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The COVID-19 pandemic has disrupted economic activity in India. Adjusting policies to contain transmission while mitigating the economic impact requires an assessment of the economic situation in near real-time and at high spatial granularity. This paper shows that daily electricity consumption and monthly nighttime light intensity can proxy for economic activity in India. Energy consumption is compared with the predictions of a consumption model that explains 90 percent of the variation in normal times. Energy consumption declined strongly after a national lockdown was implemented on March 25, 2020 and remained a quarter below normal levels throughout April. It recovered subsequently, but electricity consumption remained lower even in September. Not all states and union territories have been affected equally. While electricity consumption halved in some, it declined very little in others. Part of the heterogeneity is explained by the prevalence of COVID-19 infections, the share of manufacturing, and return migration. During the national lockdown, higher COVID-19 infection rates at the district level were associated with larger declines in nighttime light intensity. Without effectively reducing the risk of a COVID-19 infection, voluntary reductions of mobility will hence prevent a return to full economic potential even when restrictions are relaxed. Together, daily electricity consumption and nighttime light intensity allow monitoring economic activity in near real-time and high spatial granularity.

1. Introduction

The Coronavirus Disease 2019 (COVID-19) pandemic has disrupted economic activity in India. Until mid-March 2020, the economy was mainly hit by disruptions in cross-border connections. For example, tourism arrivals in India declined due to strict travel restrictions and some value chains were interrupted, especially with China. When COVID-19 started to spread in India through domestic contagion, the Indian authorities enacted a series of measures to combat the pandemic, including a strict national lockdown from March 25 to May 4 that strongly disrupted economic activity across the country. When restrictions were step-wise eased from May onward, economic activity slowly recovered, but it remained below pre-COVID levels in September. Shutdowns and other non-pharmaceutical interventions to contain the spread of COVID-19 have high economic costs and consequently tend to be accompanied by policy responses to mitigate their economic impact (Gourinchas, 2020). In line, both the Reserve Bank of India and the Government of India announced measures to assist individuals and companies that were negatively affected. Adjusting containment measures and policy responses to mitigate their economic impact requires an assessment of the magnitude of the economic situation in near real-time. In addition, since the impact can vary at different locations, an assessment at high spatial granularity is needed.

Indicators traditionally used to monitor the economic situation are available only with substantial lags and often at the national level only, and hence provide little insight into the immediate effect of strong and sudden policy measures like a national lockdown. In response to such problems, economists have suggested different proxies that are available at a higher frequency and with shorter publication lags, as well as at a higher spatial granularity. Two of these are electricity consumption and night light intensity.
Electricity is an input to activities throughout the economy, from industrial production to commerce and household activity, so changes in consumption reveal information about these activities in real-time (Cicala, 2020a; Cicala, 2020b). Similarly, nighttime light intensity contains information about economic activity at high spatial granularity. Such proxies have become especially important during the COVID-19 pandemic, as it makes data collection through surveys, which are fundamental for the traditional estimation of gross value added, more difficult. In line, the Central Statistical Office noted that data collection challenges related to India’s national lockdown will likely result in revisions to its growth estimate for the first half of this year.

Both electricity consumption and nighttime light intensity closely track economic activity and have been employed to improve national account estimates of GDP (e.g., Henderson, Squires, Storeygard, & Weil, 2018; Chen, Chen, Hsieh, & Song, 2019). Both proxies have also been used to assess the economic impact of major policy measures. Nighttime light intensity, for example, allowed assessing the impact of India’s demonetization in November 2016 (Beyer, Chhabra, Galdo, & Rama, 2018; Chodorow-Reich, Gopinath, Mishra, & Narayanan, 2020). It is also used to approximate economic activity at the sub-national level, including in India (Gibson, Datt, Murgai, & Ravallion, 2017; Prakash, Shukla, Bhowmick, & Beyer, 2019; Chanda & Kabiraj, 2020). Electricity consumption has also been shown to have closely tracked economic activity in the United States during the global financial crisis (Cicala, 2020a). And it has been employed for an assessment of the economic impact of the COVID-19 pandemic in the European Union (Cicala, 2020b).

In this paper, we first confirm a meaningful relationship between electricity consumption, nighttime light intensity, and economic activity in India. We then propose a new real-time measure of daily economic activity in India at the country and state levels based on daily electricity consumption. We estimate an electricity consumption model based on the day of the week, the week of the year, the temperature, and holidays that explains 90 percent of the variation in India’s electricity consumption. Comparing the actual electricity consumption in 2020 to the one predicted by the model allows us, first, to quantify the economic costs of the COVID-19 pandemic and the national lockdown implemented on March 25, 2020 and, second, to understand different impacts between states. In addition, we use night light intensity to gauge the impacts at the district and city level and to explore their local drivers.

We find a strong impact of the national lockdown on India’s electricity consumption. It dropped on average 28.5 percent in the week after the implementation of the lockdown and was on average still 25.8 percent below normal throughout April. When some restrictions were eased in May, electricity consumption recovered, but it remained 14 percent below normal levels. Since then, the monthly averages fluctuate around 6 and 9 percent below normal, suggesting a lingering drag on the economy. Not all Indian States and Union territories have been affected equally. While electricity consumption halved in some, it declined very little in others. During the national lockdown, when restrictions were uniform across the country, districts with higher rates of COVID-19 infections saw larger declines in nighttime light activity, suggesting additional impacts from voluntary behavioral changes when risks of an infection increase. In nearly all large Indian cities nighttime light intensity was lower between March and September 2020 than it was a year before. In Delhi and Mumbai, for example, it declined on average by around 10 percent.

The rest of the paper is structured as follows. In Section 2, we describe the measures implemented by the Indian authorities and discuss their impact on mobility. The data is presented in Section 3 and the relationship between electricity consumption, nighttime light intensity, and economic activity in Section 4. In Section 5, we present the electricity consumption model and examine the impact of the national lockdown at the country level. In Section 6, we compare the impact across states and in Section 7 we examine the change in nighttime light intensity at the district and city level. Section 8 discusses the wider economic implications of our results and concludes.

