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Abstract

The COVID-19 pandemic has disrupted economic activity in India. Adjusting policies to contain trans- mission 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 lock-down was implemented on March 25, 2020 and remained a quarter below normal levels throughout April. It recovered somewhat subsequently, but electricity consumption was on average still 13.5 percent lower than normal in May. Not all states and union territories have been affected equally. While electricity consumption halved in some, others were not affected at all. Part of the heterogeneity is explained by the prevalence of manufacturing and return migration. At the district level, higher COVID-19 infection rates were associated with larger declines in nighttime light intensity in April. Together, daily electricity consumption and night-time light intensity allow monitoring economic activity in near real-time and high spatial granularity.

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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 national lockdown from March 25 onwards that strongly disrupted economic activity across the country. When restrictions were stepwise eased in May, economic activity slowly recovered. 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 require 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 insights 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, 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 quarter of 2020.

Both electricity consumption and nighttime light intensity closely track economic activity and have been used extensively to improve national account estimates of GDP (e.g. Henderson et al. 2012, Lyu et al. 2018, Chen et al. 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, and Rama 2018, Chodorow-Reich, Gopinath, Mishra, and Narayanan 2020). It is also invaluable to approximate economic activity at the sub-national level, including in India (Gibson, Datt, Murgai, Ravallion 2017, Prakash, Shukla, Bhowmick, and Beyer 2019, Chanda and Kabiraj 2020). In concurrent work, electricity consumption has been shown to have closely tracked economic activity in the United States during the global financial crisis (Cicala 2020a).[4] And it has been employed for an assessment of the economic impact of the COVID-19 pandemic in the European Union (Cicala 2020b, Chen et al. 2020b).[5]

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 its implementation and was on average still 25.8 percent below normal throughout April. It started recovering in early May and was nearly back to normal between May 23 and May 28, before dropping again at the end of the month to -14.7 percent on May 31.[6] Not all Indian States and Union territories have been affected equally. While electricity consumption halved in some, it did not decline at all in others. It declined more for States and Union territories with a larger manufacturing sector and higher previous short-

[4]While real GDP fell 4.3 percent from peak to trough, weather-adjusted electricity consumption fell around 5 percent (Cicala 2020a).

[5]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).

[6]The deviation is statistically significant at the one percent level from March 23 to May 24 and from May 29 to May 31.

run outmigration, but not with more registered COVID-19 cases. However, districts with higher rates of COVID-19 infections saw larger declines in nighttime light activity in April, suggesting additional impacts from voluntary behavioral changes when risks of an infection increase (in line with evidence provided by Melony and Taskin 2020). In nearly all large Indian cities nighttime light intensity was lower in April 2020 than it was a year earlier. In Delhi and Chennai, for example, light intensity declined 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 of 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 where COVID-19 cases had occurred, 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.[7]

After the enactment of the national lockdown, nearly all public offices were closed, and public services suspended.[8] In addition, nearly all commercial and private establishments had to be closed and exceptions were only made 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

[7] MHA order no. 40-3/2020-DM-I(A).

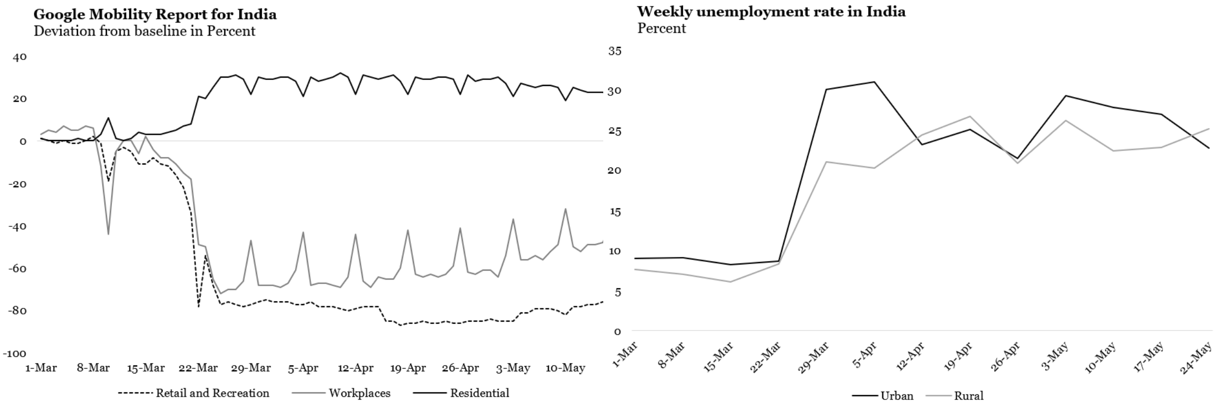
[8] Exceptions were given to several essential services like police forces and public utilities.

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 depends, 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 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. On May 17, 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.

The national lockdown enacted by the Indian authorities was successful in limiting mobility. Figure 1.a 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

(a) Mobility in India after the lockdown (b) Weekly unemployment in India



Note: (a) The decline refers to the change of visits and length of stay as of May 16, compared to a baseline period. The baseline period is defined as the median value for the corresponding day of the week, during the 5-week period from January 3 to February 6. The mobility trends for retail and recreation places include restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. (b) The unemployment rates are produced by CMIE based on household interviews using its Consumer Pyramids Household Survey machinery.
Source: (a) Google COVID-19 Community. (b) Centre for Monitoring Indian Economy Pvt. Ltd.

Figure 1: Mobility and unemployment in India after the lockdown

is tracked, the mobility data is still based on a very large sample and can hence be used to assess declines in mobility across the world (Maloney and 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. Since mid-April, presence at workplaces slowly increased again but on May 16, presence at workplaces was still 40 percent below normal.

The economic impact of the lockdown was immediate. The weekly unemployment rate reported by the Centre for Monitoring Indian Economy (CMIE 2020) increased from 10 percent both in urban and rural areas in the week before the lockdown to 30 percent in the week thereafter in urban areas, and to 20 percent in rural areas (Figure 1.b). Different from developments in other countries, unemployment rates did not increase further after that and since then are hovering around 25 percent both in urban and rural areas. The 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. An excellent discussion of the economic impact of COVID-19 on India's economy is provided by Dev and Sengupta (2020).

3 Data

3.1 Daily Electricity Consumption

We observe daily electricity consumption from April 1, 2013 to May 31, 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 one-day delay. We download the daily documents and scrap 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.

Figure 2 shows India's daily electricity consumption from April 1, 2013 to May 31, 2020.[9] A couple of features are clearly 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.[10] Fourth, around the national lockdown announced on March 24, electricity consumption dropped strongly. Fifth, at the end of May electricity consumption first recovered before falling again.

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

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

[10] This decline at the end of 2019 has been linked to weakening GDP growth.

