Journal of Asian Economics 85 (2023) 101589

Contents lists available at ScienceDirect

Journal of Asian Economics

journal homepage: www.elsevier.com/locate/asieco

Lights out? COVID-19 containment policies and economic activity☆

Robert C.M. Beyer [a], Tarun Jain [b], Sonalika Sinha [c,*]

[a] World Bank, India
[b] Indian Institute of Management Ahmedabad, India
[c] Reserve Bank of India, India

ARTICLE INFO

JEL Classifications:
E21
H12
I18

Keywords:
E21
H12
I18

ABSTRACT

This paper estimates how strongly COVID-19 containment policies have impacted aggregate economic activity. We use a difference-in-differences methodology to estimate how containment zones of different severity across India impacted district-level nighttime light intensity, as well as household income and consumption. From May to July 2020, nighttime light intensity was 9.1 % lower in districts with the most severe restrictions compared with districts with the least severe restrictions, which could imply between 5.8 % and 6.6 % lower GDP. Nighttime light intensity was only 1.6 % lower in districts with intermediate restrictions. The differences were largest in May during the graded lockdown, and tapered in June and July. Lower house-hold income and consumption corresponding to zone-wise restrictions corroborate these results. Stricter containment measures had larger impacts in districts with greater population density, older residents, and more services employment. The large magnitudes of the findings suggest that governments should carefully consider the economic costs of country-wide pandemic containment policies while weighing the trade-offs against public health benefits. Keywords: Containment policies, COVID-19, Nighttime lights, India

1. Introduction

The first COVID-19 infection in India was reported at the end of January 2020. On March 25, 2020, the government implemented one of the most stringent lockdowns globally (Hale et al., 2020). After five weeks of nationwide lockdown, uniform restrictions were replaced with targeted measures that varied in severity across districts in May 2020. The relaxation of restrictions across districts at three distinct levels allows us to examine the simultaneous spatial impacts of the differential containment measures. Specifically,

☆ We appreciate many constructive comments by the Editor, Associate Editor, and two anonymous reviewers. We thank Roshani Bulkunde and Pallavi Wats for outstanding research assistance and the Indian Institute of Management Ahmedabad for grant support. We are grateful to Viral Acharya, Areendam Chanda, Rishabh Choudhary, Rangeet Gosh, Kaushik Krishnan, Prachi Mishra, Sandeep Vupputuri, Sitikantha Pattanaik, N.R. Prabhala, Mridul Kumar Saggar and Dhruv Sharma, to the participants of the Annual Macroeconomics and Finance Conference at IGIDR, the Annual Growth and Development Conference at ISI Delhi, the Econometric Society Asian Meetings, NIPFP-IIPF Public Finance Conference, World Bank's 6th South Asia Economic Policy Conference, the SERI COVID-19 Workshop and CAFRAL seminar for helpful comments. The views expressed in the paper are those of the authors and not the institutions to which they belong. The usual disclaimer applies.

* Corresponding author.
E-mail addresses: rcmbeyer@worldbank.org (R.C.M. Beyer), tarunj@iima.ac.in (T. Jain), sonalikasinha@rbi.org.in (S. Sinha).

https://doi.org/10.1016/j.asieco.2023.101589
Received 14 June 2022; Received in revised form 20 November 2022; Accepted 6 February 2023
Available online 15 February 2023
1049-0078/

districts were classified into three zones: those with the most severe restrictions (Red), those with intermediate restrictions (Orange), and those with the least severe restrictions (Green). Mobility data from Facebook and Google on cellphone locations confirm that the zone classification was indeed effective in restricting mobility.

Using a difference-in-differences methodology that exploits the rule-based district-wise containment policy, we compare the pace of economic recovery in the three zones after the uniform national lockdown ended. Using monthly data of nighttime lights at the district level, we examine the impact of these differential relaxations of restrictions on aggregate economic activity. We also examine the period after the differential lockdown to understand how long the effect of zone-wise containment persisted even after the *de jure* restrictions were lifted. We explain the aggregate impact by analyzing nighttime light intensity at the district level and corroborate our results with household-level income and consumption patterns. More developed districts might respond differently compared with less developed ones, as the more developed districts may have better economic or administrative capacity to deal with the COVID-19 restrictions, or conversely, the more developed districts suffer larger economic losses due to concentration of more contactintensive sectors. Thus, we also compare the impact of the zone-wise containment policies across districts by population density, the share of services sector employment, outstanding credit per capita, and average age.

We use nighttime light intensity as our main proxy for economic activity for several reasons. First, a number of studies report high correlation of nighttime light intensity with other measures of economic activity (Donaldson & Storeygard, 2016). Most notably, Henderson et al. (2012) argue that for countries with poor national income accounts, the optimal estimate of growth is a composite measure with roughly equal weights on conventionally measured growth and growth predicted from nighttime lights. Nighttime lights track economic activity in India closely (Prakash et al., 2019; Beyer et al., 2021), and provide a useful approximation of economic activity at high spatial granularity (Gibson et al., 2017; Chanda & Kabiraj, 2020). In a recent study, Chodorow-Reich et al. (2020) use cross-sectional differences in nighttime light growth to assess the effect of the 2016 Indian banknote demonetization. Second, using nighttime lights is particularly appropriate for this study since this measure is available at high spatial granularity at monthly frequency.[1] This allows us to match nighttime lights to the relevant district-level zone classification to determine economic activity in the pre-period in March and April, and to compare it with activity in the postperiod in May, June, and July. In contrast, official quarterly estimates of gross domestic product (GDP) and other measures of overall economic activity, like electricity consumption are available at lower frequency and not disaggregated at the district level.[2] Finally, nighttime lights from satellites represent an objective measure of economic activity that is immune to survey non-response bias that is potentially correlated with lockdown policies.

Two caveats of using nighttime lights as a proxy for economic activity are worth pointing out. First, while the nighttime lights data used in this study track data in low-lit areas more accurately than previous generations of nighttime lights data,[3] the better tracking of economic activity in brighter areas may still bias the results (Gibson et al., 2021). Second, translating changes in nighttime lights into changes in GDP is not straightforward, and the elasticity between the two may vary substantially across levels of geographic aggregation and across contexts (Asher et al., 2021; Bickenbach et al., 2016; Bluhm & McCord, 2022). We directly address these concerns in the robustness section and when interpreting the results. Moreover, we supplement the nighttime light analysis with consumption and income data from a household survey, both to pin point the impact of the zone restrictions on these outcomes separately from economic activity, and to corroborate the qualitative conclusions from using nighttime lights data.

Our first empirical result confirms that the zone classifications impacted mobility which is consistent with the severity of the restrictions. Mobility was significantly lower in Red zone districts in May compared with Green zone districts, consistent with the most severe mobility restrictions in those districts. Orange zone districts had lower mobility than Green zone districts, but the impact was not statistically significant. During "Unlock 1.0″ in June, mobility rebounded in both Red and Orange zone districts, consistent with removal of the zone classifications. These results point to the effectiveness of the *de jure* restrictions during the pandemic.

Our main finding is that nighttime light intensity in India dimmed during the strict national lockdown in March and April, and recovery in May and subsequent months (referred to as the post period hereafter) depended on the zone classification. Overall, nighttime light intensity was 9.1 % (0.045 σ) lower in the post period (May to July 2020) for Red zone districts with the most severe restrictions and 1.6 % (0.009 σ) lower for Orange zone districts with intermediate restrictions, compared with Green zone districts with the least restrictions. Red zone districts witnessed a 12.6 % (0.061 σ) lower recovery in May compared with Orange zone districts. The recovery for districts with intermediate restrictions was 1.7 % (0.010 σ) lower. While remaining negative, the impact of the zone classification tapered off in June and July 2020, pointing to the persistent effects of pandemic containment even after restrictions were removed.

Our findings are robust to several logically orthogonal robustness checks. These include a test of the impact of the zone classification on the pre-period, where we reassuringly find no discernible differential pattern. We restrict the sample to only those districts that border a differently classified zone, to nonmetropolitan districts, and those that were not subsequently reclassified in mid-May, and find no qualitative change in our results. Finally, a test with placebo zone classifications yields coefficients that are close to zero and statistically insignificant, implying that the zone restrictions, not other district level factors, are driving the results.

[1] While data from the United States Air Force Defense Meteorological Satellite Program using the Operational Linescan System (DMSP-OLS) is only available at annual frequency, recent data from the Suomi National Polar Partnership Visible Infrared Imaging Radiometer Suite (VIIRS) are monthly.