2. Measures by Indian authorities to contain the pandemic

On March 22, 2020, India observed a 14-hour long curfew to combat the COVID-19 pandemic and assess the country’s ability to implement containment measures. The government already ordered a lockdown in 75 districts with COVID-19 cases, as well as in all major cities. Further, on March 24, the government ordered a nationwide lockdown for 21 days, effective from March 25 until April 14, affecting the entire 1.3 billion population of India.4

After the enactment of the national lockdown, nearly all public offices were closed, and public services suspended.5 In addition, nearly all commercial and private establishments had to be closed except for essential businesses like banks and insurance offices, internet and printing services, and shops selling food (which were encouraged to provide home delivery). Industrial establishments were closed, and exceptions were only made for manufacturing units producing essential commodities. Such units required permission from the state governments to operate. Moreover, all but essential transport services — whether by air, rail, or roadways — were suspended and so were hospitality services. Finally, all educational institutions were closed as well. The lockdown, intended to end on April 14, was initially extended until May 3. However, in areas where no new cases of COVID-19 arose until then, the government partially released restrictions from April 20 onwards. Agricultural activities were allowed again along with public works under the Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA). In addition, industries operating in rural areas, Special Economic Zones (SEZs), industrial estates and industrial townships could operate again, if they had arrangements for workers to stay on the premises. And construction activity in rural areas could continue as well.

On May 1, the Ministry of Home Affairs extended the lockdown for a period of two weeks from May 4 until May 17. However, many restrictions were relaxed or lifted. For example, the central government permitted again the inter-state movement of migrant workers, pilgrims, tourists and others that were stranded during the nationwide lockdown and the Ministry of Railways began to operate special trains with social distancing measures to facilitate movements. Based on risk profiling, India’s authorities divided districts into green, orange, and red zones. The profiling depended, among other things, on the amount of COVID-19 cases, recovery rates, and the extent of testing and surveillance. As of April 30, there were 130 red zone districts, 284 orange zone districts and

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1. While real GDP fell 4.3 percent from peak to trough, weather-adjusted electricity consumption fell around 5 percent (Cicala, 2020a).
2. Energy consumption at the beginning of April 2020 was down by around 10 percent with large differences between countries due to varying impacts of the pandemic and containment measures (Cicala, 2020b).
3. Such a behavior is in line with evidence provided by Maloney and Taskin (2020).
4. MHA order No. 40–3/2020-DM-I(A).
5. Exceptions were given to several essential services like police forces and public utilities.
319 green zone districts. In green zones, restrictions were eased strongly, and most economic activity could resume. In addition, all goods traffic was permitted again, and individuals could move freely again for non-essential activities from 7 AM to 7 PM. However, air, rail, metro and inter-state road travel remained prohibited and educational institutions, hospitality services and places of large public gatherings (such as cinemas and malls) remained closed. In orange zones, restrictions were also relaxed, but some related to mobility remained. In red zones, industrial establishments in urban areas remained prohibited from operating, except for those in Special Economic Zones and industrial estates/townships with access control. And while private offices could operate again even in red zones, a maximum of a third of the employees could be physically present in the office at the same time. Finally, construction remained mostly prohibited in red zones. From May 17 to May 30, the lockdown was again extended but new relaxations were announced. For the first time, states were given authority to determine the specifics of the lockdown. In addition, two new zones (containment and buffer) were added to the red, orange, and green zones.

Over the next three months, the restrictions were gradually unlocked. In June and July, lockdown restrictions were only imposed in containment zones, while most activities were permitted in other zones in a phased manner. In some states authorities continued to impose their own restrictions. In August, the central government removed the night curfews. At the same time, Maharashtra and Tamil Nadu imposed a strict lockdown for the whole month amid rising COVID-19 infections. In September, the Metro Rail was allowed to reopen gradually and marriage gatherings of up to 50 people, as well as funeral ceremonies with up to 20 people were permitted again.

The national lockdown enacted by the Indian authorities was successful in limiting mobility. Fig. (1a) uses the Google Mobility Reports for India (Google 2020) to show how mobility declined after the lockdown was enacted. This data is based on tracking smartphones, which in India have a coverage of 27.7 percent (Newzoo, 2018). While this means that not everyone is tracked, the mobility data is still based on a very large sample and can hence be used to assess declines in mobility (Maloney & Taskin, 2020). The noticeable drop in workplace presence around March 10 was due to Holi. Shortly before the national lockdown was announced on March 24, the presence at workplaces had already declined by over 10 percent and by a similar magnitude in retail and recreation locations. When the lockdown was implemented, the presence at the workplace dropped immediately by half and a few days later by an additional 20 percent. At the same time, residential places were frequented more often, confirming that Indians indeed stayed at home more due to the lockdown. From mid-April to end-May, presence at workplaces slowly recovered. Since then, however, it is relatively stable and still around a third below the pre-COVID baseline.

The economic impact of the lockdown was immediate. The weekly unemployment rate reported by the Centre for Monitoring Indian Economy (CMIE 2020) increased from 8.4 percent in the week before the lockdown to 23.4 percent in the week thereafter (Fig. 1b). Unemployment rates did not increase further after that and hovered around 25 percent until the end of May. The sudden increase in unemployment is evidence of a severe and sustained negative economic impact, which also manifests itself in other data. For example, cargo traffic and rail freight declined, oil demand collapsed, and India’s Purchase Manager Index dropped to an all-time low in April. The unemployment rate fell quickly afterward, but partly due to a strong decline in labor force participation. An excellent discussion of the economic impact of COVID-19 on India’s economy is provided by Dev and Sengupta (2020) and World Bank (2020).

3. Data

3.1. Daily electricity consumption

We observe daily electricity consumption from April 1, 2013 to September 30, 2020. The data is measured and collected from the Power System Operation Corporation Limited (POSOCO), which is a government-owned enterprise under the Ministry of Power. It is responsible for ensuring the integrated and reliable operation of India’s grid. POSOCO makes available daily reports of electricity consumption with a one-day delay. We download the daily documents and scrape the electricity information to build our electricity consumption database for India. While the total electricity consumption in these documents does not differentiate between different uses (residential, commercial, etc.), it does breakdown the electricity consumption of the different states. This will later allow us to track the specific impact of the lockdown on the different states.