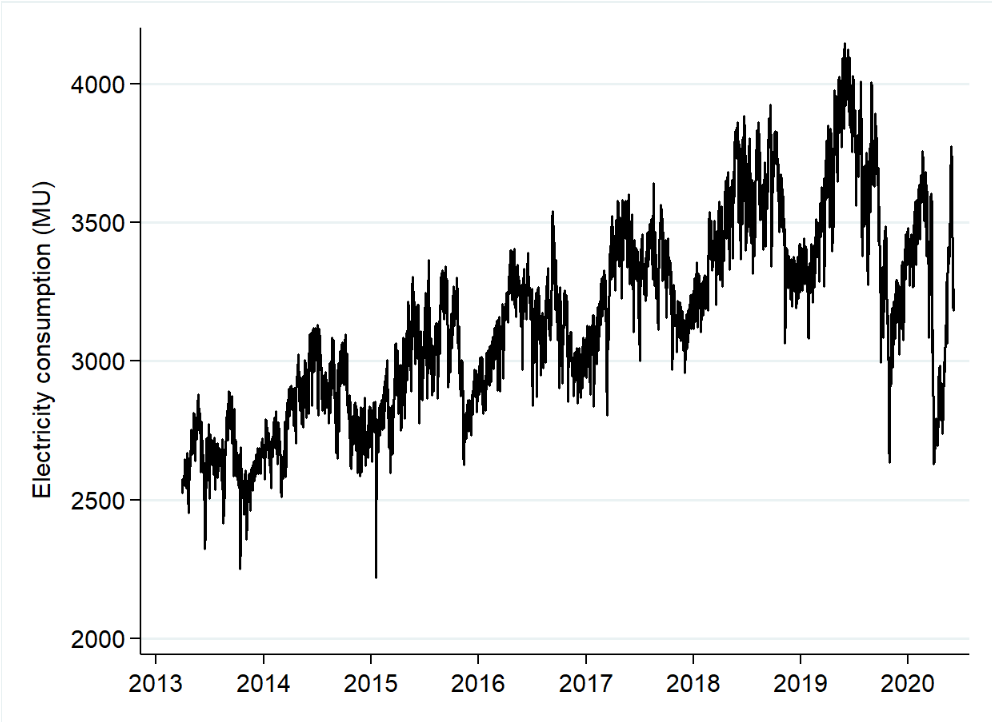


Figure 2: India's electricity evolution since April 2013

Note: In India, the kilowatt-hour is called a Unit of energy. A million units, designated MU, is a gigawatt-hour. The last day included is May 31, 2020.

Center of the National Oceanic and Atmospheric Administration (NOAA) and cover the period from April 2012 to April 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 et al. 2013), have a wider radiometric detection range and onboard calibration. These features help to correct for saturation as well as blooming effects and ensure a better time comparability. However, the raw data needs some cleaning to minimize temporary lights and background noise. 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 et al. 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 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 intensity. In practice, this approach amounts to setting to zero cells that are distant from homogenous 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. Temperature data is collected from the Average Daily Temperature Archive from the University of Dayton (2020) and based on recordings of the National Climatic Data Center. We generate an India aggregate by weighting the daily temperatures recorded in Chennai, Delhi, Kolkata, and Mumbai by population.[11] 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), the data on previous short-run inmigration and outmigration at the state and district level from the Development Data Lab (2020), and the share of employment in manufacturing and services at the state and district level 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 correlations between electricity consumption and GDP are close to one. In Appendix A, we use a sample of 123 countries to update these correlations between economic growth

[11] The weighting is done at the regional level (according to the POSOCO classification) where Chennai represents the South, Delhi the North, Kolkata the East and North-East, and Mumbai the West.

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 et al. (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:

$$\log GVA_t = \beta_1 \log electricity_t + \beta_2 \log light_t + trend_t + q_t + \varepsilon_t \tag{1}$$

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 of 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 and estimate the model for the period from the second quarter of 2013 to the first quarter of 2020.[12]

Table 1: GVA, electricity and nighttime lights

	(1) log GVA	(2) log GVA	(3) log GVA	(4) log GVA	(5) log GVA	(6) log GVA	(7) log GVA	(8) log electricity	(9) log electricity
log electricity	1.296***	0.350***			0.318***				
	(0.061)	(0.078)			(0.104)				
log night light			1.537***	0.179**	0.035			1.205***	0.451***
			(0.175)	(0.066)	(0.073)			(0.112)	(0.115)
log electricity (demean)						0.191***			
						(0.067)			
log night light (demean)							0.149***		
							(0.031)		
trend		0.012***		0.015***	0.012***				0.008***
		(0.001)		(0.001)	(0.001)				(0.001)
constant	-6.047***	5.664***	8.999***	9.874***	6.038***	0.000	0.000	11.597***	12.083***
	(0.763)	(0.969)	(0.142)	(0.046)	(1.253)	(0.001)	(0.001)	(0.090)	(0.080)
Quarter FEs	YES	YES	YES	YES	YES	NO	NO	YES	YES
N	28	28	28	28	28	28	28	28	28
r2	0.953	0.994	0.775	0.992	0.994	0.238	0.477	0.846	0.958

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

[12] The beginning of the sample coincides with the availability of the electricity daily data.

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 et al. (2020) find in Europe.[13] Columns 3 and 4 replicate the regressions for nighttime light, showing that it also follows the evolution of GVA very closely.[14] 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 GVP, 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.

[13]It is also in line with other estimates in the literature (Stern 2018).

[14]With 1.5, our coefficient is much larger than the one Henderson et al. (2012) find in an 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.

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:

$$\log Electricity_t = \tau_t + DW_t + WY_t + Holiday_t + \beta_1 Cooling_t + \beta_2 Heating_t + \beta_t Trend + \varepsilon_t \quad (2)$$

The explanatory variables are a set of fixed effects that control for the day of the week, DW_t, the week of the year, WY_t, and holidays, H_t. We include two variables that control for the daily temperature. We control for the temperature degrees above and below of $22.8°C$, such that $Cooling_t = max\{temp_t - 22.8°C, 0\}$ and $Heating_t = max\{22.8°C - temp_t, 0\}$, 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 τ_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.[15] As discussed above, electricity consumption in India grew over time and hence we include a linear time trend (trend). 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). Since electricity consumption dropped below the trend in 2020, an estimation until the end of May 2020 results in a less steep trend that explains somewhat less of the variation (column 2). When we add the daily fixed effects for 2020 as described above, only the observations until December 2019 determine the coefficient on the trend (column 3).[16] Figure 2 shows that there is some seasonality in electricity consumption, which we control for by including the week of the year. Taking care of the trend, the deviation

[15] 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.

[16] Note that the explanatory power is now slightly above the one for the model only estimated until December 2019 because the daily fixed effects take out the errors in 2020.