[2] Lourenco and Rua (2021) track daily economic activity using composite indicators for Portugal, but similar high frequency indicators are not yet available for India.

[3] Compared with data from United States Air Force DMSP-OLS, VIIRS nighttime lights data have higher resolution and much improved low light imaging (Elvidge et al., 2013).

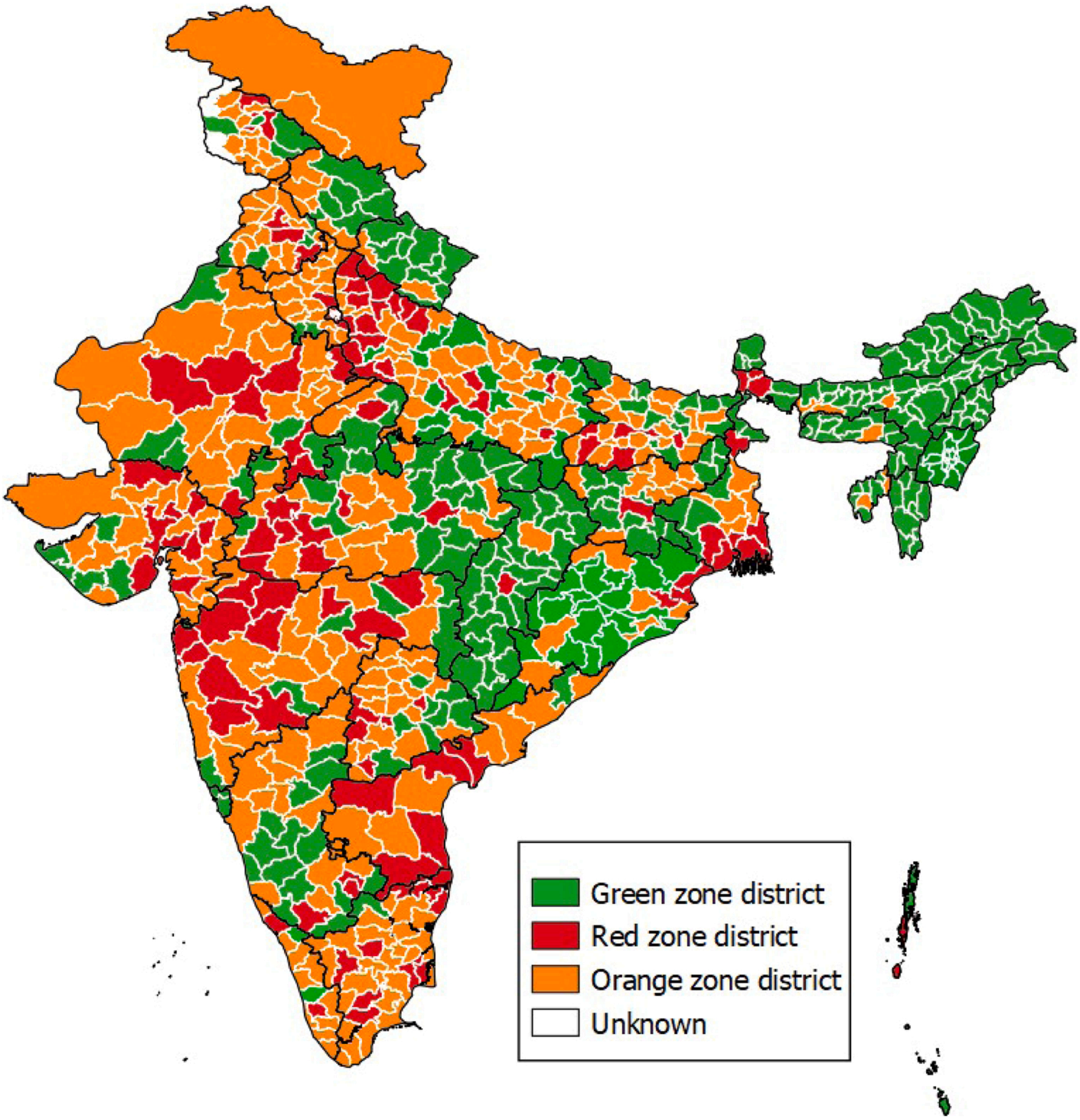

Fig. 1. Containment policies by district. *Notes:* This map shows the classification of districts (2020 boundaries) as Red, Orange and Green, as listed in Sudan (2020).

Monthly household survey data corroborate the main finding, pointing to lower household income and reduced consumption as a consequence of the zone-wise restrictions. More developed districts with above median population density, share of employment in services, credit per capita, and mean age experienced larger impacts of the restrictions, suggesting that more developed districts do not necessarily have better capacity to absorb the economic shock, and instead lose more as a result of the restrictions. Finally, varying degrees of operations under the Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA), a large public works program deployed as a counter-cyclical measure, as well as inter-district migrant shares (which proxy for reverse migration after the lockdown) do not effect these dynamics.

Our study contributes to the growing literature on the economic impacts of government interventions to mitigate health shocks. Deb et al. (2020) find large effects of containment measures to slow the spread of COVID-19 on economic activity across countries. Goolsbee and Syverson (2021) examine the drivers of the pandemic-related economic decline in the United States and compare consumer behavior across commuting zones to distinguish between government restrictions and the role of fear – both of which matter. Chetty et al. (2020) draw on considerable private sector data to analyze how household spending and business activity changed in response to the pandemic and associated government stabilization policies, whereas Baek et al. (2021) use unemployment insurance claims data to examine the effect of stay-at-home orders on employment. Kong and Prinz (2020) quantify the employment impact of different state-level containment measures in the United States, and Petroulakis (2020) shows that high non-routine jobs reduce the probability of job losses. During the 1918 pandemic in India Xu (2021) finds that Indian district officers were more effective than British officers in containing infections and deaths. While disruptive in the short-run, Correia et al. (2022) show that stricter government interventions in cities in the United States during the 1918–19 influenza pandemic had positive economic impacts in the medium run.

We also contribute to the literature on the economic and social effects of the COVID-19 pandemic in India. Beyer et al. (2021) employ state-level daily electricity consumption to assess the economic cost of the uniform lockdown during March and April 2020 in India, and use monthly nighttime light intensity to explain drivers of district-level heterogeneity. Our paper is distinct from Beyer et al. (2021) in examining differential lockdown policies with cross-sectional variation that permits us to offer causal interpretations. We are able to exploit additional data sources both to confirm the effectiveness of the mobility restrictions, as well as to corroborate our main findings. Mahajan and Tomar (2020) look at the disruption in food supply chains and find a minimal impact on prices but falling food availability. Ravindran and Shah (2020) employ the same zone classification as we do to analyze its impact on gender-based violence and find that complaints were higher in districts with more severe restrictions.

2. COVID-19 containment in India

The first COVID-19 infection reported in India was on January 30, 2020. Through February and March, the Government of India introduced restrictions on international travel, while promoting social distancing. The increasing threat of domestic spread of the infection prompted the Indian government to announce a comprehensive nationwide lockdown starting on March 25, 2020, which was uniform across all states and districts (Bhalla, 2020). During this phase, nearly all offices, commercial and private establishments, industrial units, as well as public services were closed. Most transportation services – including international and domestic flights, railways and roadways – were suspended. Hospitality services and educational institutions were shut. This nationwide lockdown was initially announced for three weeks and later extended until May 03, 2020.

Starting on May 4, 2020, the Government of India announced “Lockdown 3.0″, in which districts were classified into three zone categories based on multiple criteria including the incidence of cases, the extent of testing, and vulnerability to the pandemic more generally (Sudan, 2020). During this phase, the government classified 130 districts as *Red* zone districts, 284 as *Orange* zone districts, and 319 as *Green* zone districts.[4] Many restrictions aimed at curbing the movement and congregation of people, so that the differences between the zone classifications - especially between Red zone and the other two zones - were largely different mobility restrictions.

Fig. 1 shows how each district was classified. In Red zone districts, public transport, hospitality and entertainment, as well as construction and retail continued to be restricted. E-commerce was confined to the supply of essential goods, and private offices could only operate with one-third of their employees attending. In Orange zone districts, all activities allowed in Red zones were permitted, in addition to relaxation of restrictions on public transport enabling inter-district movement. In Green zone districts, all activities resumed except those restricted across the country. Notably, the zone restrictions announced by the central government could not be diluted by state governments. Although the central government left open the possibility of stricter reclassification of districts, no district classifications were changed during the first two weeks of Lockdown 3.0, with only 15 districts subsequently reclassified.

