Tracking India's COVID-19 impacts and recovery using high-frequency electricity and pollution data

Energy Insight

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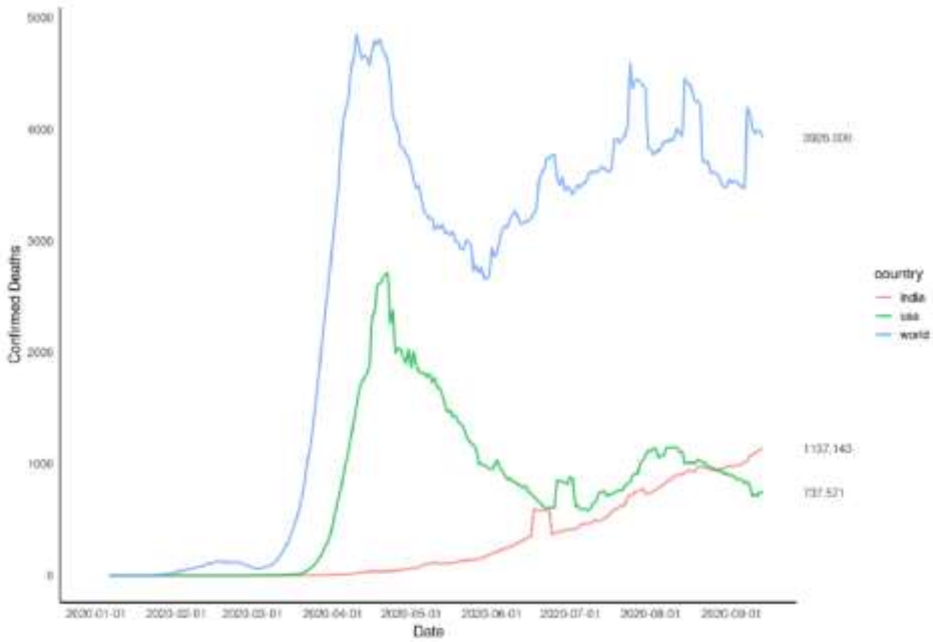
September 2020

1 Introduction

Damages from the COVID-19 pandemic stem from both the direct health costs of the pandemic and the economic costs of any corresponding policy response. India is home to the fastest-growing COVID-19 outbreak in the world and is on track to pass the United States in terms of the number of total cases.[1] However, less is currently known about the economic impacts of India's aggressive COVID-19 lockdown.

In terms of health impacts, as of 13 September 2020, India had reported 4.75 million positive COVID-19 cases, second only to 6.49 million cases in the United States.[2] Even more worryingly, India has failed to 'flatten the curve', with both cases and deaths rising quickly over time. Figure 1 compares daily reported deaths for India, the United States, and the rest of the world. Daily reported deaths in India now make up about a quarter of global deaths with no sign of a decrease or flattening of the time series. Even these figures—troubling as they are—may be underestimates, since many deaths in rural areas are not registered or do not have a cause of death documented (Burgess *et al.*, 2017).

Figure 1: Daily reported deaths due to COVID-19 (India, the United States, Rest of World)



In terms of the second measure, the economy, the limited existing evidence is not much better. Over a period of roughly one month between 25 March and 20 April, India imposed one of the most stringent lockdowns in the world and has since retained severe restrictions on movement and economic activity (Hale *et al.*, 2020). These steps have decimated the Indian economy. Between April and June 2020, the Indian economy shrank by over 25%, more than every other G-20 country.[3] The ratings agency, CRISIL, estimated that the country had plunged into the worst economic recession since independence.

The numbers we have discussed thus far provide some insight into the challenge facing India, but they are not directly helpful in understanding the geographical distribution of the economic downturn. Understanding where economic activity is steady, recovering, or falling is critical in a period following the initial surge of pandemic cases because this information provides guidance on where to target government aid. Unfortunately, the

[1] www.nytimes.com/2020/08/28/world/asia/india-coronavirus.html.
[2] Case count numbers come from 'European CDC: Situation Update Worldwide' obtained via Our World in Data (https://ourworldindata.org/coronavirus). The number of reported cases from any country is a function of both disease prevalence and testing. India has conducted fewer tests than the United States.
[3] As reported online by the Chief Economist of the International Monetary Fund: https://twitter.com/GitaGopinath/status/1301178474351202306.

combination of India's massive economic recession and its large informal sector economy creates a significant problem for policymakers seeking to track recovery.

Many traditional economic indicators such as employment numbers are generally unavailable at a high frequency in most parts of the world. In India, they can be all but impossible to collect without specialised surveys, which tend to be costly and therefore limited in scope. Other economic indicators (such as tax receipts or the value of formal sector manufacturing output) can be measured, but these indicators tend to be published well after the fact and arguably only provide insight into a small fraction of overall economic activity in the country, limiting their usefulness for real-time pandemic or aid responses.

In this paper, we use high-frequency data on electricity and pollution—variables that are both strongly correlated with economic activity and available with almost no delay—to track the Indian economy during the COVID-19 lockdowns and subsequent recovery.

Prior work has shown that electricity use is closely correlated with economic activity and indeed it has been used to detect manipulation of GDP growth statistics (Lyu *et al.*, 2018; Chen *et al.*, 2019). Electricity supply is frequently recorded at a minute-by-minute frequency, and daily or monthly totals can often be obtained by the government from utilities in the distribution sector or regulators of the transmission grid. Not all these data are necessarily public, but for the present purpose it is only relevant that they can be accessed by the state.