Fig. (2) shows India’s daily electricity consumption from April 1, 2013 to September 30, 2020. A couple of features are noticeable. First, until the end of 2019, there is a clear upward trend with electricity consumption on average growing 4.3 percent each year. Second, there is a clear seasonality in the data with electricity consumption being higher between May and September than at the beginning and end of the year. Third, there was a noticeable decline already at the end of 2019, long before the COVID-19 pandemic disrupted economic activity in India. Fourth, around the national lockdown announced on March 24, electricity consumption dropped strongly. Fifth, at the end of May electricity consumption started recovering.

3.2. Nighttime light intensity

The nighttime light data are extracted from the VIIRS-DNB Cloud Free Monthly Composites (version 1) made available by the Earth Observation Group at the National Geophysical Data Center of the National Oceanic and Atmospheric Administration (NOAA) and cover the period from April 2012 to August 2020. The data from the VIIRS satellites have a resolution of 15-arc seconds (0.5 km x 0.5 km tiles near the equator) and, compared to a previous nighttime light product known as DMSP-OLS (Elvidge, Baugh, Zhizhin, & Hsu, 2013), have a wider radiometric detection range and onboard calibration. These features help to correct for saturation as well as blooming effects and ensure better time comparability. However, the raw data needs some cleaning to deal with background noise (for example, temporary lights). In this paper, we reduce the background noise with two procedures similar to Beyer et al. (2018). The first approach takes advantage of the 2015 annual composite of stable VIIRS nighttime light to identify a background noise mask (Elvidge, Baugh, Zhizhin, & Ghosh, 2017). Only cells lying outside this background noise mask are treated as stable lights, while those inside the mask are recoded with value zero, corresponding to no light. The second approach follows Elvidge et al. (2017) and translates their cleaning algorithm based on defining a background noise mask with a clustering method using daily data, to convert daily to monthly data. While we lose some accuracy with this approach in 2015, it takes into account all later observations for creating the best possible mask for our period of analysis. And for 2015, the two approaches result in very similar light data. Clusters are identified by removing outlier observations, averaging cells over time, and clustering areas based on their nighttime light

6 The figure is in mega units. A mega unit is one million units of electricity, where one unit is equal to one kilowatt hour.

7 This decline at the end of 2019 has been linked to weakening GDP growth and was reflected in the weakness of the Industrial Production Index at the end of 2019.
intensity. In practice, this approach amounts to setting to zero cells that are distant from homogeneous bright cores. We present results based on data cleaned with the second method, but our results are robust to both cleaning methods. For this paper, cleaned monthly data are aggregated to the district and city levels and standardized by area. Nighttime light is measured in Nanowatts/cm²/steradian.

### 3.3. Other variables

Data on quarterly economic activity measured as gross value added (GVA) is from the Central Statistics Office. Average daily temperature data is collected from the Global Summary of the Day database archived by the National Climatic Data Center. We generate an India aggregate by weighting the daily temperatures recorded in Chennai, Delhi, Kolkata, and Mumbai by population.\(^8\)

Data on Indian holidays is from different online sources. The information about registered COVID-19 infections at the state and district level is from Covindia (2020) and the data on previous short-run immigration and outmigration at the state and district level from the Development Data Lab, 2020. We assess changes in mobility at a high spatial granularity using “Facebook Data For Good” (https://dataforgood.fb.com/), which relies on daily information of Facebook users to produce movement range maps. These maps measure the average number of Bing tiles (0.6 km x 0.6 km) in which a user was present during a 24-h period compared to pre-COVID levels. Finally, data on literacy and the share of employment in manufacturing and services is from the South Asia Spatial Database (Li, Rama, Galdo, and Pinto, 2015).

### 4. Electricity, nighttime lights, and economic activity

Intuitively, electricity consumption and economic activity are closely related since most economic activity needs electricity. Plenty of studies analyze the relationship of the two over longer periods, often with a focus on the direction of causality. Chen, Kuo, and Chen, 2007, for example, study 10 newly industrializing and developing Asian countries and find a bi-directional long-run causality between real GDP and electricity consumption and a uni-directional short-run causality running from economic growth to electricity consumption. Ferguson, Wilkinson, and Hill (2000) find that the correlation between electricity consumption and GDP is close to one. In Appendix A, we use a sample of 123 countries to update these correlations between economic growth and electricity consumption. We find that electricity consumption increased by 0.95 percent for each percent additional economic activity. For India, electricity increased slightly above 1 percent. Similarly, data on nighttime lights has also shown to be able to track economic activity. Henderson, Storey, and Weil (2012) develop a statistical framework to use satellite data on night lights to augment official income growth measures. They show that for countries with poor national income accounts, the optimal estimate of growth is a composite with roughly equal weights on conventionally measured growth and growth predicted from lights.
In this section, we explore the usefulness of electricity consumption and satellite night light as proxies for economic activity in India. To do so, we estimate the following quarterly (t) model:

\[ \log \text{GVA}_t = \beta_1 \log \text{electricity}_t + \beta_2 \log \text{light}_t + \text{trend}_t + q_t + \epsilon_t \] (1)

where the log of GVA is regressed on the log of electricity consumption and the log of nighttime light intensity. In addition, we include a trend and quarter fixed effects, \( q_t \), to control for the intra-year seasonality of the data. We aggregate the electricity consumption and nighttime light data to quarterly frequency to match the frequency of the GVA data and estimate the model for the period from the second quarter of 2013 to the first quarter of 2020.9

Table (1) shows the results of regressing GVA on electricity consumption and nighttime light intensity. Columns 1 and 2 show that electricity consumption and GVA move together closely both in levels and as deviations around a trend. In both cases the relationship is statistically significant at the one percent level. For each percentage point increase in electricity consumption, GVA grew 1.3 percentage points. This relationship is very similar to the one-to-one relationship Cicala (2020a) finds for the United States, including during the global financial crisis, and even closer to the elasticity of 1.4 that Chen, Igan, Pierri, and Presbitero (2020) find in Europe.10 Columns 3 and 4 replicate the regressions for nighttime light, showing that it also follows the evolution of GVA very closely.11 However, GVA shares more of its variation with electricity consumption than with nighttime light intensity, as reflected in a lower R2 of the latter regression. This could be due to larger measurement errors in nighttime lights compared to electricity consumption. Since both move together with economic activity, they are related. Consequently, nighttime light turns out not to be significant when we include both electricity and light in the same regression (column 5). In columns 6 and 7, we demean the data by regressing GVA, electricity consumption and nighttime lights on year and quarter fixed effects. We then regress the residuals of GVA on the residuals of electricity and lights. This allows us to understand the relationships between the quarterly fluctuations of GVA, electricity and lights. Columns 6 and 7 confirm that both electricity and lights are able to track quarterly fluctuations, with both coefficients turning out to be significant at the one percent level. Finally, we regress electricity on lights to examine how strongly they are correlated in India. Columns 8 and 9 show a strong relationship both in levels and around a common trend. A 1 percent increase in light intensity is associated with a 1.2 percent increase in electricity consumption.