After May, state governments could alter the initial zone containment, for example to respond to infection progression and economic consequences. We analyze the April 30 declaration as the most exogenous implementation of government containment policies to combat the COVID-19 pandemic. We also conduct robustness analyses excluding the 15 districts where the zone classifications were changed by state governments.

The unlock phase of containment policies commenced from June 1, 2020. Several restrictions were eased and primary rule-making authority devolved to state governments. Thus, our analysis compares the severe restrictions which were uniform across the country in March and April 2020, with the period after May 4 when restrictions varied by district, until July 2020.

3. Data

We combine multiple sources of district-level information on mobility, nighttime light intensity, household consumption and income, and district-specific characteristics. This information is merged with the government’s district level zone classification and COVID-19 infection data. We use 2020 district boundary classifications to match how zone containment policies and infections are reported.

We extract district level nighttime light data from the VIIRS-DNB Cloud Free Monthly Composites (version 1) provided by the Earth Observation Group at the Colorado School of Mines.[5] Due to a wider radiometric detection range and onboard calibration correcting for saturation and blooming effects, these data are more comparable over time than previous nighttime light products. However, the monthly composite still includes some temporary lights like fires and gas flaring. In a regression analysis, this noise would create a mean-reverting error (rather than a white noise one) and bias our parameter estimates. We hence apply a background noise mask to

[4] Regardless of zone classification, domestic and international air travel, inter-state bus transport, and metro and local trains remained shut. Only special inter-state trains started operations on May 12. Educational institutions, hotels, movie theaters, malls, gyms, swimming pools and bars were shut, and religious and social gatherings were banned across India.

[5] We employ the vcm configuration starting from April 2012. For information about the different versions, visit https://eogdata.mines.edu/products/vnl/.

strengthen the relationship between nighttime lights and economic activity. Following Beyer et al. (2018, 2021), we identify different clusters by removing monthly outlier observations, averaging cells over time, and clustering areas based on their monthly nighttime light intensity. Based on the clustering, we then define a background noise mask and only consider those lights outside of it. In practice, this approach amounts to setting to zero cells that are distant from homogeneous bright cores.[6] The advantage of using a background mask is shown clearly by Gibson and Boe-Gibson (2021), who compare results using masked and unmasked VIIRS data, for both within and between estimators on a panel of about 3000 U.S. counties. Our adjusted monthly data are aggregated to the district level and standardized by area.

We accessed mobility information from Facebook Data for Good,[7] which is based on individuals who use Facebook on a mobile device, provide their precise location, and are observed for a meaningful period of the day.[7] Facebook quantifies how much people move around by counting the number of level-16 Bing tiles (approximately 600 m by 600 m) in which they are seen within a day, with the idea that people seen in fewer tiles are less mobile. The specific metric calculates the percentage of eligible people who are only observed in a single tile during the course of a day, and hence represents small distance mobility.[8] We aggregate Facebook's tile-level information to match contemporary Indian districts, and then invert and standardize the metric.

We obtained location data from Google Mobility, which draws on aggregated and anonymized data from smartphone users with Android operating systems who opt-in to share location history (Google LLC, 2020).[9] This measures how visits and length of stay at different places change compared with a baseline. Changes for each day are compared with a baseline value which is the median for the corresponding day of the week between January 3 and February 6, 2020. Google classifies destinations based on reports from mobility trends. Thus "grocery and pharmacy" represent grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies, "retail and recreation" are restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters, "residential" are places of residence and "workplaces" are where mobility trends suggest people work.[10]

We use household-level total expenditure (as a proxy for consumption) and total income using the Centre for Monitoring Indian Economy's Consumer Pyramids Household Survey (CPHS).[11] These data are collected through stratified multi-stage surveys of the 2011 Census district classification in India, covering 28 states and union territories and 514 districts.[12] The CPHS is conducted every four months with every household surveyed in every round, with one wave conducted between May and August 2020. The monthly time-series is created by seeking data on income and expenses from households for each of the four months preceding the month of the survey. By combining all the data from multiple surveys, we created a monthly time-series of income and expenses of households. We correct for response bias in the CPHS using weights for non-response, which was a concern during the lockdown period.

Additional data are from Covid19India.org, the 2011 Census, the Socioeconomic High-resolution RuralUrban Geographic (SHRUG) dataset (Asher et al., 2021) and the Reserve Bank of India Database on the Indian Economy. We aggregate daily district-level information on infections from Covid19India.org, which collates information from the central and state governments, and verifies it against media reports, to monthly data. Since the 2011 district boundaries used by the Census and the SHRUG database are different from the 2020 boundaries used for the zone classification, we convert information from these sources using official orders for rearranging district boundaries and 2011 data on population in the relevant sub-districts. From the Census, we compute the average age for each district. From the SHRUG database, which consolidates village and urban ward characteristics from a large number of official sources (Asher et al., 2021), we obtained the population density and the fraction of workers in the service sector. We also use quarter-end outstanding aggregate credit for scheduled commercial banks from the Reserve Bank of India's Quarterly Statistics on Deposits and Credit of Scheduled Commercial Banks (Database on Indian Economy). We use per capita credit to measure access to finance. Finally, we accessed monthly data on persons working under.

MNREGA for fiscal year 2019–20 from the program's public data portal.

Table 1 describes the summary statistics. In panel A, the number of observations is 3665, which reflects 733 districts across India each observed over five months (March 2020 to July 2020). Red zone districts have much higher levels of nighttime lights compared with Orange and Green districts. If the level of nighttime lights matters for the elasticity between the light intensity and economic activity, this could bias the results. As a robustness check, we hence exclude large metropolitan cities, which have the highest light intensity. The levels of mobility are similar across zone types. Red zone districts had an average of 1324 infections per month compared with 260 in Orange districts, and 89 in Green districts. These patterns are consistent with higher infection rates in large urban areas

[6] The approach basically replicates the procedure Elvidge et al. (2017) propose to aggregate the monthly composites to a clean annual composite. We also retained three out of ten clusters, which we found to result in the highest correlation of Indian nighttime light growth with Indian GDP growth.[7] https://dataforgood.fb.com.

[7] Facebook has 310 million users in India (Statistica 2020), although the fraction with the app installed is not known.

[8] Maas et al. (2019) and Bonaccorsi et al. (2020) provide more details about this data.

[9] India has 696 million smartphones, with Android holding a 95.23 % market share in 2020 (StatCounter, 2020).

[10] Chan et al. (2020) and Drake et al. (2020) also use this dataset.

[11] Anand, Sandefur, and Subramanian (2021), Chanda and Cook (2022), Chodorow-Reich et al. (2020), Deshpande (2022), Deshpande and Ramachandran (2020), Gupta and Kishore (2022), Malani and Ramachandran (2022), Mohanan et al. (2021), Narayanan and Karmakar (2020) and Wadhwa (2020) use this dataset for analysis of the demonetization episode of 2016–17 and the COVID-19 pandemic. Abraham and Shrivastava (2022) compare labor force estimates from the CPHS and the official Periodic Labour Force Surveys, and report that employment estimates for men are broadly comparable. See criticisms and assessments of the CPHS sampling methodology by Dreze and Somanchi (2021), Pais and Rawal (2021), and Sanyal (2021), comprehensively assessed by Gupta, Malani, and Woda (2021).

[12] CPHS does not cover Arunachal Pradesh, Nagaland, Manipur, Mizoram, Andaman and Nicobar Islands, Dadra and Nagar Haveli and Daman and Diu.

Table 1
Summary statistics by zone classification.