Table 2: Electricity consumption dynamics model

	(1) log electricity	(2) log electricity	(3) log electricity	(4) log electricity	(5) log electricity	(6) log electricity	(7) log electricity
Trend	0.133***	0.115***	0.133***	0.137***	0.137***	0.133***	0.133***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Holiday						-0.022***	-0.022***
						(0.003)	(0.003)
Cooling						0.021***	0.021***
						(0.001)	(0.001)
Heating						-0.001	-0.001
						(0.001)	(0.001)
End of data	Dec 2019	May 2020	May 2020	May 2020	May 2020	Dec 2019	May 2020
2020 daily FEs	NO	NO	YES	YES	YES	NO	YES
Week of the year FEs	NO	NO	NO	YES	YES	YES	YES
Day of the week FEs	NO	NO	NO	NO	YES	YES	YES
N	2143	2292	2292	2292	2292	2143	2292
R2	0.711	0.608	0.729	0.860	0.872	0.896	0.902

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

from trend in 2020, and the seasonality already explains over 80 percent of the variation in electricity consumption (column 4).[17] 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 5). 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 heating is significant at the one percent level. If temperature exceeds 22.8°C, electricity consumption increases on average by 2.1 percent for every one °C increase in temperature (column 5). With 90 percent, the variation explained by our preferred specification is very high and hence it is well suited to analyze deviations from its predictions.[18]

5.2 Changes in Indian electricity consumption and nighttime light intensity

Figure 3 plots the estimated daily deviation of actual electricity consumption from the model prediction from the beginning of 2020 until May 31, and the dashed lines show the 95 percent confidence interval.[19] From the beginning of the year, with the exception of Holi, the deviations

[17] 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.

[18] The increase of the explanatory power by the inclusion of daily 2020 fixed effects for 2020 is only half a percent (column 6).

[19] 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).

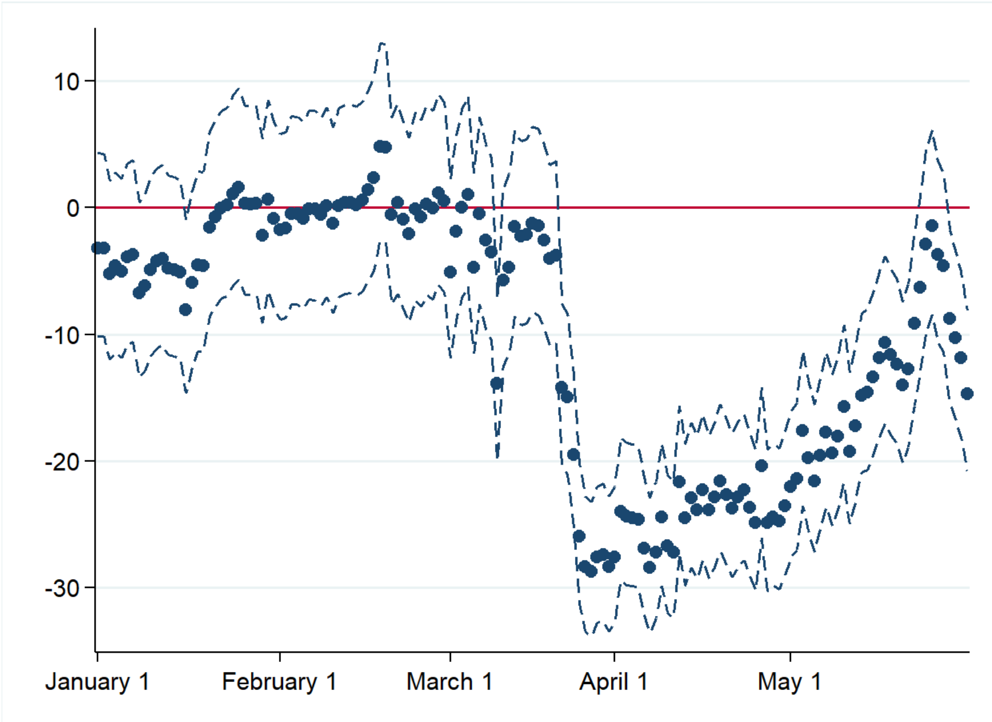
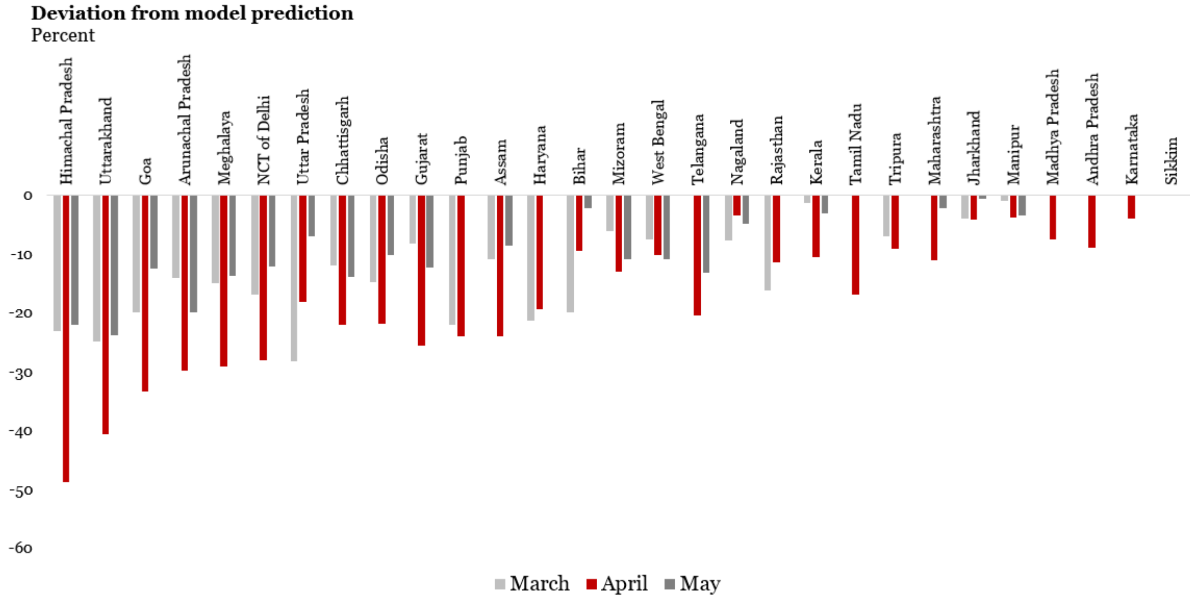


Figure 3: Deviations from predicted electricity consumption in India from January 1, 2020 and until May 31, 2020.

hover around the model's prediction and are not statistically significantly different from them until Sunday, March 22.[20] 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 -21 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 -25 percent throughout April. Following the different relaxations of the lockdown, electricity consumption increased again in May. Between May 23 and May 28, while still somewhat below normal levels, electricity consumption was not statistically significantly different from the model prediction at one percent anymore, suggesting that economic activity has had largely resumed. However, it dropped again subsequently and on May 31 electricity consumption was again -14.7 percent below prediction. On average, electricity consumption in

[20] 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.



Note: States are ordered according to average deviations over all three months. Only negative deviations from model prediction are shown.

Figure 4: Changes in electricity consumption across Indian states

May was 13.5 percent below normal levels, and hence roughly half way back compared to April. With the exception of the rebound and subsequent decline at the end of May, the changes in electricity consumption follow closely the Oxford stringency index of government interventions used for international comparisons of containment measures.[21] Going forward, it will be interesting to see whether electricity consumption will remain below normal levels, returns to previous levels, or whether it will even overshoot to compensate for foregone activity during the lockdown.

6 Heterogeneity across Indian states

The decline in electricity consumption after the lockdown was not uniform across Indian states. Figure 4 shows the deviation from the model prediction for March, April, and May by running the model in Equation (2) at the state level.[22] The average deviations from normal levels over all three months vary from below -30 percent in Himachal Pradesh and Uttarakhand to small positive deviations in Karnataka and Sikkim. In most of the states, electricity consumption

[21] We plot the change in electricity consumption against the stringency index in the Appendix D.