Electricity consumption seems to have a somewhat stronger relationship, especially when both variables are combined. We, therefore, rely on electricity consumption to track economic activity at the country and state level, for which electricity data is available, and rely on nighttime light intensity for districts and cities.

5. The impact of COVID-19 on electricity consumption in India

5.1. Modeling daily electricity consumption

To understand the magnitude of the decline of electricity consumption due to the lockdown, we need to control for factors affecting electricity consumption like the season and the weather.

We hence estimate the following model of electricity consumption using daily (t) data:

\[ \log \text{Electricity}_t = \tau_t + DW_t + \text{Holiday}_t + \beta_4 \text{Cooling}_t + \beta_5 \text{Heating}_t + \beta_6 \text{Trend}_t + \epsilon_t \] (2)

The explanatory variables are a set of fixed effects that control for the day of the week, \( DW_t \), the week of the year, \( \text{Holiday}_t \), and holidays, \( H_t \). We include two variables that control for the daily temperature. We control for the temperature degrees above and below 22.8 °C, such that \( \text{Cooling}_t = \max(\text{temp}_t - 22.8, 0) \) and \( \text{Heating}_t = \max(22.8 - \text{temp}_t, 0) \), respectively. This temperature is associated with the minimum electricity consumption in India, which we confirmed by regressing log electricity consumption on temperature and a quadratic term of temperature suggesting that electricity consumption increases above and below this temperature (see Appendix (B)). The variables of interest are the set of dummy variables \( \tau_t \) that indicate each day in 2020 until the last day of the sample. These variables capture how daily consumption in 2020 differs from consumption in previous years, conditional on the temperature and holidays.12 As discussed above, electricity consumption in India grew over time and hence we include a linear time trend (\( \text{Trend}_t \)). This model is estimated separately for India and for all Indian states and Union territories.

Table (2) presents the estimation results for different versions of the electricity consumption model. Until December 2019, the upward trend in electricity consumption alone explains over 70 percent of the variation (column 1). Fig. (2) shows that there is some seasonality in electricity consumption, which we control for by including the week of the year fixed effects (column 2). As an alternative to the week of the year, we also included the month. Since it resulted in a slightly lower fit of the model, we use the week of the year in the baseline estimation. Next, we also include the days of the week to account for within-week variation, which results for example from different activities over weekends (column 3). Taking care of the trend and the seasonality already explains over 80 percent of the variation in electricity consumption (columns 2 to 3). Finally, we add holidays and the two variables for cooling and heating periods, as described above. On holidays, the electricity consumption tends to be 2.2 percent lower than on usual days and the effect is statistically significant at the one percent level. Of the two temperature variables, only the one for cooling is significant at the one percent level. If the temperature exceeds 22.8 °C, electricity consumption increases on average by 2.1 percent for every °C increase in temperature (column 4). With almost 90 percent, the variation explained by our preferred specification is very high and hence it is well suited to analyze deviations from its predictions. Column 5 includes the data for all the days in 2020 and daily fixed effects during 2020. Since the latter result in a one-to-one fit in 2020, the explanatory power increases slightly by 0.08.

5.2. Changes in Indian electricity consumption and nighttime light intensity

Fig. (3) plots the estimated daily deviation of actual electricity consumption from the model prediction from the beginning of 2020 until September 30, and the dashed lines show the 95 percent confidence interval.13 From the beginning of the year, with the

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9 The beginning of the sample coincides with the availability of the electricity daily data.
10 It is also in line with other estimates in the literature (Stern 2018).
11 With 1.5, our coefficient is much larger than the one Henderson et al. (2012) find in a global annual panel regression using the DMSP-OLS data (their Table 2, column 1). One reason could be that VIIRS data allows for greater comparability over time as explained in Section 3.2.
12 As an alternative, one can also estimate the model until the end of December 2019 and compute the (out-of-sample) prediction errors. These are identical to the daily fixed effects.
13 These are the daily dummies for 2020 that we include in the estimation. They absorb the variation unexplained by the model and are identical to (out-of-sample) prediction errors. Using instead the latter and identifying outliers based on robust standardized residuals, as suggested by (Kirachi 2013), results in the same days with below normal electricity consumption (see Appendix C).
exception of Holi, the deviations hover around the model’s prediction and are not statistically significantly different from them until Sunday, March 22.\textsuperscript{14} That day, however, the national curfew caused a drop in electricity consumption to 15 percent below predicted levels, and that drop is statistically significant at the one percent level. On Monday, March 23, a day before the national lockdown was announced, electricity consumption was 16 percent lower than predicted and it declined further to \( \sqrt{C_0} \) percent on Tuesday, the day the national lockdown was announced. After the lockdown was enacted, electricity consumption dropped further and on March 27 and 28, electricity consumption troughed at more than 30 percent below normal levels. Subsequently, it started to recover slightly, and deviations were around \( \sqrt{C_0} \) percent throughout April. Following the different relaxations of the lockdown, electricity consumption increased again in May. Apart from a few exceptional days, the deviations remained statistically significantly different from the model prediction at the one percent level until the end of June. Since then, electricity consumption is still below normal, though most deviations are within the confidence interval. Following the large drop in April, one may have expected a overshoot of electricity consumption subsequently to compensate for foregone activity dur-

\textsuperscript{14} While not statistically significant, actual electricity consumption fell below the prediction already from mid-February onwards, which may indicate first economic disruptions due to broken cross-border connections.
ing the lockdown. Instead, electricity consumption remained on average 6.3 below normal in July, 8.1 percent below normal in August, and 5.9 percent below normal in September. The changes in electricity consumption follow closely the Oxford Stringency Index of Government Interventions used for international comparisons of containment measures. We plot the change in electricity consumption against the index in the Appendix (A.3).

