial malaria						-0.620*** (0.145)	0.663*** (0.165)
Latitude							-0.604*** (0.034)
Longitude							-1.013*** (0.046)
Constant	18.177*** (0.469)	21.518*** (0.756)	21.532*** (0.755)	43.638*** (2.389)	-20.383*** (2.990)	-18.917*** (3.012)	91.007*** (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:** Nightlight Inequality varies at the state level. Average district level 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*** (0.138)	0.690*** (0.138)	0.645*** (0.138)	0.604*** (0.138)	0.436*** (0.137)	0.618*** (0.142)	0.584*** (0.142)	0.476*** (0.139)
Days since Jan1. 2020		-0.010*** (0.000)	-0.010*** (0.000)	-0.010*** (0.000)	-0.011*** (0.000)	-0.011*** (0.000)	-0.011*** (0.000)	-0.008*** (0.001)
Nightlight		0.054*** (0.001)	0.071*** (0.002)	0.072*** (0.002)	0.072*** (0.002)	0.071*** (0.002)	0.071*** (0.002)	0.072*** (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 (0.005)	-0.014*** (0.005)	-0.010** (0.005)	-0.011** (0.005)	-0.094*** (0.006)
Rainfall				0.026*** (0.001)	0.026*** (0.001)	0.024*** (0.001)	0.024*** (0.001)	0.020*** (0.001)
BCG vaccination					0.004 (0.003)	0.006** (0.003)	0.007** (0.003)	0.007** (0.003)
Total vaccination					0.014*** (0.002)	0.011*** (0.002)	0.009*** (0.002)	0.009*** (0.002)
Colonial malaria						-0.152*** (0.017)	-0.137*** (0.018)	-0.142*** (0.017)
Latitude							-0.058*** (0.015)	-0.071*** (0.015)
Longitude							-0.058*** (0.012)	-0.053*** (0.012)
Constant	2.286*** (0.121)	3.832*** (0.133)	3.863*** (0.132)	3.617*** (0.274)	3.346*** (0.349)	3.611*** (0.355)	9.487*** (1.037)	13.799*** (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 nightlight-inequality and state fixed effect. Nightlight Inequality, average district level 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 (2.834)	-7.603** (3.404)
Days since Jan1. 2020	0.018 (0.452)	0.155 (0.503)
Nightlight	-0.006 (0.031)	-0.135*** (0.040)
Daily tested	0.000 (0.000)	0.000 (0.000)
Population density	0.001*** (0.000)	0.002*** (0.000)
Temperature	-0.750*** (0.165)	-0.074 (0.184)
Rainfall	-0.190 (0.122)	-0.009 (0.101)
BCG vaccination	0.221*** (0.060)	0.069 (0.076)
Total vaccination	-0.123*** (0.038)	-0.034 (0.046)
Colonial malaria	-2.345*** (0.349)	-1.813*** (0.434)
Latitude	0.860*** (0.290)	-0.405 (0.359)
Longitude	-0.609** (0.237)	-1.059*** (0.293)
Constant	38.124 (23.447)	98.519*** (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 district level 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*** (4.079)	-5.23 (5.658)	-6.16 (6.382)	16.04*** (3.217)	24.86*** (2.420)	22.83*** (3.652)	17.68*** (1.694)	6.09*** (1.560)
Days since Jan1. 2020	0.77*** (0.271)	0.18 (0.365)	-0.32 (0.410)	0.02 (0.215)	0.03 (0.156)	-0.48** (0.239)	-0.85*** (0.110)	-0.14 (0.088)
Nightlight	0.03 (0.049)	0.73*** (0.068)	0.90*** (0.076)	1.45*** (0.039)	1.33*** (0.029)	1.31*** (0.043)	0.71*** (0.019)	0.22*** (0.017)
Daily tested	-0.00 (0.000)	0.00 (0.000)	0.00*** (0.000)	0.00*** (0.000)	0.00*** (0.000)	0.00*** (0.000)	0.00*** (0.000)	0.00*** (0.000)
Population density	0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)
Temperature	0.01 (0.198)	-0.46 (0.307)	-1.48*** (0.460)	-0.82*** (0.238)	-1.08*** (0.176)	-2.18*** (0.323)	-0.40*** (0.102)	-0.54*** (0.096)
Rainfall	0.28*** (0.048)	0.07* (0.040)	-0.03 (0.040)	0.00 (0.024)	0.01 (0.034)	-0.06 (0.074)	-0.03 (0.051)	-0.11* (0.067)
BCG vaccination	-0.17* (0.091)	-0.05 (0.126)	0.19 (0.142)	0.08 (0.072)	0.00 (0.054)	0.17** (0.081)	0.03 (0.038)	0.02 (0.036)
Total vaccination	0.08 (0.055)	-0.03 (0.076)	-0.18** (0.085)	0.47*** (0.043)	0.32*** (0.033)	0.10** (0.049)	0.22*** (0.022)	0.12*** (0.021)
Colonial malaria	1.10** (0.511)	-1.06 (0.701)	0.55 (0.794)	2.82*** (0.401)	-2.49*** (0.301)	-7.57*** (0.447)	-1.70*** (0.203)	-0.28 (0.192)
Latitude	-1.00** (0.430)	-2.22*** (0.594)	-2.18*** (0.673)	-0.46 (0.339)	-0.78*** (0.255)	0.02 (0.404)	0.54*** (0.189)	-0.44** (0.171)
Longitude	-1.24*** (0.348)	-2.50*** (0.481)	-1.40** (0.547)	-1.74*** (0.273)	0.32 (0.206)	1.82*** (0.310)	0.29** (0.141)	0.12 (0.130)
Constant	93.02*** (32.564)	201.56*** (46.190)	414.09*** (51.584)	215.92*** (28.642)	267.60*** (23.068)	41.19 (37.819)	121.31*** (19.637)	36.47** (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 district level 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: Number of people moving across districts in '0000								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nightlight Inequality	40.598*** (0.659)	26.038*** (0.535)	26.193*** (0.534)	24.412*** (0.512)	23.409*** (0.515)	25.676*** (0.558)	25.769*** (0.557)	25.789*** (0.557)
Days since Jan1. 2020		-0.017*** (0.001)	-0.017*** (0.001)	-0.016*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	-0.014*** (0.002)	-0.029*** (0.005)
Nightlight		1.240*** (0.005)	1.168*** (0.007)	1.368*** (0.007)	1.359*** (0.007)	1.355*** (0.007)	1.363*** (0.007)	1.363*** (0.007)
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)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Temperature				0.013 (0.020)	0.036* (0.020)	0.045** (0.021)	0.066*** (0.021)	0.096*** (0.024)
Rainfall				0.002 (0.005)	-0.001 (0.005)	-0.000 (0.006)	0.001 (0.006)	0.002 (0.006)
BCG vaccination					0.116*** (0.012)	0.106*** (0.013)	0.111*** (0.013)	0.110*** (0.013)
Total vaccination					0.127*** (0.008)	0.138*** (0.008)	0.140*** (0.008)	0.141*** (0.008)
Colonial malaria						-0.109 (0.077)	0.400*** (0.079)	0.408*** (0.079)
Latitude							0.391*** (0.061)	0.397*** (0.061)
Longitude							-1.369*** (0.048)	-1.371*** (0.048)
Constant	-11.981*** (0.571)	-0.624 (0.517)	-0.719 (0.517)	-0.730 (1.067)	-17.913*** (1.358)	-18.797*** (1.452)	76.700*** (4.168)	75.356*** (4.211)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trend	No	No	No	No	No	No	No	Yes
Observations	142,933	142,147	142,147	141,756	140,392	133,735	133,735	133,735
Adjusted R-squared	0.134	0.437	0.438	0.484	0.488	0.484	0.487	0.487