Classification	Red	Orange	Green	All	Sample Period
	(1)	(2)	(3)	(4)	(5)
Panel A: District level variables					
Number of observations	650	1420	1595	3665	
Sum of lights per sq. km (nanowatts)	27.68	3.03	1.56	6.76	March-July, 2020
	(57.27)	(5.17)	(3.87)	(26.32)	
Number of infection per month	1324.16	260.08	88.94	374.32	March-July, 2020
	(5005.03)	(892.77)	(399.37)	-2239.59	
Total population ('000 s)	3101.67	1808.94	966.05	1669.43	NSS, 2011
	(2500.41)	(1193.4)	(898.69)	(1609.15)	
Population density (thousands per sq. km)	4.99	0.62	0.42	1.31	NSS, 2011
	(15.57)	(0.52)	(0.52)	(6.82)	
2019Q4 bank deposit (Rupee Billions)	620.08	129.45	54.38	179.03	FY 2019–20
	(1440.36)	(177.44)	(90.73)	(634.96)	
2019Q3 bank deposit (Rupee Billions)	600.87	124.04	52.17	173.74	FY 2019–20
	(1375.06)	(170.91)	(86.51)	(609.81)	
2019Q2 bank deposit (Rupee Billions)	589.5	121.21	51.24	170.28	FY 2019–20
	(1358.27)	(164.3)	(84.52)	(601.4)	
2019Q1 bank deposit (Rupee Billions)	574.17	117.09	49.45	165.27	FY 2019–20
	(1346.78)	(159.73)	(81.76)	(594.85)	
Average district age (years)	28.08	27.88	26.88	27.48	NSS, 2011
	(2.38)	(2.67)	(2.46)	(2.59)	
Urban population ('000 s)	1578.99	463.3	167.81	518.18	NSS, 2011
	(2307.37)	(505.78)	(219.31)	(1116.97)	
Employment by sector, services (percent of total employment)	34.78	23.32	22.95	25.31	NSS, 2011
	(18.64)	(10.03)	(12.37)	(13.74)	
Other variables:					
No. of observations	435	1130	1135	2700	
Persons Worked under NREGA	640,745	616,265	431,574	542,570	March-July, 2020 (NREGA)
	(1033641)	(1019306)	(672938)	(897600)	
No. of observations	454	1070	1136	2660	
Short-term in-migration share	0.0037	0.00138	0.0007	0.00149	March-July, 2020 (NSS, 2011)
	(0.0059)	(0.0013)	(0.00088)	(0.00286)	

with greater international connectivity and lower distancing. Correspondingly, Red zone districts are more populous with greater density, have higher bank credit, and have a larger fraction of the population employed in the service sector. The mean age in Red, Orange and Green districts is similar. Panel B in Table 1 summarizes per capita household-level CPHS variables. The mean of monthly consumption and income are similar across zone types.[13]

Panel C in Table 1 summarizes the Google and Facebook mobility data. Compared with the baseline of January and February 2020, all types of mobility reported by Google, except residential, fell, which is consistent with more people staying at home in the study period. Stay-at-home is greatest in the Red zone districts, lower in Orange zone districts and least in Green zones. This pattern matches what the pandemic control measures imply and suggests that these data are an appropriate proxy for short-distance population mobility.[14]

4. Specification

4.1. Mobility and nighttime light intensity analysis

We use a difference-in-differences specification to estimate the impact of variation in relaxing lockdown restrictions on mobility and aggregate economic activity (Goodman-Bacon & Marcus, 2020). We specify the following equation for our analysis. Table 2.

$$y_{it} = \beta_0 + \beta_1 Red_i * Post_t + \beta_2 Orange_i * Post_t + \beta_3 X_{it} + \beta_4 Infections_{i,t-k=0,1} + DistrictFE_i + StateMonthFE_{it} + {}_{it} \quad (1)$$

We first use Eq. (1) to examine if *de jure* restrictions imposed by the central government translated into *de facto* restrictions. For this, we examine district level short-distance mobility as an outcome to measure where and how severely the zone containment policies impacted population mobility. Thus, y_{it} is the standardized mobility measure from Facebook and Google in district i for month t.

We also conduct month-wise analysis. Since individual movement across the country was most severely restricted in April, we expect an increase in mobility in subsequent months. In May, we expect lower mobility in Red and Orange zone districts compared with

[13] Since several explanatory variables are different across zone types, we include district fixed effects in subsequent regressions to control for these differences.

[14] These trends are corroborated in Appendix Figure 1, which shows substantially lower movement to shops, parks, work-places and transit and greater staying-at-home in April 2020. Movement outside the home rebounded in May, June, and July 2020 as restrictions were lifted.

Table 2
Summary statistics by zone classification.

Classification	Red	Orange	Green	All	Sample Period
	(1)	(2)	(3)	(4)	(5)
Panel B: Household level variables					
No. of observations	101869	154460	65685	322014	
Monthly Expenditure (per household)	9385.071	9390.26	8660.03	9239.665	March-June, 2020
	(6089.095)	(5278.06)	(5599.917)	(5619.116)	
Monthly Income (per household)	17245.48	17351.48	16272.42	17097.84	March-June, 2020
	(21196.47)	(22045.45)	(20619.37)	(21497.71)	
Panel C: Mobility data					
No. of observations	540	1110	1198	2848	
Retail and Recreation	-59	-52	-51	-53	March-July, 2020 (Google Mobility)
	(21)	(19)	(20)	(20)	
Grocery and Pharmacy	-16	1	-2	-4	March-July, 2020 (Google Mobility)
	(32)	(33)	(33)	(33)	
Workplaces	-34	-22	-16	-22	March-July, 2020 (Google Mobility)
	(20)	(15)	(14)	(17)	
Residential	19	15	13	15	March-July, 2020 (Google Mobility)
	(8)	(7)	(6)	(8)	
Number of observations	650	1420	1595	3665	
Facebook Mobility	0.22	0.19	0.21	0.2	March-July, 2020 (Facebook)
	(0.07)	(0.05)	(0.05)	(0.06)	

Green zone districts. In June, when mobility restrictions were lifted under "unlock 2.0," mobility should have revived.

For the main analysis, we use Eq. (1) with the standardized nighttime light intensity per square kilometer in district i for month t to estimate the impact of COVID-19 restrictions on economic activity. Red_i and $Orange_i$ indicate the zone classification in May 2020, with Green zone districts as the excluded category. $Post_t$ indicates the months of May, June and July, which was when the lockdown varied across the country, compared with March and April (Pre_t) when the lockdown was uniformly severe. Thus, the OLS estimate for β_1 is the marginal effect of Red zone compared with Green zone districts on changes in mobility and economic activity during the unlock period. Similarly, β_2 is the marginal effect of Orange versus Green zones on changes in mobility and nighttime light intensity from March/April to May/June/July 2020.[15]

We add controls X_{it} for a range of factors that might influence district level mobility and nighttime light intensity. This vector includes the nighttime lights for each district for every month from January 2013 to February 2020 to control for pre-trends, including seasonality, in the outcome variable. This also helps control for the potential impact of 2019 economic growth, as well as the level of economic development, on changes in nighttime light intensity due to COVID-19 infections and the corresponding government containment. Since y_{it} might be influenced by local pandemic conditions, we control for per capita monthly infections ($Infections_{i,t-k=0,1}$, both contemporary month infections as well as one-month lagged infections). Since the inclusion of contemporaneous infections might be over-controlling, we estimate a specification omitting these, and report both results.

We include district fixed effects in the specification to account for all time-invariant observable and unobservable characteristics of the district that might impact mobility, economic activity and nighttime lights. These include the level of development, transportation links, health facilities, and governance aspects. The independent effect of *Red* and *Orange* are absorbed by $DistrictFE_i$ and therefore both are omitted from the specification.

State-month fixed effects ($StateMonthFE_{it}$) in Eq. (1) are the most non-linear way to capture timevariant and invariant state specific factors during the pandemic period. These include state level policies to control the pandemic, since health is a state subject in India. The state-month fixed effects also control for policing and other governance measures used to restrict the movement of people. Such rules were common across districts but implementation may have varied by state, since law and order also falls within the purview of state governments. The inclusion of state-month fixed effects subsumes the stand alone $Post_t$ variable in the equation. Finally, $_{it}$ represents robust standard errors clustered at the state level (since implementation of most health policies was at the state level).[16]

[15] One concern is that economic activity is correlated between neighboring districts, for example due to supply chains, particularly across districts of different zone classifications. If these cross-zone economic factors are important, then the coefficients would be biased towards the null. Therefore, the reported coefficients represent a lower bound on the true estimates of the effects of the zone classifications on nighttime light intensity.

[16] Clustering at the district level rather than the state level yields smaller standard errors.

4.1.1. Robustness

We conduct a number of robustness checks of the main analysis to confirm the effect of zonewise containment policies on nighttime light intensity. First, we analyze the impact of the zone classifications on pre-period outcomes for several months before the pandemic. Zone classifications created in May 2020 in response to the COVID-19 pandemic beginning in March 2020 should not have impacted nighttime light intensity in the months prior to the pandemic. We regress the following standard difference-in-differences specification.

$$y_{it} = \beta_0 + \beta_1 Red_i * \text{Month}_t + \beta_2 Orange_i * \text{Month}_t + \beta_3 \text{Month}_t + \beta_4 \text{X}_{it} + DistrictFE_i + StateMonthFE_{it} + {}_{it} \quad (2)$$

Our primary outcome variable remains nighttime light intensity for district i in month t. In this specification Month_t is a vector of indicators for months from July 2019 to February 2020. If the zone classifications were not a function of pre-existing trends in the data, we expect β_1 and β_2 to be close to the null and statistically insignificant.