6. Heterogeneity across Indian states and Union territories

The decline in electricity consumption after the lockdown was not uniform across Indian states. Table (3) shows the deviation from the model prediction for March to September by running the model in Eq. (2) at the state level. The average deviations from normal levels over all seven months vary from below –45 percent to just below zero. The drops are the largest in the Union territories of DNH and DD, where electricity consumption was more than 40 percent below the model’s prediction. In Goa, Arunachal Pradesh and Gujrat, consumption was on average more than 20 percent below. At the other end, electricity consumption declined on average very little in Jharkhand and Rajasthan. Yet, both experienced strong temporary declines as well. In Rajasthan, electricity consumption was 14 percent below the model’s prediction in March and 18 percent below in April. In September, electricity consumption was still more than 10 percent below the prediction in around a third of the States and Union territories.

In order to understand some of the heterogeneity in electricity changes across states, we first analyze the effect of the number of registered COVID-19 cases (per capita). For two reasons we expect the latter to be positively correlated with the decline in electricity consumption. First, a higher number of cases makes it more likely that people voluntarily reduce mobility (Maloney & Taskin, 2020) and, second, a higher number of registered cases makes it more likely that state governments enact own measures and enact national ones more strictly. There is indeed a positive correlation between the average decline in electricity consumption between March and September and the number of COVID-19 infections per capita recorded by the end of September (Table (4), column 1). The effect becomes statistically significant at the ten percent level after dropping the three states and Union Territories with the lowest number of infections. A doubling of the COVID-19 infections results on average in an additional drop of electricity by 1.9 percent (Table (4), column 2). Next, we control for different socio-economic characteristics. The impact of COVID-19 infections remains nearly unchanged and two additional findings emerge (Table (4), column 3). First, states with a larger manufacturing sector experienced much larger declines in electricity consumption, in line with manufacturing being more energy intensive than other sectors. Second, in line with the large backward migration after the enactment of the national lockdown, electricity consumption declined stronger in states with higher previous in-migration and less in states with higher previous out-migration. The former impact is statistically significant at the 5 percent level, the latter is not.

7. Shedding light on developments below the state-level

7.1. District-level changes in nighttime light intensity

In absence of high-frequency official statistics at low levels of spatial disaggregation, data collected from outer space has become a reliable alternative. The use of satellite-derived data has made substantive inroads in the recent economic literature (Burchfield, Overman, Puga, & Turner, 2006; Donaldson & Storeygard, 2016). Nighttime light data has been extensively used in a wide array of economic studies ranging from monitoring economic activity (Henderson et al., 2012; Keola, Andersson, & Hall, 2015; Henderson et al., 2018) to assessing regional economic convergence (Chanda & Kabiraj, 2020) to identifying urban spaces and markets (Gibson et al., 2017; Baragwanath, Goldblatt, Hanson, & Khandelwal, 2019; Ch, Martin, & Vargas,2020; Ch et al., 2020; Galdo, Li, & Rama, 2020) to predicting welfare (Jean et al., 2016), and to assessing the quality of national account statistics (Pinkovskiy & Sala-i-Martin, 2016; Morris & Zhang, 2019), among others. More recently, nighttime light data has been used to evaluate the economic impact of India’s demonetization in November 2016 (Beyer et al., 2018; Chodorow-Reich et al., 2020). We confirm that changes in electricity consumption and nighttime light intensity are strongly related at the state level in Appendix (D).

The COVID-19 pandemic has dimmed India since March (Fig. (4)), when the sum of made-made lights emitted by India was 5.6 percent lower than a year earlier. It was 6.8 percent lower in April, 10.4 percent lower in May, and 8.9 percent lower in June. Subsequently, it recovered, but it was still below levels recorded in the years before in July and August. Changes in nighttime light growth suggest an even larger impact of the COVID-19 pandemic as shown by the line. In May, for example, growth in nighttime lights was 16.5 percentage points lower compared to the average growth in May over the last three years.

The impact of the COVID-19 pandemic has spread across districts in India, but some districts are affected more than others. Despite limited testing especially in rural areas, nearly all districts in India have confirmed COVID-19 infections as of end-August 2020 (Fig. (5a)). While 8 percent of districts have less than 50 cases per 100,000 people, roughly 30 percent of districts have more than 240 cases. Mobility has declined in nearly all Indian districts between March and August (Fig. (5b)). In around a third of the districts, the average decline was between 20 and 30 percent, for half of them it declined between 30 and 35 percent, and for 15 percent it declined even more. Average nighttime light intensity declined in most districts as well (Fig. (5c)). In three quarters of districts, the average nighttime light intensity between March and August was lower in absolute terms compared to last year.

7.2. The impact of COVID-19 infections during the national lockdown

With more registered cases of COVID-19, the perceived local infection risk rises and in response risk-aversion may prompt people to either follow the containment measures more strictly or voluntarily change their behavior beyond the measures. For example, they may decide to reduce their mobility completely and shelter at home. One may hence expect the economic impact in districts with a higher prevalence of COVID-19 to be larger, even if the restrictions are the same. To test this hypothesis, one can study Indian districts during the national lockdown, when restrictions were uniform across the country. We hence examine drivers of the observed heterogeneity across districts in the change of nighttime lights intensity in April 2020. Moreover, in order to back the hypothesis that the additional loss in economic activity is related to additional reductions of mobility, we analyze the impact of these drivers on district-level mobility.

As expected, Columns 1 to 3 in Table (5) show that there is a large negative and statistically strongly significant correlation between the number of COVID-19 cases per capita and the change in nighttime light intensity. Districts with more COVID-19 cases per capita turned darker than others, with a doubling of the cases

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15 For this we fit a separate model for each state.