**Table 6:** Regression with Facebook-migration across districts as the dependent variable. Nightlight Inequality, average district level 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)
Nightlight inequality	1.371*** (0.127)	0.283** (0.128)	0.593*** (0.127)	0.106 (0.128)
FB migration		0.026*** (0.001)		0.019*** (0.001)
Days since 1 Jan, 2020			-0.008*** (0.001)	-0.007*** (0.001)
Nightlight			0.074*** (0.002)	0.048*** (0.002)
Daily Covid tests			0.000*** (0.000)	0.000*** (0.000)
Population density			-0.000*** (0.000)	-0.000*** (0.000)
Temperature			-0.122*** (0.006)	-0.124*** (0.006)
Rainfall			0.015*** (0.001)	0.015*** (0.001)
BCG vaccination			0.006** (0.003)	0.004 (0.003)
Total vaccine			0.013*** (0.002)	0.010*** (0.002)
Colonial malaria			-0.270*** (0.018)	-0.278*** (0.018)
Latitude			-0.076*** (0.014)	-0.082*** (0.014)
Longitude			-0.030*** (0.011)	-0.004 (0.011)
Constant	1.989*** (0.111)	2.313*** (0.110)	12.894*** (0.962)	11.482*** (0.960)
State FE	Yes	Yes	Yes	Yes
State Trend	No	No	Yes	Yes
Observations	139,720	139,720	130,875	130,875
Adjusted R-squared	0.099	0.116	0.186	0.191