Second, to address the concern that variables omitted from the specification do not potentially drive zone classification as well as the economic output of a district, we estimate Eq. (1) with a restricted sample of districts that border each other but have different containment policies (600 districts). Geographical proximity implies that districts have similar economic, health and cultural characteristics, so the comparison in the restricted sample is more precise (Jain, 2017).

Our third robustness check omits the 17 districts with the largest metropolitan cities from the sample, since these districts generate a disproportionate share of the nighttime light and also experienced high COVID-19 infections.[17] These highly developed districts could also experience reversion as a consequence of COVID-19 restrictions. Results from the remaining sample should more reliably indicate the effect of the zone classification on nighttime light intensity in the average Indian district.

Fourth, we check the sensitivity of our results to removing 15 districts where the zone classifications changed after two weeks.

Finally, to ensure that the results are directly attributable to zone classification and not to unobserved omitted variables or spurious correlations in the data, we follow Card and Giuliano (2013) and Jain and Langer (2019) to conduct a placebo exercise. We randomly rematch districts to zone classifications in the data.[18] We then estimate Eq. (1) with these rematched placebo districts. Since the randomly assigned classifications do not correspond to what actually happened, the estimated coefficients should yield nulls. Thus, if β_1 and β_2 are null and statistically insignificant, we have greater confidence that the main results are due to the zone classifications.

4.2. Impacts on household income and consumption

We analyze whether the impacts of the zone classifications on household income and consumption corroborate the main findings on the effects of the pandemic containment policies on nighttime light intensity. We estimate the following model with monthly household-level (indexed by h) consumption and income, and $Household_h$ representing household fixed effects.

$$Y_{hit} = \gamma_0 + \gamma_1 Red_{hi} * May_t + \gamma_2 Orange_{hi} * May_t + \gamma_3 Red_{hi} * June_t + \gamma_4 Orange_{hi} * June_t + \gamma_5 May_t + \gamma_6 June_t + \gamma_7 Infections_{i,t-k=0,1} + Household_h + StateMonthFE_{it} + \varepsilon_{hit} \quad (3)$$

If the changes in income and consumption are consistent with the main effects, we expect that both coefficients are lower in May and June in Red ($\gamma_1,\gamma_3 < 0$) and Orange ($\gamma_2,\gamma_4 < 0$) zone districts compared with Green zone districts.

4.3. Subsample analysis

How do district-specific characteristics determine the responsiveness to lockdown? One answer could be that more developed districts might have better capacity to absorb the economic shocks from the zone restrictions. For instance, service sector employees might continue being productive if they work from home. Similarly, better access to credit might allow firms in Red districts to continue operations. Conversely, more developed districts have more to lose from more severe restrictions, which could imply greater losses of aggregate economic activity. Further, local economic and demographic conditions could impact the effectiveness of pandemic restrictions. For example, younger populations are potentially more mobile, and in the case of COVID-19, they are less susceptible to infections and hospitalization (Davies et al., 2020). Similarly, higher population density comes with economic benefits from agglomeration effects, but also facilitates infections that could dampen economic activity when restrictions are in place.

To examine the role of district-specific characteristics, we conduct sub-sample analyses on a number of dimensions. We divide the main dataset into sub-samples with above-median and below-median population density, share of employment in services, average population age, and credit per capita.[19] We then estimate Eq. (1) on both sub-samples for each of the specified variables.

First, we examine heterogeneity by district-level population density, which may drive the spread of infections and determine the type and extent of economic activity.

Next, we analyze the role of the sectoral composition of economic activity. The service sector relies significantly on personal interactions and is strongly impacted by containment measures. Consequently, services have been hit hardest during the national

[17] The districts correspond to the cities of Delhi, Mumbai, Chennai, Kolkata, Hyderabad, Bengaluru and Ahmedabad, which are the seven largest in India.

[18] Other control variables are not reassigned.

[19] We use the medians within the Red and Orange zone classifications and all the Green zone districts.

Table 3
Effect of zone classification on individual mobility.

	Facebook	Google mobility			
		Retail	Grocery	Workplaces	Residential
	mobility	Recreation	Pharmacy		
	(1)	(2)	(3)	(4)	(5)
Red zone district*May	-0.26 * **	-0.48 * **	0.41 * **	-0.56 * **	-0.15 * **
	(0.038)	(0.04)	(0.036)	(0.051)	(0.029)
Orange zone district*May	-0.034	-0.10 * **	0.066 * *	-0.12 * **	-0.03
	(0.022)	(0.027)	(0.027)	(0.044)	(0.026)
Post*May	0.11	0.65	0.28 *	0.48 * **	-1.75 * **
	(0.118)	(0.726)	(0.151)	(0.091)	(0.068)
Red zone district*June	0.10 * **	-0.16 * **	0.087 * **	-0.30 * **	-0.023
	(0.031)	(0.034)	(0.03)	(0.06)	(0.034)
Orange zone district*June	0.079 * **	-0.006	-0.024	0.0025	0.052 *
	(0.02)	(0.023)	(0.021)	(0.051)	(0.031)
Post*June	0.88 * **	1.32 *	-0.19	1.17 * **	-1.01 * **
	(0.118)	(0.725)	(0.131)	(0.094)	(0.078)

lockdown (World Bank, 2020). We use the share of employment in services to assess whether more severe restrictions continued to have a greater impact on the districts with more services activity.

Our analysis also examines the role of a district's average population age on the effect of zone restrictions on economic activity. Mobility restrictions might impact districts with older populations less if older workers are less likely to travel for work. Conversely, if older workers are more productive, then restrictions due to the zone classifications might disproportionately impact older districts.

We examine the role of average credit per capita in the district as an indicator for access to finance. High credit districts might have more resources to cope with zone restrictions, potentially mitigating the impact of the mobility restrictions on economic activity. Conversely, the impact of mobility restrictions on high value businesses might have disproportionate negative impact on aggregate economic activity.

4.4. MNREGA employment and migration analysis

We examine the effect of the zone restrictions by the extent of MNREGA operations, and by the degree of migration in each district. MNREGA is the world's largest public works program, operated by the Indian government since 2005. Following the pandemic restrictions and large-scale urban-to-rural reverse migration, the Government of India scaled up MNREGA operations in rural districts to mitigate the economic impact of the restrictions (Government of India, 2020). MNREGA is driven by existing capabilities, so we expect that the effect of the restrictions on overall economic activity might be tempered in high MNREGA districts. Hence, we examine the effects of the zone restrictions on nighttime lights separately for MNREGA districts above and below median employment.

Our analysis of migration is motivated by large-scale return migration that took place in India following the lockdown announcement (Pandey, 2020). Migration may have been greater following the more intense lockdown in Red and Orange zone districts, which could have further dampened economic activity which relies on migrant labor. In the absence of data on inter-district migration during the pandemic, we proxy the potential migration using the 2011 migrant share in each district reported in the National Sample Survey 2011. We estimate the differential impact of the zone-wise containment on nighttime light intensity for districts above and below the median in migration share.

5. Results

5.1. Mobility results

We first report the results on mobility behavior as a consequence of the zone-wise restrictions. Table 3 shows the results from estimating Eq. 1 with the standardized measures of Facebook and Google mobility. Column (1) in Table 3 shows that Facebook mobility in May was 0.26 σ lower in Red zone districts compared with Green zone districts ($p < 0.01$), consistent with the most severe mobility restrictions in those districts. Mobility was also lower in Orange zone districts compared with Green zone districts, but the difference is not statistically significant even at the 10 % level (-0.034 σ, $p > 0.10$). During unlock 1.0 in June, mobility rebounded in both Red ($+0.10$ σ, $p < 0.01$) and Orange ($+0.079$ σ, $p < 0.01$) zone districts, consistent with removal of the zone classifications.

Columns (2) to (5) in Table 3 report the results using Google mobility measures as outcome variables. Google mobility data cover a larger population than Facebook since the Android OS is more universally installed on smartphones compared with the Facebook app, and reports destination-wise movements. The coefficients on *Post * May* suggest that travel to groceries and pharmacies ($+0.28$ σ, $p < 0.10$) and work ($+0.48$ σ, $p < 0.01$) was higher in May compared with March and April, and staying at home declined (-1.75 σ, $p < 0.01$).