[22] For this we fit a separate model for each state. The temperature used to determine heating and cooling periods is the same for every state.

declined most strongly in April. The decline in April was strongest in Himachal Pradesh, where electricity consumption nearly halved. The negative deviation from the model prediction was also larger than 20 percent during this month in Uttarakhand, Goa, Arunachal Pradesh, Meghalaya, Delhi, Gujarat, Punjab, Assam, Chhattisgarh, Odisha, and Telangana. On the other side of the spectrum, there are some states for which electricity consumption in April was nearly unaffected. In Jharkhand, Karnataka, Manipur, and Nagaland, the deviation from the model prediction was only between 5 percent and 3 percent, and in Sikkim it was even slightly above (but not statistically significant). In May, the electricity consumption was still more than 20 percent below normal in Himachal Pradesh and Uttarakhand, but it was already back to normal levels in nine of the states, including in Punjab, Haryana, and Rajasthan. The heterogeneity is even larger across Union territories.[23] In March, the decline was largest in DNH and DD, where the deviation from the model's prediction was over 35 percent. In Puducherry and Jammu and Kashmir, on the other hand, the deviation in March was only around 3 percent. The national lockdown affected most Union Territories very strongly in April, when actual electricity consumption was 86 percent, 71 percent, and 56 percent below normal in DNH, DD and DVC, respectively. The monthly deviations of actual from predicted electricity consumption and the explanatory power of the electricity consumption model for all States and Union Territories are reported in Appendix F.

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) and the share of manufacturing employment, which approximates the share of manufacturing production. Both are expected to be positively correlated with the decline in electricity consumption. The former for two reasons: first, a higher number of cases makes it more likely that people voluntarily reduce mobility (Maloney and Taskin 2020) and, second, because a higher number of registered cases makes it more likely that state governments enact the lockdown more strictly. The latter because manufacturing output tends to be more electricity intense than output in services and agriculture. Table 3 reports the estimation results for a cross-section of States and Union territories in April and May. For the full sample, both variables have the expected sign but are not statistically significant even at the 10 percent level. Restricting the sample to those states and Union territories for which our model explains at least half of the variation reduces the number of observations from 29 to 28, and results in a statistically significant effect of the share of manufacturing. As expected, a higher share of manufacturing is associated with a larger decline

[23]See figure in the Appendix E.

	Deviation of electricity in April/May		
	(1)	(2)	(3)
COVID-19 cases	-0.273	-0.290	0.614
	(0.237)	(0.218)	(0.319)
Share of manufacturing	-0.187	-0.387**	-0.609***
	(0.177)	(0.184)	(0.186)
Share of services			-0.215
			(0.181)
Past in-migration			-0.245***
			(0.0794)
Past out-migration			0.623***
			(0.178)
Constant	-0.0810**	-0.0565	0.0414
	(0.0392)	(0.0377)	(0.136)
Number of observations	29	28	28
R2 of elect. consumption model	all	>0.5	>0.5
R2	0.076	0.181	0.525

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

Table 3: Driving factors for state-level heterogeneity

in electricity. With this share increasing by 10 percentage points, the decline in electricity was roughly 4 percentage points larger. While more COVID-19 cases are still negatively related to electricity consumption, the effect is again not statistically significant at the ten percent level. In an alternative specification – again using the sample for which more than half of the variation is explained – we include also the share of services as well as previous short-term in and out-migration. While the share of services does not matter, previous migration patterns are important. 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 much less in states with higher previous out-migration. The COVID-19 infection rate is again statistically insignificant. The reason for this result could be that states are too large to measure the risk for individuals that could motivate additional voluntary behavioral changes. We return to the latter issue in the next section when analyzing local drivers at the district-level.

Before moving to the analysis of changes in nighttime light intensity at the district level, we confirm that changes in electricity consumption and nighttime light intensity are strongly

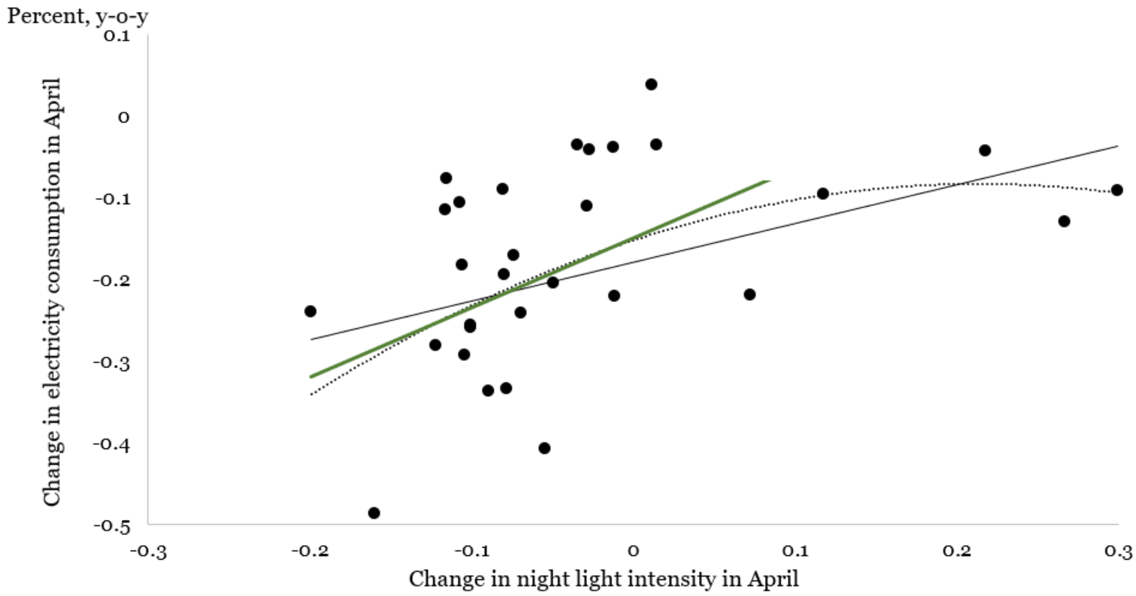
	Δ Electricity consumption in April 2020		
	(1)	(2)	(3)
Δ light intensity, April 2020	0.579**	0.892***	1.251***
	(0.230)	(0.287)	(0.519)
Δ light intensity squared, April 2020		-2.789*	
		(1.607)	
Constant	-0.188***	-0.138***	-0.135***
	(0.0277)	(0.0393)	(0.04)
N	30	30	26
light intensity	all	all	<0.1
R2	0.184	0.266	0.195

Note: Standard errors are in paranthesis. Arunachal Pradesh, Dadra & Nagar Haveli, and Daman and Diu are dropped from the analysis. * p <0.1, ** p <0.05, *** p <0.01

Table 4: Relationship between changes in electricity consumption and changes in nighttime light intensity at the state level

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).[24] For the whole sample, the linear coefficient is statistically significant at the 5 percent level (Table 4, column 1). However, as visible in Figure 5, 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 4, 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 1.4 percent (Table 4, column 3). Note that this monthly cross-sectional relationship of the two proxies is very similar to the

[24]For this analysis we drop 3 outliers. For Arunachal Pradesh, we have issues with cleaning the night light data, so that year-on-year quarterly growth rates as well as DDH and DD for which declines in electricity have been very large.