**Table 7:** Baseline with control for Facebook-migration. Columns 1 and 2 correspond to Column 1 of Tabel 3. Columns 3 and 4 correspond to Column 8 of Table 3. Nightlight Inequality, average district level 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-FE+Trend
Nightlight Inequality*	Unemployment	-0.070*** (0.020)	-0.318*** (0.027)	-0.178*** (0.024)	-0.293*** (0.033)
Nightlight Inequality		4.457*** (0.284)	14.790*** (0.844)	-	-
Unemployment		-0.098* (0.058)	0.267*** (0.077)	-0.256*** (0.072)	-0.367*** (0.094)
Days since Jan1. 2020		-0.094*** (0.004)	-0.223*** (0.006)	-0.136*** (0.004)	-0.090*** (0.010)
Nightlight		0.624*** (0.017)	0.730*** (0.016)	0.719*** (0.017)	0.725*** (0.016)
Daily tested		0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Population density		-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Temperature		-0.746*** (0.048)	-0.477*** (0.054)	-0.176*** (0.050)	-0.736*** (0.057)
Rainfall		0.221*** (0.014)	0.162*** (0.013)	0.196*** (0.013)	0.161*** (0.013)
BCG vaccination		0.515*** (0.030)	0.083*** (0.031)	0.072** (0.032)	0.073** (0.031)
Total vaccination		0.229*** (0.016)	0.060*** (0.018)	0.099*** (0.019)	0.099*** (0.019)
Colonial malaria		0.531*** (0.166)	-1.181*** (0.171)	-1.288*** (0.174)	-1.309*** (0.170)
Latitude		-0.544*** (0.034)	0.221** (0.088)	-0.620*** (0.148)	-0.702*** (0.145)
Longitude		-0.960*** (0.047)	-0.086 (0.093)	-0.570*** (0.120)	-0.550*** (0.117)
Constant		93.860*** (4.835)	39.418*** (8.031)	118.980*** (10.295)	157.303*** (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 8:** Interaction between unemployment and nightlight and its effect on Covid infection rate. Nightlight Inequality, Average district level 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

State Name	Variable Name	Availability	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 A1:** Data availability