Column (4) in Table 3 shows that travel to workplaces in May was 0.56 σ ($p < 0.01$) lower in Red zone districts and 0.12 σ ($p < 0.01$) lower in Orange zone districts relative to Green zone districts. Travel to retail and recreational destinations was also lower

Table 4
Effect of zone classification on change in nightlight intensity.

	(1)	(2)	(3)	(4)
Red zone district*Post	-0.13 *	-0.26 * **	-0.044 * **	-0.043 * **
	(0.066)	(0.087)	(0.009)	(0.010)
Orange zone district*Post	-0.0090 * *	-0.033 * *	-0.0094 *	-0.0093 *
	(0.004)	(0.015)	(0.005)	(0.005)
Lagged per-capita COVID Infections		1.04 * **	-0.061 * **	-0.043
		(0.207)	(0.017)	(0.042)
Per-capita COVID infections				-0.024
				(0.050)
Mean of dependent variable	6.76	6.76	6.76	6.76
Std. dev. of dependent variable	26.32	26.32	26.32	26.32
Previous year nightlight	No	Yes	Yes	Yes
District fixed effects	No	No	Yes	Yes
State*Months(2020) fixed effects	No	No	Yes	Yes
No. of Observations	3665	3628	3628	3628
R Squared	0.138	0.667	0.996	0.996

Notes: The unit of observation is a district-month. Data from 733 districts over five months. Asterisks denote significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at state level.

in May ($-0.48\,\sigma$, $p < 0.01$) and June ($-0.16\,\sigma$, $p < 0.01$) in Red zone districts, and in May in Orange zone districts ($-0.10\,\sigma$, $p < 0.01$). Conversely, travel to groceries and pharmacies was higher in May and June in Red zone districts and in May in Orange zone districts, compared with Green zone districts, consistent perhaps with greater purchases of necessities after the nationwide lockdown in April.

Collectively, the pattern of these results corroborates that the containment policy was indeed effective in reducing mobility, despite concerns that weak state capacity may have mitigated the impact of government.

orders.[20]

5.2. Main results

Table 4 reports the results from estimating Eq. (1) with standardized nighttime light intensity per square kilometer as the main outcome variable, March and April 2020 as the pre-period, and May, June and July 2020 as the post-period. Column 1 is a basic analysis with only the zonal classifications, post and interacted variables, but excluding all control variables and fixed effects. Column 2 reports an enhanced analysis with the *Zone* * *Post* interacted variables, including only trailing night-time lights till 2013 as controls. Column 3 in Table 4 reports the results from our preferred specification, including all controls and fixed effects, but excluding the contemporaneous per-capita infections. The R-squared is 0.996, suggesting that the observable variables and fixed effects in the model explain nearly all the variation in the outcomes.

Our main finding is that the recovery in nighttime light intensity over the entire post period was 0.044 σ lower in Red zone districts than in Green zone districts ($p < 0.01$). Similarly, the recovery in nighttime light intensity in Orange zone districts was 0.0094 σ lower ($p < 0.10$). Another way to interpret these coefficients is that nighttime light intensity was lower by 9.1 % for Red zone districts, and by 1.6 % for Orange zone districts compared with Green zone districts. The two coefficients are statistically different from each other, confirming that Red zone districts had significantly lower nighttime light intensity compared with Orange zone districts in the post period. Given the high correlation between economic activity and nighttime light intensity, this implies that economic activity revived faster in Green zone districts than in Red and Orange zone districts.

The impact of the COVID-19 infections and containment policies might have dampened or exacerbated over time. As restrictions were lifted starting from June, the marginal increase in nighttime lights might have been greatest in Red zone districts that experienced economic revival. Conversely, the impact might have been exacerbated if the zone restrictions created a path-dependence (Durlauf, 1994), and Red and Orange zone districts could not revive as quickly. Over a longer term, the containment policies might intertemporally shift economic activities instead of causing permanent loss. Thus, we extend our dataset to.

October 2020 and examine the impact of containment policies on nighttime lights separately for each of the.

$Post_t$ months. Appendix Table 1 shows that the zonewise differences reduce over time, and are statistically indistinguishable from each other by October 2020. Since the Red and Orange zone nighttime light intensity coefficients in October are not significantly positive, we do not find evidence of an intertemporal shift in economic activity.

The infection rate in a district also negatively impacts nighttime lights. Columns (2) and (3) in Table 4 show that the one-month lagged infection rate impacts nighttime light intensity. In column (4) where we additionally control for contemporary infections, the coefficient on lagged as well as same-month infections is insignificant and close to zero. Importantly, our main coefficients on the zone classifications remain essentially unchanged.

Our findings contrast with those for the impacts of shutdown orders in the United States. While COVID19 had a large economic impact, Goolsbee and Syverson (2021) report that legal restrictions only accounted for 7 % of this impact. Similarly, Correia et al.

[20] These findings echo Drake et al. (2020) who also use Google Mobility data for the United Kingdom to report 63 % overall reduction in mobility. Facebook data from Italy show nearly 90 % reduction in mobility associated with lockdown orders (Bonaccorsi et al., 2020).

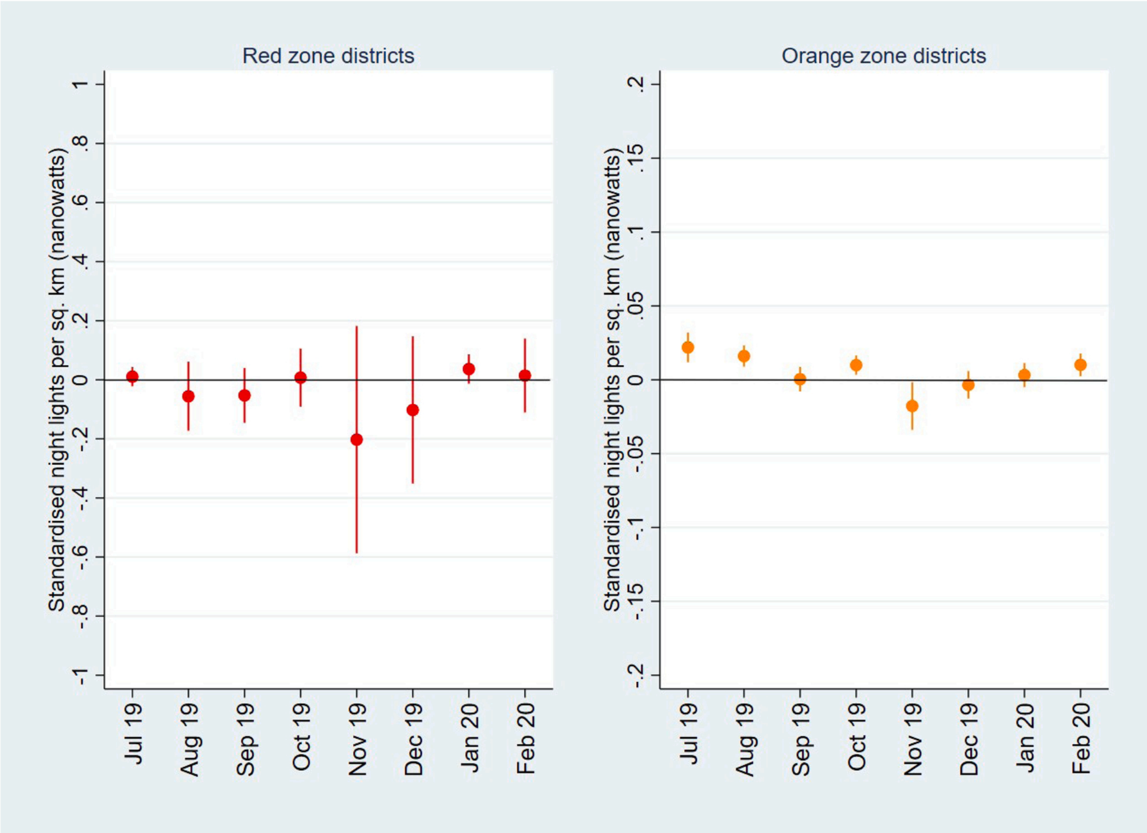

Fig. 2. Pre-period placebos.

Table 5
Effect of zone classification on change in nightlight intensity (Robustness).