Note: Arunachal Pradesh, Dadra Nagar Haveli, and Daman and Diu are dropped from the analysis. The green line is a linear approximation conditional on $\Delta < 0.1$; the black solid line a linear approximation for the full sample, and the dashed black line a quadratic approximation.

Figure 5: Relationship between changes in electricity consumption and changes in nighttime light intensity at the state level

quarterly one emerging from the time-series dimension at the country level (Table 2, column 8). We conclude that in the absence of electricity data, nighttime light intensity offers a valuable alternative to analyze economic activity.

7 Using night light intensity to look 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 et al. 2006, Donaldson and 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 et al. 2015, Henderson et al. 2018) to assessing regional economic convergence (Chanda and Kabiraj 2020) to identifying urban spaces and markets (Gibson et al. 2017, Baragwanath et al. 2019, Galdo et al. 2019, Ch et al. 2020) to predicting welfare (Jean et al. 2016), and to assessing the quality

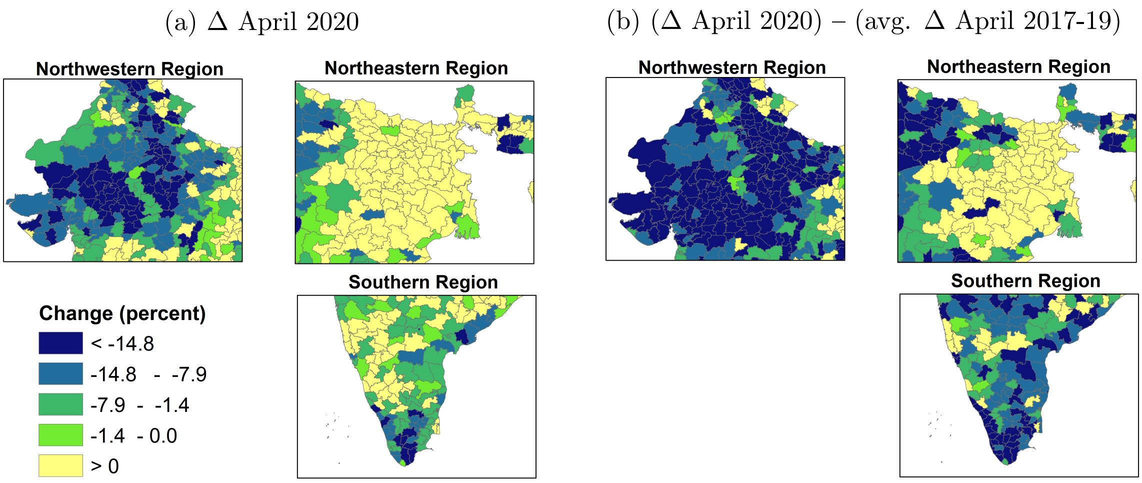


Figure 6: Changes in night light intensity across Indian districts in April 2020

of national account statistics (Pinkovskiy et al. 2016, Morris and Zhang 2019), among other. 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).

The changes in nighttime light intensity due to the COVID-19 pandemic and the national lockdown were heterogeneous across districts in India, but some spatial patterns are clearly recognizable. Figure 6 (a) shows the year-on-year change in light intensity in April 2020.[25] The map clearly shows that the decline in light intensity was larger among districts in the north-west and south-east than in others. More than two-thirds of the districts experienced an absolute decline in light intensity in April 2020 compared to a year before – and one-fifth of the districts experienced declines above 15 percent. The average (median) decline in nighttime intensity across districts was 12 percent (10 percent). Over the last years, nighttime light intensity has been increasing strongly in some districts, while it is only moderately increasing in others. Instead of the absolute change, we hence analyze the change in the growth rate of districts' light intensity. In order to reduce noise in the data, we compare the growth in light intensity in April 2020 to the average growth in April the three years before. Figure 6 (b) shows that about 80 percent of the districts experienced a decline of their light intensity growth in April of 2020. For half of them, the decline was larger than 15 percentage points. The average (median) decline in nighttime light intensity growth across districts was 18 percentage points (15 percentage points).

Next, we examine drivers of the observed heterogeneity across districts in the change of

[25] The year-on-year change accounts for seasonality in the data.

nighttime lights intensity in April 2020. To do so, we link the change to the number of COVID-19 cases per million residents, the share of manufacturing employment, as well as to migration patterns (as we did before for states).[26] Column 1 in Table 5 replicates the first column of Table 3 for districts and shows that there is, as expected, a positive and significant correlation between the share of manufacturing employment and the decline in nighttime light intensity. A larger share of manufacturing is associated with larger decreases in light intensity as the lockdown cut important light emissions sources. A one percentage point increase in the share of manufacturing employment is associated with a decline in light intensity of 0.19 percentage points. The numbers of COVID-19 cases per million residents, though negative in sign, is not statically significant at the ten percent level. Measurement issues of COVID-19 infections at district level could be a source of noise in the data hiding a linear relationship. We hence create four categorical variables of COVID-19 infections: the first category takes the value of 1 if a district does not register any case and zero otherwise; the second category takes the value of 1 if a district registered cases but less than 10 per million residents and zero otherwise; the third category takes the value of 1 if a district registered between 10 to 50 cases per million residents and zero otherwise; and the fourth category takes the value of 1 if a district registered more than 50 cases per million residents and zero otherwise. In addition, we also control for past in and out-migration. Columns 2 and 3 in Table 5 report the results of this analysis. They show a significant positive correlation of COVID-19 cases and the decline in light intensity. Districts with more COVID-19 cases per million residents experienced larger declines in light intensity. While having had less than 10 COVID-19 cases per million residents was associated with a 3.7 percent points larger decline in light intensity, having had more than 50 COVID-19 cases per million residents was associated with a 12.6 percentage points larger decline. Note that in April districts were not yet divided into different categories and hence these results suggest that with higher local risks of infection, people either followed the national lockdown more strictly or changed their behavior voluntarily. While the share of service employment has a negative and significant correlation with declines in light intensity, the share of manufacturing employment is positively correlated with the decline though statistically insignificant. In line with the results at the state level, previous out-migration is negatively correlated with declines in light intensity, suggesting that those districts with a lot of past out-migration have experienced substantive return migration after the lockdown was enacted.

[26] Districts from Arunachal Pradesh are excluded from the analysis.