Phase	Dates	Number of days	Regulations	Source
<b>Pre-Lockdown</b>	1 Jan, 2020- 24 Mar, 2020	84	Business as Usual	
<b>Lockdown 1</b>	25 Mar, 2020 – 14 April, 2020	21	<p>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.</p> <p>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.</p> <p>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.</p>	<a href="https://www.mha.gov.in/sites/default/files/Guidelines_0.pdf">https://www.mha.gov.in/sites/default/files/Guidelines_0.pdf</a>
<b>Lockdown 2</b>	15 Apr, 2020 – 3 May, 2020	19	<p>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.</p> <p>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.</p> <p>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.</p> <p>On 25 April, small retail shops were allowed to open with half the staff. Again, social distancing norms were to be followed.</p> <p>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.</p>	<a href="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.businesstoday.in/current/economy-politics/new-coronavirus-lockdown-guidelines-issued-check-full-list-of-relaxations-lockdown-rules-by-mha/story/401030.html</a>  <a href="https://www.dnaindia.com/india/report-centre-issues-fresh-set-of-guidelines-for-coronavirus">https://www.dnaindia.com/india/report-centre-issues-fresh-set-of-guidelines-for-coronavirus</a>



				<a href="#">us-lockdown-20-relaxation-for-some-areas-from-april-20-2821074</a>
<b>Lockdown 3</b>	4 May, 2020 -- 17 May, 2020	14	<p>On 1 May, the Government of India (GOI) further extended the lockdown period to two weeks beyond 4 May, with some relaxations.</p> <p>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.</p>	<a href="https://www.mha.gov.in/sites/default/files/MHA%20Order%20Dt.%201.5.2020%20to%20extend%20Lockdown%20period%20for%202%20week%20w.e.f.%204.5.2020%20with%20new%20guidelines.pdf">https://www.mha.gov.in/sites/default/files/MHA%20Order%20Dt.%201.5.2020%20to%20extend%20Lockdown%20period%20for%202%20week%20w.e.f.%204.5.2020%20with%20new%20guidelines.pdf</a>
<b>Lockdown 4</b>	18 May, 2020 – 31 May, 2020	14	<p>On 17 May, GOI extended the lockdown for a period for two weeks from 18 May, with additional relaxations.</p> <p>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.</p>	<a href="https://www.thehindu.com/news/resources/article31608347.ece/binary/MHAOrderdatedMay17-GuidelinesofLockdownextension.pdf">https://www.thehindu.com/news/resources/article31608347.ece/binary/MHAOrderdatedMay17-GuidelinesofLockdownextension.pdf</a>

<b>Unlock 1</b>	1 June, 2020 – 30 June, 2020	30	<p>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.</p> <p>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.</p>	<a href="https://www.mha.gov.in/sites/default/files/MHAOrderDt_30052020.pdf">https://www.mha.gov.in/sites/default/files/MHAOrderDt_30052020.pdf</a>
<b>Unlock 2</b>	1 July, 2020 – 31 July, 2020	31	<p>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.</p> <p>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.</p> <p>Educational institutions, metro railway, recreational activities remained closed till 31 July. Only essential activities were permitted in containment zones.</p>	<a href="https://www.mha.gov.in/sites/default/files/MHAOrder_29062020.pdf">https://www.mha.gov.in/sites/default/files/MHAOrder_29062020.pdf</a>
<b>Unlock 3</b>	1 Aug, 2020 – 31 Aug, 2020	31	<p>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.</p> <p>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</p>	<a href="https://www.mha.gov.in/sites/default/files/DOLrDt_29072020.pdf">https://www.mha.gov.in/sites/default/files/DOLrDt_29072020.pdf</a>
<b>Unlock 4</b>	1 Sept, 2020 – 30 Sept, 2020	30	<p>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.</p> <p>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.</p>	<a href="https://www.mha.gov.in/sites/default/files/MHAOrder_Unlock4_29082020.pdf">https://www.mha.gov.in/sites/default/files/MHAOrder_Unlock4_29082020.pdf</a>