	Border districts (1)	No metro districts (2)	Unchanged zones (3)	Shuffled zones (4)
Post	1.16 * **	1.13 * **	1.16 * **	1.16 * **
	(0.006)	(0.004)	(0.004)	(0.004)
Red zone district*Post	-0.040 * **	-0.032 * **	-0.045 * **	
	(0.012)	(0.007)	(0.010)	
Orange zone district*Post	-0.012 * *	-0.0098 * *	-0.011 *	
	(0.006)	(0.004)	(0.006)	
Shuffled Red zones*Post				0.00070
				(0.002)
Shuffled Orange zones*Post				-0.0025
				(0.006)
Mean of dependent variable	6.76	6.76	6.76	6.76
Std. dev. of dependent variable	26.32	26.32	26.32	26.32
All controls	Yes	Yes	Yes	Yes
No. of Observations	2969	3549	3554	3629
R Squared	0.996	0.992	0.996	0.996

Notes: The unit of observation is a district-month. Data from 733 districts over five months. Asterisks denote significance: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at state level.

(2022) also report negligible impacts of restrictions in the US during the 1918 Spanish Flu. Our results can also be viewed in context of other recent economic shocks in India. For instance, Chodorow-Reich et al. (2020) estimate the impact of India's demonetization shock as a 11.7 % contraction in nighttime light intensity, similar to the gap between Red and Green zone districts in May.

Robustness.

Fig. 2 shows month by month coefficients from estimation of Eq. (2). Most of the coefficients are close to and statistically indistinguishable from the null, with no discernible pattern in the pre-period. This finding offers greater confidence that the main results are

Table 6
Impacts on household income and consumption.

	Income (1)	Consumption (2)
Red zone district*May	-0.063 * **	-0.020 *
	(0.019)	(0.012)
Orange zone district*May	-0.15 * **	-0.027 * **
	(0.017)	(0.010)
Post*May	0.053 * **	0.045 * **
	(0.015)	(0.015)
Red zone district*June	-0.079 * **	0.054 * **
	(0.017)	(0.012)
Orange zone district*June	-0.068 * **	0.073 * **
	(0.016)	(0.010)
Post*June	0.20 * **	0.27 * **
	(0.014)	(0.019)
Mean of dependent variable	17097.8	9239.7
Std. dev. of dependent variable	21497.7	5619.1
All controls	Yes	Yes
No. of Observations	299,246	299,777
R Squared	0.475	0.716

Notes: The unit of observation is a household. Asterisks denote significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at state level.

not driven by differential pre-existing trends in nighttime light intensity across zones.

Column (1) in Table 5 reports the results from estimating Eq. (1) with a restricted sample of districts that border one with a different zone classification. We find that the main coefficients are qualitatively consistent with those in column (1) in Table 4, suggesting that the differences across district classifications are not driven by omitted factors. Column (2) in Table 5 reports the results from a sample that omits large metropolitan cities that disproportionately drive nighttime light intensity in India. The reported coefficients (-0.032 σ, $p < 0.01$ for Red zone districts and -0.01 σ, $p < 0.01$ for Orange zone districts) are qualitatively consistent with those from the main sample. Column (3) in Table 5 reports the results after dropping the 15 districts where zone classifications changed during the second half of the differential lockdown, and finds no change from the main findings.

Finally, column (4) reports the results after randomly scrambling the zone classifications, while retaining the other district characteristics. The placebo assignments yield null coefficients for *Shuffled Red zones* * .

Post and *Shuffled Orange zones* * *Post*, which suggests that the results in Table 4 are not driven by omitted variables or spurious correlations. As a result of these analyses, we have greater confidence in the robustness of the main findings.[21]

5.3. Household income and consumption

Table 6 reports the impact of the differential zone restrictions on household income and consumption. Income, reported in column (1), was lower by 0.063 σ ($p < 0.01$) in May, although the decrease in consumption was considerably lower in magnitude (-0.020 σ $p < 0.10$). Orange zone districts experienced relatively lower incomes (-0.15 σ, $p < 0.01$) as well as consumption (-0.027σ, $p < 0.01$). Since most household income in India is related to labor, these results are consistent with Gupta, and Montenovo, Nguyen et al. (2022), who find that 60 % of the decline in employment rates in the United States was driven by state-imposed social distancing policies. In contrast, using unemployment claims data, Baek et al. (2021) show each week of stay-at-home exposure increased an American state's weekly initial unemployment insurance claims by 1.9 % of its employment level relative to other states. Our findings are also in line with Baker et al. (2020), who show that pandemicinduced lockdowns decreased household expenditure, and spending responded most strongly in states with active shelter-in-place orders.

The pattern of these results diverged in June as unlock 1.0 commenced. Income gaps persisted in June (-0.079 σ, $p < 0.01$ for Red, and -0.068 σ, $p < 0.01$ for Orange zone districts), but consumption rebounded sharply (0.054 σ, $p < 0.01$ for Red, and 0.073 σ, $p < 0.01$ for Orange zone districts). One possible reason for this rebound is pent-up demand in Red zone districts with households catching up with consumption in other districts after a relaxation of the restrictions. The pattern of widespread job and income losses and reduced consumption corroborates the main findings of the effects of zone containment policies on aggregate economic activity.

5.4. Sub-sample analyses

This subsection discusses how the role of COVID-19 containment policies on economic activity differed by pre-existing district characteristics such as population density, share of services employment, average age, and per capita bank credit. Table 7 reports that Red zone districts with above-median population density had 0.091 σ ($p < 0.01$) lower nighttime light intensity compared with Green

[21] Appendix Table 3 shows the results from another robustness test where the estimating equation compares Red versus Green zones, and Orange versus Green zones in separate regressions. These coefficients are qualitatively similar to the main results in Table 4.

Table 7
Heterogeneity Analysis.

	Population Density		Services employment		Mean Age		Bank Credit	
	Above	Below	Above	Below	Above	Below	Above	Below
	median	median	median	median	median	median	median	median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	1.23 * **	-0.038 * **	0.27 * **	0.20 * **	1.16 * **	0.0067 * *	1.16 * **	0.0036 * *
	(0.011)	(0.002)	(0.011)	(0.008)	(0.006)	(0.003)	(0.008)	(0.001)
Red zone district*Post	-0.091 * **	-0.017 * *	-0.088 * **	-0.017 * *	-0.061 * **	-0.031 * **	-0.094 * **	-0.016 * **
	(0.033)	(0.008)	(0.026)	(0.008)	(0.015)	(0.009)	(0.031)	(0.005)
Orange zone district*Post	-0.024 * **	-0.0021	-0.017 * *	-0.0016	-0.013	-0.0074 *	-0.028	-0.0055 *
	(0.009)	(0.004)	(0.007)	(0.002)	(0.010)	(0.004)	(0.019)	(0.003)
Red*Post (Above)=Red*Post (Below)		-0.074		-0.071 * **		-0.03		-0.078 * **
Orange*Post (Above)=Orange*Post (Below)		-0.0219		-0.0154		-0.0056		-0.0225
Mean of dependent variable	6.76	6.76	6.76	6.76	6.76	6.76	6.76	6.76
Std. dev. of dependent variable	26.32	26.32	26.32	26.32	26.32	26.32	26.32	26.32
All controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	2576	2540	2214	2243	2768	2454	2483	2494
R Squared	0.997	0.993	0.996	0.992	0.996	0.996	0.993	0.994

Notes: The unit of observation is a district-month. Asterisks denote significance: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at state level.

Table 8
MNREGA employment and migration analysis.

	NREGA employment		Migration share	
	Above	Below	Above	Below
	median	median	median	median
	(1)	(2)	(3)	(4)
Post	0.49 * **	1.29 * **	0.25 * **	0.057 * **
	(0.003)	(0.015)	(0.019)	(0.001)
Red zone district*Post	-0.013	-0.016	-0.041 *	-0.0055
	(0.017)	(0.052)	(0.024)	(0.004)
Orange zone district*Post	0.019 * **	0.0042	-0.013	-0.0029
	(0.005)	(0.020)	(0.010)	(0.002)
Mean of dependent variable	542,570	542,570	0.0015	0.0015
Std. dev. of dependent variable	897600	897600	0.0028	0.0028
All controls	Yes	Yes	Yes	Yes
No. of Observations	1034	948	1056	1056
R Squared	0.996	0.997	0.994	0.995

Notes: The unit of observation is a district-month. Asterisks denote significance: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at state level.

zone districts, while Orange zone districts had 0.024 σ ($p < 0.01$) lower nighttime light intensity. In contrast, Red zone districts with below median population density had 0.017 σ ($p < 0.05$) lower nighttime light intensity compared with Green zone districts, while Orange zone districts did not differ significantly from Green zone districts (Orange zone: −0.002 σ, $p > 0.10$). Our aggregate results are hence driven by the more densely populated areas.