	Δ nighttime light intensity	Δ nighttime light intensity 1/	Δ nighttime light intensity 1/
	(1)	(2)	(3)
COVID-19 cases	-0.00369		
	(0.00272)		
Less than 10 COVID-19 cases		-3.294**	-3.687***
		(1.412)	(1.415)
Between 10 to 50 COVID-19 cases		-6.896***	-7.340***
		(1.720)	(1.733)
More than 50 COVID-19 cases		-10.97***	-12.65***
		(2.749)	(2.970)
Manufacturing employment share	-0.198***	-0.0780	-0.0905
	(0.0667)	(0.0700)	(0.0712)
Service employment share			0.114**
			(0.0518)
Past in - migration			-0.146
			(0.161)
Past out - migration			0.583*
			(0.339)
N	624	624	623
R2	0.017	0.052	0.063

Note: 1/ Base category: no COVID-19 cases as of Apr 30, 2020. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Drivers of the declines in nightlight intensity across districts

7.2 Changes in night light intensity in India's major cities

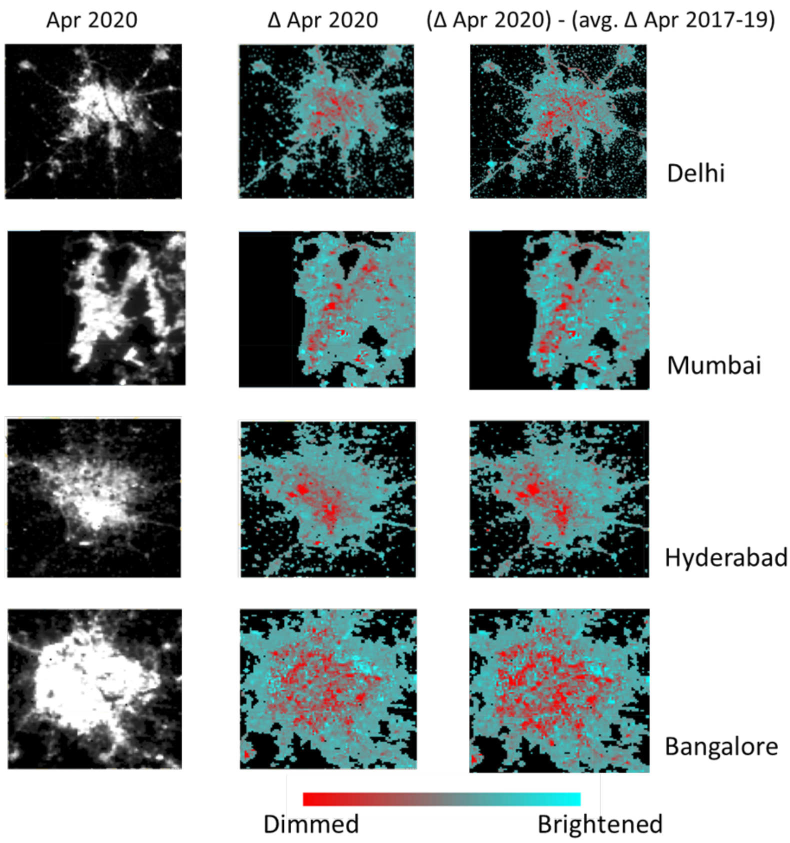


Figure 7: Changes in night light intensity across selected cities in India

At a more granular level, it is possible to observe the change in light intensity in April 2020 within cities. Since the data on nighttime light intensity is available at a very fine grid, their aggregation is very flexible. In the following, we aggregate data for India's 26 largest metropolitan areas. For selected mega cities, Figure 7 shows the light intensity in April 2020 (first column) and whether light intensity dimmed or brightened in April 2020 (column 2). Subtracting the light intensity in April 2019 from the one in April 2020 controls for seasonality in light emissions. The maps in column 2 clearly indicate a substantive decline in light intensity in April 2020, as shown by the many reddish cells that show an absolute decline. As in the analysis of states, we compare the growth rate in April 2020 to the average growth rate in April over the last three years and show results in column (3). This "dif-in-dif" analysis confirms that declines April 2020 were not part of a general trend but specific to that month.

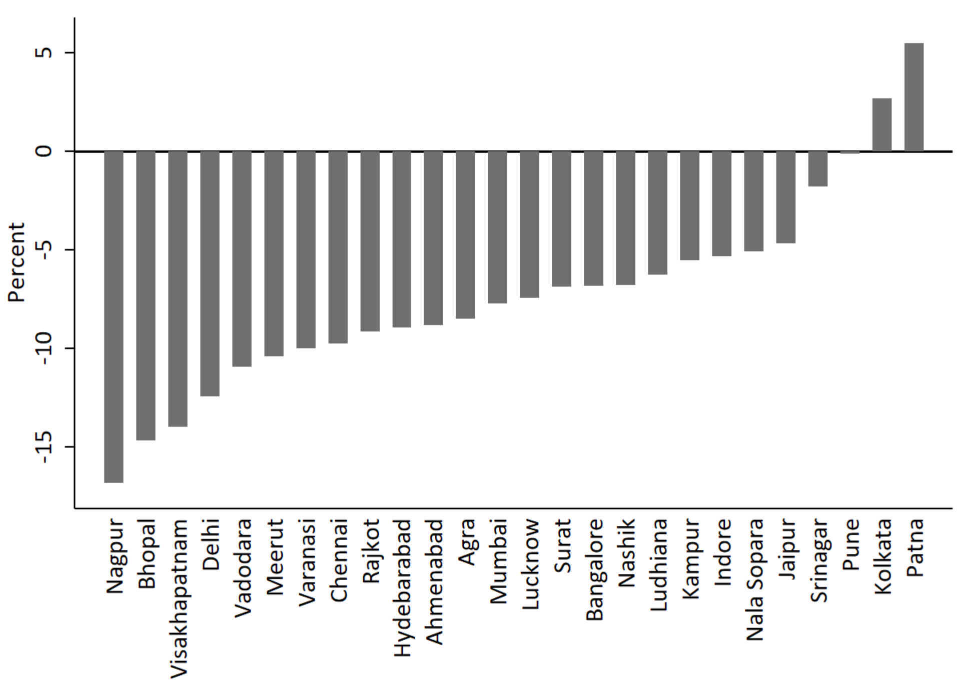


Figure 8: Changes in nightlight intensity across major Indian cities in April 2020

Figure 8 shows the change in light intensity in April 2020 compared to a year before for the 25 largest Urban Metropolitan Areas in India. As for states and districts, the economic impact of the lockdown varied across them. While nearly all of them report declines in light intensity in April 2020, the declines range from 16.8 percent in Nagpur to 0.5 percent in Pune. And for Kolkata and Patna, located in Bihar and West Bengal in the north-east of India, light intensity did not decline at all. The average (median) decline in nighttime light intensity across these major metropolitan areas was 8.1 percent (8.3 percent). Nagpur, the city with the largest decline in light intensity in April 2020, is the third largest city of the state of Maharashtra, India's fifth fastest growing city, and a top performer in the smart city project execution. In the metropolitan area of Delhi, nighttime light intensity declined by 13 percent. Using a sample of 54 cities and proxying city-level COVID-19 cases with district-level information, we find a significant positive correlation between COVID-19 cases per million residents and decline in light intensity. Having more than 50 cases per million residents is associated with a 15 percentage points larger decline in light intensity.

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 onwards. 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 somewhat, following the stepwise relaxation of restrictions, but was on average still 13.5 percent lower than normal in May.