<b>Unlock 5</b>	1 Oct, 2020 – 31 Oct, 2020	31	<p>On 30 September 2020, the Ministry of Home Affairs issued guidelines for activities permitted in Unlock 5.0.</p> <p>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.</p> <p>Lockdown shall remain in force strictly in the Containment Zones till 30 November 2020.</p> <p>Also, swimming pools being used for training of sportsperson would be allowed to open.</p> <p>Cinema halls, that had remained close all this while, could be opened from 15 October 2020, with a 50% of their seating capacity.</p> <p>On 3 November the Government of Kerala opened its tourism sector by reopening hill stations, beaches, national park, and inter-state public transport movement.</p>	<a href="https://www.mha.gov.in/sites/default/files/MHA_OrderDt_30_092020.pdf">https://www.mha.gov.in/sites/default/files/MHA_OrderDt_30_092020.pdf</a>
<b>Unlock 6</b>	1 Nov, 2020 – 30 Nov, 2020	30	<p>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.</p> <p>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.</p> <p>The GOI extended the ban on scheduled international passenger flights till January 31.</p>	<a href="https://www.india.com/news/india/mha-issues-unlock-6-guidelines-check-here-whats-allowed-whats-not-in-november-4187769/">https://www.india.com/news/india/mha-issues-unlock-6-guidelines-check-here-whats-allowed-whats-not-in-november-4187769/</a>

**Table A2:** Lockdown Phases and Restrictions

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

**Table A3:** List of essential goods

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](https://seednet.gov.in/PDFFILES/Essential_Commodity_Act_1955(No_10_of_1955).pdf)

Dependent Variable:	Inter District migration	Within District Migration
	(1)	(2)
Unemployment	-1.030*** (0.131)	-0.518*** (0.100)
Constant	503.437*** (2.155)	245.222*** (1.647)
State FE	Yes	Yes
Day of Year FE	Yes	Yes
Observations	4,392	4,392
Adjusted R-squared	0.994	0.984

**Table A4:** Regression with inter-district Facebook-migration as the dependent variable in column (1) and within-district Facebook-migration in column (2). Sample covers the entire unlock period starting with the month of May 2020 till the end of the data. Standard errors in parentheses: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Dependent Variable: Total Confirmed Covid19 per million population		
	(1)	(2)
	Column-8 (Table 3)	+ NonLinear-Time
Nightlight inequality	0.476*** (0.139)	0.493*** (0.137)
Days since 1 Jan, 2020	-0.008*** (0.001)	0.126*** (0.002)
Days-squared		-0.000*** (0.000)
Nightlight	0.072*** (0.002)	0.073*** (0.002)
Daily Covid tests	0.000*** (0.000)	0.000*** (0.000)
Population density	-0.000*** (0.000)	-0.000*** (0.000)
Temperature	-0.094*** (0.006)	-0.105*** (0.006)
Rainfall	0.020*** (0.001)	0.003** (0.001)
BCG vaccination	0.007** (0.003)	0.006** (0.003)
Total vaccine	0.009*** (0.002)	0.011*** (0.002)
Colonial malaria	-0.142*** (0.017)	-0.133*** (0.017)
Latitude	-0.071*** (0.015)	-0.072*** (0.014)
Longitude	-0.053*** (0.012)	-0.061*** (0.012)
Constant	13.799*** (1.024)	-0.673 (1.029)
State FE	Yes	Yes
State Trend	Yes	Yes
Observations	139,309	139,309
Adjusted R-squared	0.157	0.184