16 Districts from Arunachal Pradesh are excluded from the analysis.
resulting in a 2.5 percentage points larger decline of nighttime light intensity. Columns 4 to 6 in Table (5) study mobility as the channel that may explain the observed reductions in nighttime light intensity associated with the COVID-19 pandemic. Columns 4 to 6 report a negative correlation between the number of COVID-19 cases per capita and mobility that is statistically significant at the 1 percent level. The full specification (column 6) suggests that doubling the number of COVID-19 cases per capita reduces mobility by 1.7 percentage points. Larger shares of manufacturing and services are associated with larger declines in mobility, presumably because agriculture was less impacted by the lockdown.

### Table 3
Declines in electricity consumption across India, percent.

| Rank | Average | March | April | May | June | July | August | September | R2 |
|------|---------|-------|-------|-----|------|------|--------|-----------|----|
| DNH  | -44.71  | -36.49 | -85.94 | -58.65 | -39.29 | -26.73 | -21.18 | -9.34     | 0.79|
| DD   | -42.03  | -37   | -71.58 | -45.45 | -38   | -33.83 | -26.29 | -12.37    | 0.65|
| Goa  | -26.52  | -23.66 | -38   | -18.45 | -26.21 | -25.71 | -27.09 | -24.35    | 0.74|
| DVC  | -23.43  | -23.05 | -56.74 | -31.48 | -13.93 | -9.24  | -6.11  | -4.4       | 0.75|
| Arunachal Pradesh | -23.20 | -16.05 | -32.77 | -23.89 | -16.05 | -23.51 | -26.95 | -19.43    | 0.64|
| Gujarat | -21.37 | -15.04 | -33.57 | -21.57 | -21.49 | -14.1  | -22.43 | -17.47    | 0.68|
| Uttarakhand | -19.01 | -23.51 | -43.84 | -28.32 | -8.7   | -5.07  | -4.59  | -0.7       | 0.67|
| Maharashtra | -17.91 | -6.95  | -23.51 | -15.38 | -21.73 | -18.21 | -21.65 | -16.39    | 0.7 |
| Delhi | -16.93  | -14.44 | -34.82 | -22.97 | -9.7   | -9.24  | -10.42 | 0.2        | 0.95|
| HP   | -16.66  | -22.82 | -49.69 | -23.2  | -7.23  | -2.86  | 3.87   | 8.87       | 0.66|
| West Bengal | -15.32 | -15.13 | -23.05 | -26.95 | -10.95 | -7.5   | -8.33  | -4.5       | 0.8 |
| Chhattisgarh | -15.14 | -17.06 | -28.54 | -19.67 | -13.41 | -0.5   | -11.66 | -8.15      | 0.7 |
| Puducherry | -14.75 | -14.7  | -41.26 | -12.01 | -6.48  | -10.24 | -3.82  | -8.38      | 0.76|
| Tamil Nadu | -14.50 | -8.88  | -27.96 | -10.95 | -8.15  | -18.54 | 12.54  | -14.36     | 0.72|
| Odisha | -14.08  | -16.72 | -25.25 | -15.13 | -10.42 | -4.88  | -12.1  | -4.59      | 0.67|
| Average across states | -14.14 | -14.13 | -28.41 | -16.52 | -9.17  | -7.82  | -8.82  | -5.83      | 0.76|

| State     | Number of observations | 10% fewest cases | 10% fewest cases |
|-----------|------------------------|------------------|------------------|
| Bihar     | 16                     | 13.76            | 24.57            |
| Meghalaya | 17                     | 11.61            | 13.67            |
| Assam     | 18                     | 11.37            | 11.93            |
| Andhra Pradesh | 19               | 10.79            | 5.54             |
| Telangana | 20                     | 10.74            | 5.02             |
| UP        | 21                     | 10.33            | 26.51            |
| Haryana   | 22                     | 10.24            | 18.05            |
| Tripura   | 23                     | 9.93             | 11.13            |
| Chandigarh| 24                     | 9.31             | 7.04             |
| Kerala    | 25                     | 8.84             | 4.88             |
| Punjab    | 26                     | 8.72             | 19.1             |
| Mizoram   | 27                     | 8.69             | 6.39             |
| Karnataka | 28                     | 7.76             | 0.8              |
| MP        | 29                     | 6.44             | 6.67             |
| Nagaland  | 30                     | 6.24             | 9.15             |
| Manipur   | 31                     | 5.50             | 3.82             |
| JK        | 32                     | 2.95             | 5.64             |
| Jharkhand | 33                     | 1.26             | 27.66            |
| Rajasthan | 34                     | 0.90             | 14.02            |

Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.
7.3. Changes in night light intensity in India’s major cities

At a more granular level, it is possible to observe the change in light intensity across cities. Since the data on nighttime light intensity is available at a very fine grid, their aggregation is very flexible. For selected mega cities, Fig. (6) visualizes changes from the previous year in light intensity from April to August. Subtracting the month-specific light intensity in 2019 from the one in 2020 controls for seasonality in light emissions. The maps in columns 1 to 5 indicate substantive declines in light intensity between April and June 2020, as shown by the many reddish cells that show an absolute decline. The timing in which cities experienced their largest decline is not uniform. In Fig. (A.4), in the Appendix, we compare the month-specific growth in 2020 to the average month-specific growth rate over the last three years. This “dif-in-dif” analysis confirms that the observed declines were not part of a general trend but specific to these months.

Table (6) shows the change in light intensity in 2020 compared to a year before for the 26 largest Urban Metropolitan Areas in India. As for states and districts, the economic impact of the COVID-19 pandemic varied across them. The average (median) decline in light intensity between March and August 2020 was 6.5 percent (6.6 percent). This average (median) decline is largest during the months of April and May. During the month of April, in which the uniform national lockdown was in place, nearly all cities report declines in light intensity. The average (median) decline in nighttime light intensity across these major metropolitan areas was 8.9 percent (9.2 percent). The declines range from 18.8 percent in Nagpur to 1.0 percent in Pune. Surprisingly, light intensity did not decline in April in Kolkata and Patna, located in Bihar and West Bengal in the north-east of India. In the metropolitan area of Delhi, nighttime light intensity declined by 13 percent.