The observed decline in electricity consumption clearly says something about the overall economic costs that have occurred during this period. To estimate the costs emerging from our measure, we consider all days for which electricity consumption has been statistically significantly lower than predicted.[27] We utilize the elasticity of 1.3 between changes in electricity consumption and GVA that we estimated in Section 4 and that 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 until the end of May has already been 17.0 percentage points. For the full calendar year, this amounts to economic costs of 5.1 percent of GVA so far, or to around US$ 150 billion. This estimate is a bit lower but roughly in line

[27] We use a significance level of 1 percent.

with approximations reported in the media. The actual growth in the second quarter of 2020 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 during the lockdown. The strength of the rebound can also be well tracked by our measure based on daily electricity consumption.[28]

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 economic structure of the states and previous migration patterns. We find that a larger number of COVID-19 infections resulted in a larger decline in nighttime light intensity in districts, but not in states.

Concluding, electricity consumption tracks GVA fluctuations closely and has been used to assess the economic impact of lockdowns in the European Union. We showed that electricity consumption can also be used in emerging markets and developing economies. For India, 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 policy makers and researchers alike. We also provided a first assessment of the impact at the district and city level based on nighttime light intensity that can be further refined as more data becomes available.

[28] In a recent note Chinoy and Sajjid (2020: 2) agree that the energy consumption will be an "important real-time tracker to judge the extent to which economic utilization levels increase in the coming weeks".

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Appendix

A Electricity consumption and GDP in the world and in India

Table A1: Electricity consumption and GDP in the world and in India

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

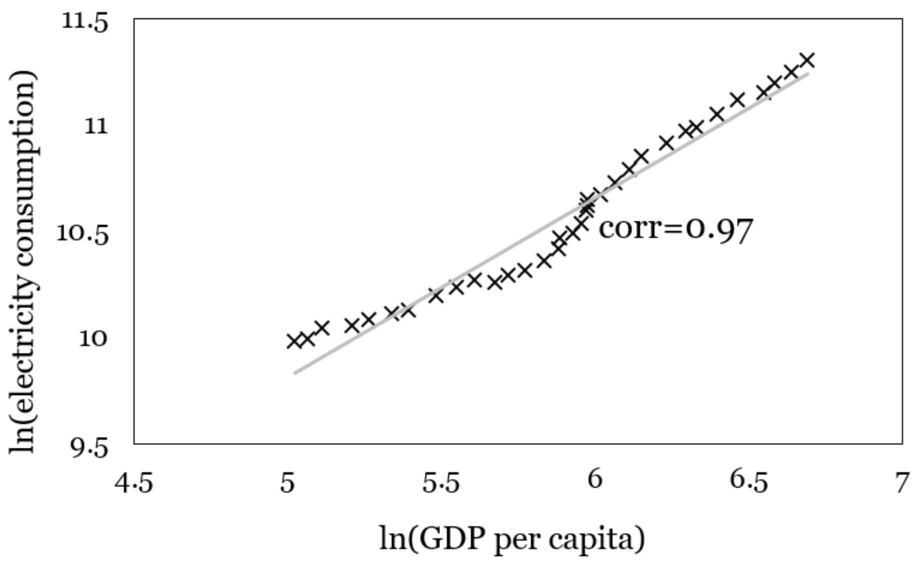


Figure A1: Electricity consumption and GDP in India

B Temperature and Electricity Consumption

Temperature is an important variable to control for when studying the dynamics of daily electricity consumption. In Table A2 we study this relationship. It shows that there is a quadratic relationship between temperature and electricity consumption in India. Figure A2 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.

	(1) Energy.Met.
Temperature	-202.403***
	(18.822)
Temperature^2	4.444***
	(0.371)
Constant	5320.117***
	(232.098)
N	2287.000
R2	0.133

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

Table A2: Electricity consumption and temperature

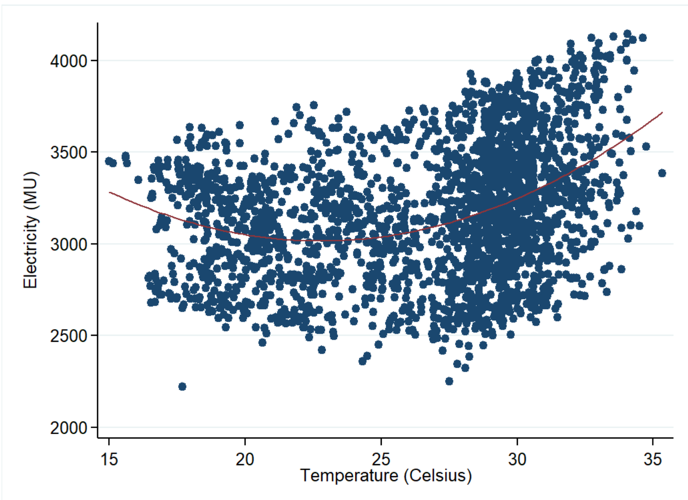


Figure A2: Electricity consumption and temperature

C Robustness check for identifying outliers

Figure 3 plots the estimated daily deviations of electricity consumption for 2020 and the respective confidence intervals obtained from the regression presented in column 7 of Table 2. This allows us to detect which observations are statistically different from the rest. While dummy variables can be used to detect outliers, but Kiraci (2013) questions whether the tstatistic, based on the standard errors of each dummy, is sufficient to validate an observation as an outlier and recommends to instead rely on the robust standardized residual (RSR) statistic to detect outliers. We hence calcuate that staistic for all days in 2020 based on deviations from an out-of-sample prediction as a robustness check for concluding that some of days are outliers. Figure A3 plots the RSR statistic for each 2020 dummy and the -2.5 beyond which the observation is identified as an outlier, as explained in Kiraci (2013). The results coincide with the ones from the fixed effects when outliers are defined with a statistical significance level of 1 percent. The first observation identified as an outlier both by our fixed effects and by the RSR is March 22, when a curfew and lockdown in major cities and some districts caused a collapse in electricity consumption. And at the end of May the same days are not considered outliers with both methods.