**Table A5:** Baseline with neighbourhood nightlight-inequality and state fixed effect. Column (2) additionally allows for non-linear time trend. Nightlight Inequality, Average district level 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 (5.205)	-9.727 (6.001)
Days since Jan1. 2020	0.023 (0.453)	0.168 (0.504)
Nightlight	0.020 (0.062)	-0.223*** (0.082)
Daily tested	-0.000 (0.000)	0.000 (0.000)
Population density	0.000 (0.001)	0.003*** (0.001)
Temperature	-0.765*** (0.165)	-0.050 (0.184)
Rainfall	-0.193 (0.123)	0.004 (0.101)
BCG vaccination	0.216*** (0.061)	0.082 (0.077)
Total vaccination	-0.121*** (0.038)	-0.038 (0.046)
Colonial malaria	-2.334*** (0.349)	-1.878*** (0.434)
Latitude	0.850*** (0.292)	-0.353 (0.360)
Longitude	-0.561** (0.243)	-1.181*** (0.299)
Constant	35.780 (24.643)	107.397*** (29.556)
State FE	Yes	Yes
State Trend	Yes	Yes
Observations	6,105	6,920
Adjusted R-squared	0.146	0.104

**Table A6:** Regression with industrial heterogeneity index. Column 1 includes the full sample. Columns 2 and 3 are for Lockdown phases 3 and 4, respectively. Average district level 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*** (7.078)	-61.526*** (9.714)	18.548* (10.958)	93.785*** (5.369)	14.053*** (4.105)	5.833 (6.262)	19.651*** (2.863)	19.081*** (2.693)
Days since Jan1. 2020	0.768*** (0.271)	0.178 (0.364)	-0.320 (0.410)	-0.029 (0.207)	-0.000 (0.153)	-0.488** (0.237)	-0.863*** (0.109)	-0.142 (0.088)
Nightlight (average)	0.375*** (0.098)	1.715*** (0.136)	1.545*** (0.152)	3.169*** (0.074)	2.684*** (0.057)	2.604*** (0.085)	1.224*** (0.039)	0.442*** (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*** (0.001)	-0.013*** (0.002)	-0.010*** (0.002)	-0.026*** (0.001)	-0.019*** (0.001)	-0.019*** (0.001)	-0.008*** (0.000)	-0.003*** (0.000)
Temperature	0.058 (0.199)	-0.468 (0.306)	-1.510*** (0.457)	-1.269*** (0.229)	-1.342*** (0.172)	-2.377*** (0.318)	-0.453*** (0.101)	-0.564*** (0.096)
Rainfall	0.294*** (0.049)	0.076* (0.040)	-0.027 (0.040)	-0.019 (0.024)	-0.002 (0.033)	-0.058 (0.074)	-0.036 (0.051)	-0.108 (0.067)
BCG vaccination	-0.133 (0.092)	-0.028 (0.127)	0.148 (0.143)	-0.095 (0.070)	-0.075 (0.053)	0.104 (0.081)	-0.006 (0.037)	-0.014 (0.036)
Total vaccination	0.075 (0.055)	0.004 (0.076)	-0.171** (0.085)	0.482*** (0.042)	0.351*** (0.032)	0.138*** (0.048)	0.236*** (0.022)	0.121*** (0.021)
Colonial malaria	0.958* (0.510)	-0.731 (0.699)	0.341 (0.793)	2.636*** (0.386)	-2.140*** (0.294)	-7.206*** (0.443)	-1.533*** (0.201)	-0.260 (0.191)
Latitude	-0.889** (0.431)	-2.346*** (0.595)	-2.129*** (0.675)	-0.785** (0.327)	-1.187*** (0.250)	-0.435 (0.399)	0.304 (0.187)	-0.514*** (0.170)
Longitude	-1.550*** (0.355)	-2.699*** (0.490)	-1.029* (0.558)	-0.202 (0.269)	0.979*** (0.205)	2.404*** (0.313)	0.662*** (0.143)	0.379*** (0.133)
Constant	128.119*** (33.955)	266.552*** (47.870)	368.544*** (53.611)	80.060*** (28.360)	255.917*** (23.103)	39.426 (38.179)	103.813*** (19.819)	11.134 (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 A7:** 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