8. Conclusion

In this paper, we showed that both electricity consumption and nighttime light intensity can proxy economic activity in India. We then quantified the drop in electricity consumption in response to the COVID-19 pandemic and the national lockdown, which the Indian authorities implemented from March 25 onward. Compared to predicted consumption based on a model explaining 90 percent of the variation in electricity consumption, actual electricity consumption declined around 20 percent shortly after the lockdown was implemented. It fell further subsequently, to a maximum decline of 30 percent at the end of March. It was around 25 percent below normal throughout April and subsequently recovered, though it remained below normal levels even in September.

The observed decline in electricity consumption clearly says something about the overall economic costs that have occurred during this period. We utilize the elasticity of 1.3 between changes in electricity consumption and GVA that we estimated in Section 4, which is very much in line with typical values found in the literature. Doing so suggests that year-on-year quarterly growth in the first quarter of 2020 was 3.4 percentage points lower than it would have otherwise been. For the second quarter of 2020, it suggests that the negative growth effect was 20.8 percent, and for the third quarter it suggests that growth was 6.8 percent lower. The additional loss will of course depend on whether the economy will continue to be held back by the COVID-19 pandemic, whether it will revert to previous levels, or whether it will overshoot to compensate for forgone activity. The strength of the rebound can also be well tracked by our measure based on daily electricity consumption.

We also document that the economic impact of the lockdown was not equal across states, districts, and cities. Some of the heterogeneity in the decline in electricity consumption is related to the prevalence of COVID-19 infections, the economic structure of the states, and previous migration patterns. We also find that a larger number of COVID-19 infections during the national lockdown resulted in a larger decline in nighttime light intensity in dis-
These results have strong implications for the rebound of the economy. Without effectively reducing the risk of a COVID-19 infection, voluntary reductions of mobility make it unlikely that the economy will return to full potential even when restrictions are relaxed. This may explain why the recovery has recently slowed in some parts of India.

Concluding, electricity consumption tracks Indian GVA fluctuations closely and we can update this measure of economic activity with only a one-day delay, which provides a near real-time view on economic activity. This provides a valuable source of information for policymakers and researchers alike. We also provided an assessment of the impact and the drivers at the district and city level based on nighttime light intensity. Both approaches can be applied to other emerging markets and developing economies as well.

Table 5
Drivers of the declines in nighttime light intensity and movement range mobility across districts.

|                     | Δ nighttime light intensity | Δ movement range |
|---------------------|----------------------------|-----------------|
|                     | (1)                        | (2)            | (3)            | (4)          | (5)          | (6)          |
| Log COVID-19 cases  | 2.409***                   | 2.620***       | 2.553***       | 2.933***     | 1.797***     | 1.674***     |
|                     | (0.397)                    | (0.453)       | (0.466)        | (0.194)      | (0.200)      | (0.205)      |
| Manufacturing       | -0.0934                    | -0.0750       | -0.259***      | -0.253***    | -0.253***    |
| employment share    | (0.0703)                   | (0.0708)      | (0.0310)       | (0.0311)     |
| Service employment  | 0.106***                   | 0.190***       | -0.152***      | -0.142***    |
| share               | (0.0482)                   | (0.0648)      | (0.0213)       | (0.0286)     |
| Past in - migration | 0.0478                     | 0.118          | 0.0794         |
|                     | (0.181)                    |               |               |
| Past out - migration| 0.537                      |               | -0.0589       |
|                     | (0.339)                    |               | (0.149)       |
| Literacy rate       | 0.0512                     |               | 0.0302         |
|                     | (0.0480)                   |               | (0.0213)      |
| Nighttime light     | -0.0350                    |               | -0.0332***    |
| intensity 2019      | (0.0255)                   |               | (0.0112)      |
|                     | 624                        | 624            | 623            | 619          | 619          | 618          |
| N                   | 624                        | 624            | 623            | 619          | 619          | 618          |
| R2                  | 0.056                      | 0.065          | 0.074          | 0.271        | 0.408        | 0.420        |

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Fig. 6. Changes in night light intensity across selected cities in India.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Table 6
Changes in nightlight intensity across major Indian cities in 2020.

| Rank | Average | March | April | May | June | July | August |
|------|---------|-------|-------|-----|------|------|--------|
| Varanasi | 1 -17.5 | -13.0 | -13.2 | -26.3 | -23.0 | -3.6 | -26.0 |
| Bhopal | 2 -17.4 | -10.8 | -16.1 | -16.5 | -18.5 | -12.0 | -30.8 |
| Lucknow | 3 -14.0 | -19.0 | -8.7 | -13.1 | -11.1 | -14.2 | -18.0 |
| Chennai | 4 -12.4 | -6.1 | -12.3 | -10.8 | -8.3 | -25.4 | -11.6 |
| Nala Sopara | 5 -11.9 | -8.7 | -8.5 | -21.9 | -8.7 | -2.8 | -21.1 |
| Mumbai | 6 -10.9 | -8.1 | -10.3 | -16.8 | -22.8 | 1.7 | -9.1 |
| Indore | 7 -10.3 | 4.9 | -8.1 | -8.6 | -13.5 | -1.6 | -35.0 |
| Delhi | 8 -9.4 | -9.4 | -13.3 | -7.6 | -8.8 | -12.1 | -5.1 |
| Nagpur | 9 -9.0 | -15.1 | -18.8 | -14.1 | -3.7 | -12.0 | 9.7 |
| Visakhapatnam | 10 -8.9 | -6.9 | -16.3 | -4.6 | -19.2 | -3.9 | -2.7 |
| Vadodara | 11 -7.5 | -0.9 | -14.1 | -6.8 | -1.4 | 1.4 | -23.3 |
| Kolkata | 12 -6.9 | 0.5 | 1.4 | -23.0 | -5.1 | 5.8 | -20.6 |
| Hyderabad | 13 -6.6 | -6.7 | -11.8 | -9.4 | -5.1 | -7.4 | 0.6 |
| Meerut | 14 -6.5 | -14.7 | -11.3 | -3.4 | -10.0 | -1.4 | 1.9 |
| Ahmedabad | 15 -6.4 | -5.7 | -10.0 | -4.9 | -7.9 | -0.6 | -9.2 |
| Agra | 16 -5.7 | -11.3 | -9.8 | -11.3 | 5.8 | -3.7 | -3.9 |
| Bangalore | 17 -5.3 | -6.1 | -8.1 | -11.4 | 3.1 | -3.9 | -5.5 |
| Patna | 18 -5.3 | 9.6 | 4.1 | -14.6 | -21.3 | -1.6 | -8.1 |
| Jaipur | 19 -4.7 | 1.9 | -10.1 | -7.0 | -7.1 | -1.6 | -4.1 |
| Nashik | 20 -4.1 | -8.7 | -5.1 | -4.9 | -4.7 | 4.2 | -5.4 |
| Surat | 21 -3.7 | -9.9 | -7.1 | -9.7 | -7.8 | 8.2 | 4.2 |
| Kampur | 22 -2.6 | -4.0 | -7.6 | -5.0 | -6.9 | 5.8 | 1.9 |
| Ludhiana | 23 -1.8 | -4.3 | -6.7 | -0.9 | 0.3 | -3.5 | 4.5 |
| Pune | 24 -2.6 | 0.2 | -7.7 | -1.3 | 7.3 | 6.6 | 10.4 |
| Srinagar | 25 -3.4 | -1.5 | -1.0 | -7.7 | 2.8 | 19.8 | 8.3 |
| Srinagar | 26 -13.5 | 34.9 | -1.8 | 13.6 | 22.8 | 0.8 | 10.5 |