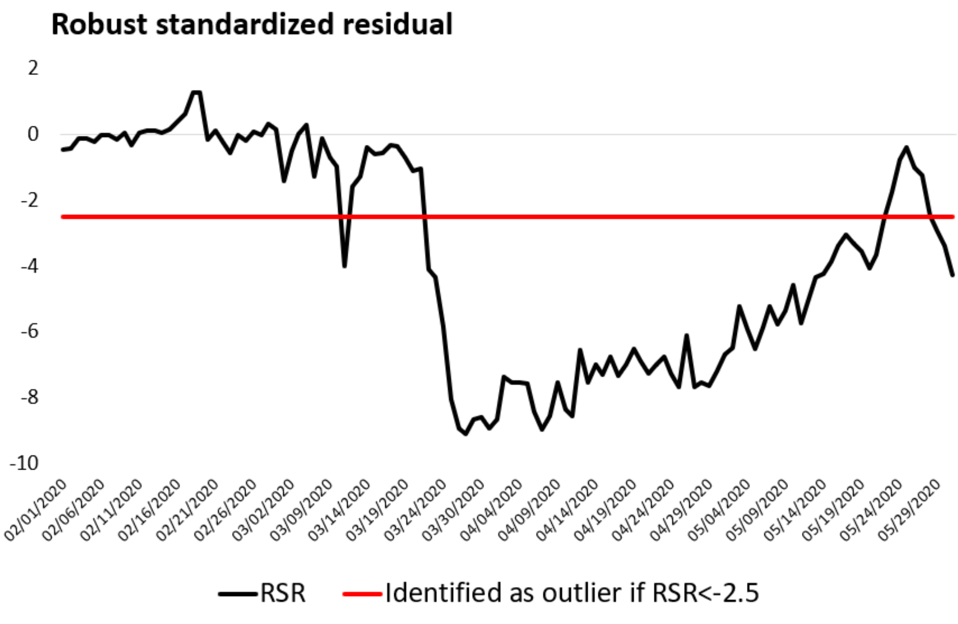


Figure A3: Robust standardized residual (RSR) statistic for 2020 daily dummies

D Electricity consumption and stringency of measures

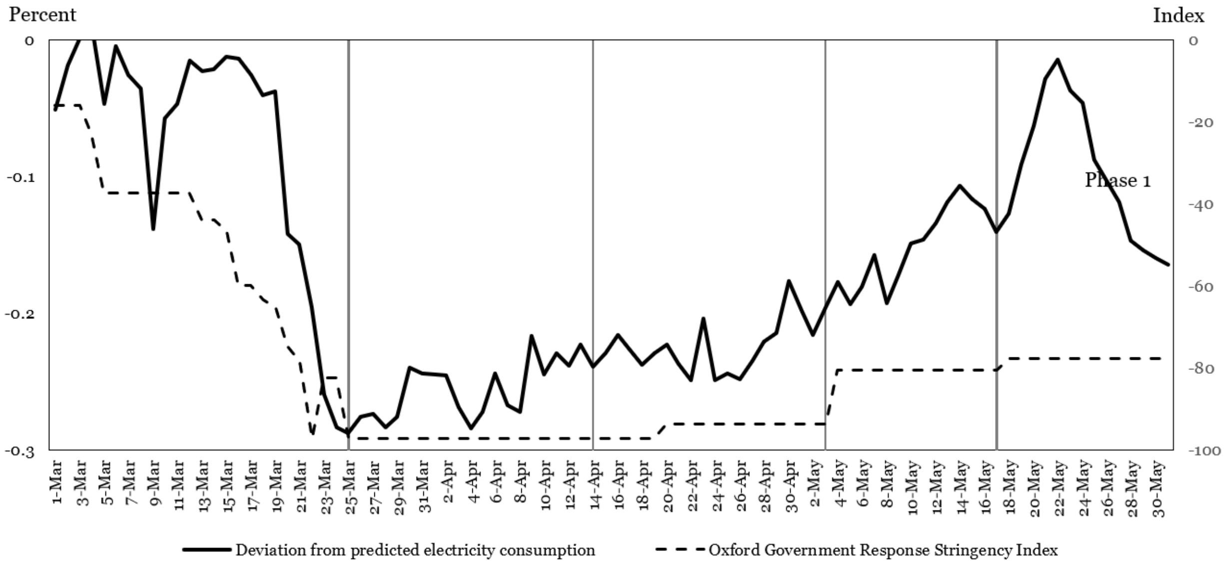
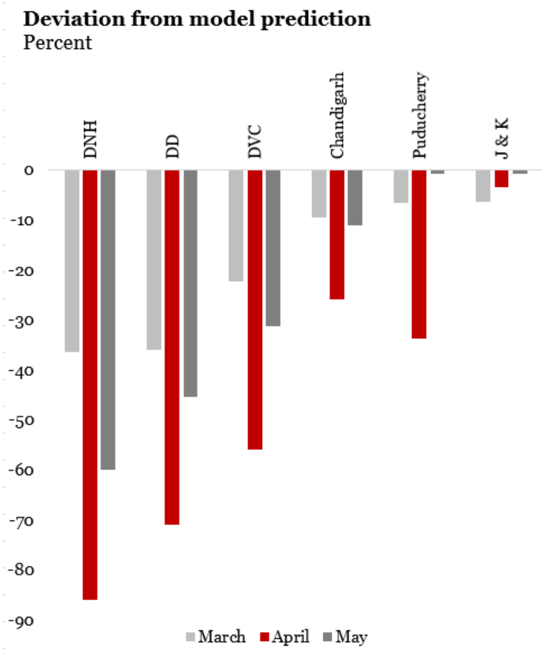


Figure A4: Electricity consumption and stringency of government measures

E Changes in electricity consumption across Union Territories



Note: Union Territories are ordered according to average deviations over all three months.

Figure A5: Changes in electricity consumption across Indian Union Territories

F Declines in electricity consumption across India

	Rank	Average March/April/May	March	April	May	Explanatory power of consumption model
Himachal Pradesh	1	-31.3	-23.1	-48.7	-22.0	0.67
Uttarakhand	2	-29.7	-24.8	-40.7	-23.7	0.74
Goa	3	-21.9	-19.8	-33.4	-12.5	0.75
Arunachal Pradesh	4	-21.3	-14.1	-29.9	-19.9	0.55
Meghalaya	5	-19.3	-15.0	-29.2	-13.8	0.64
NCT of Delhi	6	-19.1	-17.0	-28.1	-12.2	0.95
Uttar Pradesh	7	-17.8	-28.2	-18.2	-6.9	0.81
Chhattisgarh	8	-15.9	-12.0	-22.0	-13.8	0.48
Odisha	9	-15.6	-14.7	-21.8	-10.1	0.66
Chandigarh	10	-15.5	-9.6	-25.8	-11.0	0.93
Gujarat	11	-15.4	-8.2	-25.5	-12.3	0.60
Punjab	12	-15.0	-22.0	-24.0	1.0	0.92
Assam	13	-14.5	-11.0	-24.0	-8.5	0.79
Puducherry	14	-13.7	-6.6	-33.7	-0.7	0.80
Haryana	15	-11.6	-21.3	-19.4	5.9	0.88
Bihar	16	-10.6	-20.0	-9.5	-2.2	0.76
Mizoram	17	-10.0	-6.1	-13.0	-11.0	0.70
West Bengal	18	-9.5	-7.5	-10.1	-11.0	0.79
Telangana	19	-9.1	6.4	-20.4	-13.2	0.79
Nagaland	20	-5.4	-7.8	-3.5	-4.9	0.33
Rajasthan	21	-5.2	-16.2	-11.5	12.1	0.63
Kerala	22	-5.0	-1.3	-10.5	-3.1	0.71
Tamil Nadu	23	-4.3	1.2	-17.0	2.7	0.68
Tripura	24	-3.9	-6.9	-9.1	4.3	0.57
Jammu and Kashmir	25	-3.6	-6.3	-3.5	-0.9	0.54
Maharashtra	26	-3.4	3.0	-11.0	-2.2	0.59
Jharkhand	27	-2.9	-4.0	-4.2	-0.6	0.34
Manipur	28	-2.8	-1.0	-3.7	-3.5	0.47
Madhya Pradesh	29	-0.8	1.4	-7.6	3.7	0.77
Andhra Pradesh	30	-0.5	2.5	-9.0	5.0	0.70
Karnataka	31	2.4	5.8	-4.0	5.5	0.66
Sikkim	32	4.0	4.3	3.9	3.8	0.48

Table A3: Declines in electricity consumption across India