We find that Red zone districts with an above median share of services employment experienced 0.088 σ ($p < 0.01$) lower and Orange zones 0.017 σ lower ($p < 0.05$) nighttime light intensity compared with Green zones. In contrast, differences in nighttime light intensity in districts with below median services employment were quantitatively smaller both for Red zone districts (0.017 σ, $p < 0.05$) as well as for Orange zone districts (0.0016 σ, $p > 0.10$).

Table 7 also reports the influence of the population age structure on the impact of COVID-19 containment policies. Nighttime light intensity in the sub-sample of older districts were 0.061 σ ($p < 0.01$) lower in Red zone districts, and 0.013 σ ($p > 0.10$) lower in Orange zone districts than Green zone districts. The nighttime light intensity gaps in the relatively younger sub-sample was lower in both Red zone (−0.031 σ, $p < 0.01$) and Orange zone districts (−0.0074 σ, $p < 0.10$). This indicates that the marginal impact of the restrictions was relatively greater in districts with above median average age.

Finally, nighttime light intensity gaps were greater (Red zone: −0.094 σ, $p < 0.01$; Orange zone: −0.028 σ, $p > 0.10$) in the sub-sample of districts with above median bank credit per capita, compared with the sub sample of districts with below median per capita credit (Red zone: −0.016 σ, $p < 0.01$; Orange zone: −0.0055 σ, $p < 0.10$). These results point to greater economic contraction when districts with higher access to finance faced disruption in business activity.

Taken together, we find that the Red and Orange zone districts in more developed areas (greater population density, with older residents, more services employment, and higher bank credit) experienced relatively greater nightlight intensity gaps during the differential lockdown period.

Table A1
Effect of zone classification on change in nightlight intensity (Extended).

	(1)
Red zone district*May	-0.070 * *
	(0.027)
Orange zone district*May	-0.0071
	(0.007)
Red zone district*June	-0.070 * **
	(0.025)
Orange zone district*June	-0.0082 *
	(0.005)
Red zone district*July	-0.058 * **
	(0.019)
Orange zone district*July	-0.0077
	(0.005)
Red zone district*Aug	-0.070 * **
	(0.014)
Orange zone district*Aug	-0.013 * *
	(0.005)
Red zone district*Sep	-0.065 * *
	(0.026)
Orange zone district*Sep	-0.0065
	(0.007)
Red zone district*Oct	-0.047
	(0.038)
Orange zone district*Oct	0.0050
	(0.010)
Lagged per-capita COVID Infections	0.0052
	(0.042)
Mean of dependent variable	6.76
Std. dev. of dependent variable	26.32
All controls	Yes
No. of Observations	4744
R Squared	0.994

Notes: The unit of observation is a district-month. Data from 733 districts over eight months. Asterisks denote significance: $*p < 0.10$, $* * p < 0.05$, $* ** p < 0.01$. Standard errors clustered at state level.

Table A2
Pre-period night-time light intensity as baseline.

	(1)	(2)
	Above median	Below median
Red zone district*Post	-0.12 * **	-0.0029 * *
	(0.032)	(0.001)
Orange zone district*Post	-0.029 * **	0.0041 * **
	(0.010)	(0.001)
Lagged per-capita COVID Infections	Yes	Yes
Previous year nightlights	Yes	Yes
District fixed effects	Yes	Yes
State*Months(2020) fixed effects	Yes	Yes
No. of Observations	2511	2713
R Squared	0.996	0.994

Notes: The unit of observation is a district-month. Asterisks denote significance: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Standard errors clustered at state level.

5.5. MNREGA employment and migration sub-sample analysis

Table 8 reports how the impact of the zone classifications on nighttime light intensity might vary by the fraction of the population employed in MNREGA and by the share of the population who are inter-district migrants. The reported coefficients are mostly insignificant, suggesting that the MNREGA employment shares do not have a meaningful influence on the impact of zone classifications on economic activity. Similarly, pre-pandemic migration levels did not significantly influence how the zone-wise containment strategy impacted nighttime lights.

Table A3
Effect of zone classification on change in nightlight intensity (Pairwise comparison).

	(1)	(2)	(3)	(4)
Red zone district*Post	-0.059 * **			
	(0.020)			
Orange zone district*Post		0.021 * *		
		(0.010)		
Red zone district*May			-0.031	
			(0.022)	
Red zone district*June			-0.030 *	
			(0.017)	
Red zone district*July			-0.018 * *	
			(0.009)	
Orange zone district*May				0.010
				(0.007)
Orange zone district*June				0.0090
				(0.009)
Orange zone district*July				0.0042
				(0.004)
Lagged per-capita COVID Infections	0.0047	0.0013	0.0034	0.0012
	(0.043)	(0.043)	(0.043)	(0.043)
Mean of dependent variable	6.76	6.76	6.76	6.76
Std. dev. of dependent variable	26.32	26.32	26.32	26.32
All controls?	Yes	Yes	Yes	Yes
No. of Observations	4742	4742	4742	4742
R Squared	0.994	0.994	0.994	0.994

Notes: The unit of observation is a district-month. Data from 733 districts over five months. Asterisks denote significance: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Standard errors clustered at state level.

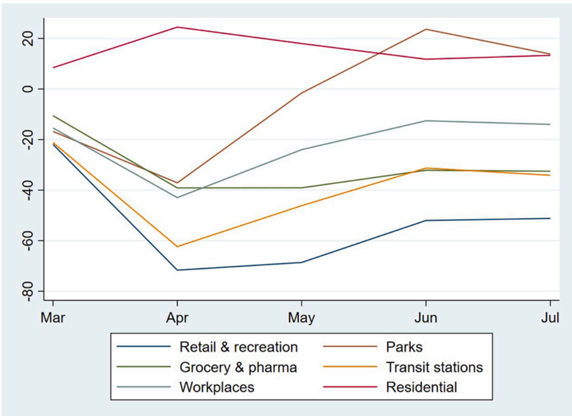

Fig. A1. Google mobility trends by destination, 2020.

6. Conclusion

Government intervention is critical to mitigate the impact of pandemics. In this paper, we focused on the economic cost of centralized containment measures by examining the impact of spatially heterogeneous policies on nighttime light intensity. Districts with the most severe restrictions witnessed 9.1 % lower nighttime light intensity compared with those with the least restrictions in May to July 2020. The decrease in districts with intermediate restrictions was 1.6 % lower compared with those with the least restrictions. Lower household income and consumption corroborate these findings. These estimates point to large short-run costs of containment policies and especially the mobility restrictions that differentiated Red zone districts from Orange and Green zone districts.

The main results reported in nighttime light intensity cannot be directly converted to GDP. Instead, the conversion requires a properly estimated elasticity between nighttime light intensity and economic activity applicable to our setting and estimation strategy. Hu and Yao (2022) provide such an elasticity based annual DMSP-OLS data, a global sample, and a new estimation strategy overcoming previous challenges. Using a similar but simpler approach, Beyer et al. (2022) provide an elasticity based on quarterly VIIRS data for a sample of emerging markets and developing economies. A one percent decline in nighttime light intensity is associated with a 0.73 % decline in economic activity using the former elasticity, and with 0.64 % using the latter. Using these elasticities implies that Red zone districts had between 5.8 % and 6.6 % lower GDP than Green zone districts from May to July 2020. Due to the uncertainty about the actual elasticity (Bluhm & McCord, 2022) and the possibility that the elasticity varies across Indian districts, this conversion needs to be interpreted carefully, particularly during COVID-19. In addition, the COVID-19 pandemic and related containment policies have added uncertainty to the conversion. Analyzing potential changes to the elasticity would be interesting, but is beyond the scope of this paper.

Our findings should be read with two additional caveats. First, the estimates of the impact of government containment policies on economic activity in this context might be different in other economic and social contexts. The nature of government containment policies could also vary, and different types or intensity of policies could produce qualitatively different aggregate responses. Second, we do not develop a comprehensive model of epidemics and pandemics, associated containment policies, and the corresponding economic response. Absent such a model, policy counterfactuals such as more targeted containment or subsidies for private initiatives are difficult to estimate.

Nonetheless, our work points to the cost of centralized government containment policies, much debated around the world for the COVID-19 pandemic, on aggregate economic outcomes. We hope that the results will guide future research and policy analysis.

Declarations of Competing interest

None.

Data Availability

Data will be made available on request.

Acknowledgements

We have acknowledged a grant support received by IIM Ahemdabad, IIMA/R&P/20-21/SMP-1/3.

Appendix

See in Table A1–A3.
See in Fig. A1.

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