Fig. A.4. Changes in night light intensity across selected cities in India.
Appendix A. A electricity consumption and GDP in the world and in India

Fig. A.1 and Table A.1.

![Figure A.1. Electricity consumption and GDP in India.](image)

Table A.1
Electricity consumption and GDP in the world and in India.

|                      | (1)             | (2)             |
|----------------------|-----------------|-----------------|
| GDP per capita       | 0.951***        | 0.948***        |
| (0.0777)             | (0.0791)        |                 |
| GDP per capita × India | 0.188**        | 0.188**         |
| (0.0791)             | (0.0791)        |                 |
| Constant             | YES             | YES             |
| Country fixed effect | YES             | NO              |
| Time trend           | YES             | NO              |
| N                    | 3725            | 3725            |
| R2                   | 0.529           | 0.529           |

Appendix B. Temperature and Electricity Consumption

Temperature is an important variable to control for when studying the dynamics of daily electricity consumption. In Table (A.2) we study this relationship. It shows that there is a quadratic relationship between temperature and electricity consumption in India. Fig. A.2 plots the temperature against the electricity consumption for India and adds a quadratic fit. It shows that the quadratic curve fits the data well and that there are more observations for higher temperatures than for lower ones. This motivates the inclusion of two terms for temperature in the electricity consumption model in Section 4. From this quadratic fit we obtain the temperature associated with the lowest electricity consumption, which is 22.8 °C.

Table A.2
Electricity consumption and temperature.

|                        | (1)                | (2)                |
|------------------------|--------------------|--------------------|
| Temperature            | −207.596***        | 4.605***           |
| (19.003)               | (0.374)            |                   |
| Temperature²           | 5359.098***        |                   |
| (234.731)              |                   |                   |
| Constant               | YES                | YES                |
| N                      | 2422               | 2422               |
| R2                     | 0.148              | 0.148              |

Standard errors in parentheses. * p < .1, ** p < .05, *** p < .01.

Appendix C. Electricity consumption and stringency of measures

Fig. A.3.

Appendix D. On the relationship between nighttime light intensity and electricity consumption

In order to employ changes in nighttime light intensity at the district level in April to study the impact of local COVID-19 infections, we confirm that changes in electricity consumption and nighttime light intensity are strongly related at the state level. To do so, we aggregate electricity consumption to monthly data and re-estimate the electricity consumption model presented above with monthly frequency. We can then compare the deviations of actual electricity consumption from the model prediction in April to the change in nighttime light intensity in April (compared to the year before). For the whole sample, the linear coefficient is statistically significant at the 5 percent level (Table (A.3), column 1). However, since large increases in nighttime light intensity in some states have not been accompanied by increases in electricity consumption, a quadratic model provides a better fit (Table (A.3), column 2). This suggests that the relationship between changes in electricity consumption and nighttime light intensity is stronger if both are declining, or if nighttime light intensity is at least not increasing strongly. In fact, abstracting from those states in which nighttime light intensity increased more than 10 percent results in a strong linear relationship that is significant at the one percent level. For a one percent larger decline in nighttime light intensity, electricity consumption declined by 1.25 percent (Table (A.3), column 3). Note that this monthly cross-sectional relationship of the two proxies is very similar to the quarterly one emerging from the time-series dimension at the country level (Table (1), column 8). We conclude that in the absence of electricity data, nighttime light intensity offers a valuable alternative to analyze economic activity.

17 For this analysis we drop 3 outliers. Arunachal Pradesh, for which we have issues with cleaning the night light data, and DDH and DD for which declines in electricity consumption have been very large.
Table A.3. Relationship between changes in electricity consumption and changes in nighttime light intensity at the state level.

|                      | $\Delta$ Electricity consumption in April 2020 |              |              |
|----------------------|----------------------------------------------|--------------|--------------|
|                      | (1)                                          | (2)          | (3)          |
| $\Delta$ light intensity, April 2020 | $0.579^{**}$                                 | $0.892^{***}$| $1.251^{***}$|
|                      | ($0.230$)                                    | ($0.287$)    | ($0.519$)    |
| $\Delta$ light intensity squared, April 2020 | $-2.789^*$                                   |              |              |
|                      | ($1.607$)                                    |              |              |
| Constant             | $-0.188^{***}$                               | $-0.138^{***}$| $-0.135^{***}$|
|                      | ($0.0277$)                                   | ($0.0393$)   | ($0.04$)     |
| $N$                  | 30                                           | 30           | 26           |
| $\Delta$ light intensity | all                                         | all          | $<0.1$       |
| $R^2$                | $0.184$                                       | $0.266$      | $0.195$      |

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix E. Changes in night nighttime light intensity across selected cities in India

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