Air pollution has also been linked to economic activity, including in the aftermath of the coronavirus pandemic (Chay and Greenstone, 2003; Burke, 2020). In some ways, information on pollution is even more accessible than electricity, thanks to rich satellite datasets that now provide us with near-real-time measures of several common pollutants. In particular, nitrogen dioxide (NO_2, a common pollutant associated with the transport sector) and measures of Aerosol Optical Density (a proxy for particulate matter pollution) are measured across the globe at an approximately daily frequency by the Ozone Monitoring Instrument (OMI) and the Moderate Resolution Imaging Spectroradiometer (MODIS) respectively.

Using these data, we show how to create recovery indices based on measuring changes in electricity consumption and air pollution. The first is an input that also cuts across different sectors, formal and informal alike. The second is an output-based measure, an externality that derives from economic activity across a range of sectors. We construct daily measures of electricity use and air quality spanning a period of over five years. These datasets are used to generate measures of deviation in these variables from predictions based on historical behaviour. The sign and magnitude of these deviations is informative about the degree to which the local economy in a region has been damaged or has recovered. As an example, we find that, at the height of the Indian lockdown in April 2020, far less electricity was consumed than we would expect based on observing previous years. More than a month after opening up, electricity use remained depressed across large parts of the country.

To complement the use of electricity and pollution data, we also provide national-level evidence on remittance flows, which sheds light on the vulnerability of India's informal economy. This is particularly important in the Indian context, where there are virtually no safety nets during economic downturns for the vast majority of India's workforce.

Overall, this paper provides one solution to the challenge of tracking economic activity at a high temporal frequency and high spatial resolution. The data we analyse reflect the overall damage to the Indian economy during the coronavirus lockdowns, but also provide insight into the variation in impact across different regions.

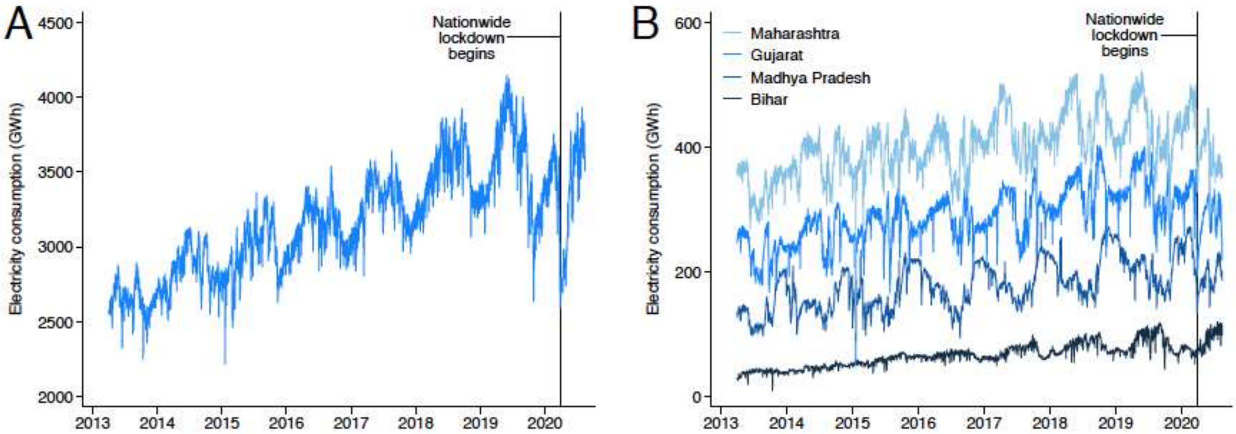
The remainder of this paper is structured as follows. In Section 2, we summarise our data sources. In Section 3, we describe the empirical methods used to create a recovery indicator. We present results in Section 4 and conclude in Section 5.

2 Data

2.1 Electricity data

We collected daily state-specific electricity consumption data from the Power System Operation Corporation Limited (POSOCO), India's government-owned electricity grid operator. We obtained data covering 01 April 2013 through 31 July 2020 from POSOCO's daily power supply position reports.[4] Our main electricity variable of interest is the GWh[5] of 'energy met', or electricity consumption.[6] Panel A of Figure 2 plots total daily electricity consumption for all of India over our sample period. The right-hand panel plots electricity use for each state in our sample, highlighting as well as breaking out consumption for four key states: Maharashtra, Gujarat, Madhya Pradesh, and Bihar.

Figure 2: Daily electricity consumption data, all-India and select states



2.2 Air pollution data

Our air pollution data consider two pollutants: NO_2 and particulate matter. We chose these because they are emitted by a large number of sources while also reflecting local variability. Although both fine particulate matter and NO_2 are measured by India's Central Pollution Control Board through a network of ambient air quality monitors, the data are far from uniform across the country and sparse, or non-existent, in smaller towns and rural India. In addition, we found that ground monitoring data were frequently missing as we looked further back in time. This makes the use of this source of information unfeasible for the strategy we follow in this paper, which relies on building a high quality predictive model of pollution (or electricity use) based on historic data.

As an alternative, therefore, we rely on two satellite datasets that provide both the high-frequency historical coverage and the spatial resolution we need to carry out our analysis. For NO_2, we use a gridded 0:25° × 0:25° dataset from the OMI. For particulates, we substitute with a commonly used proxy, the AOD, from the NASA MODIS mission. In both cases, we download over five years of data at the daily level covering 01 January 2015 to 31 July 2020 and average over all observations (grid-points) within state or district boundaries to construct a dataset of daily pollution readings for the corresponding administrative unit.

Pollution stems from many sources and does not necessarily reflect the same type of economic activity as leads to increasing electricity consumption. For this reason, using both measures can be quite valuable. For instance, transportation fuels are a major contributor of NO_2, so as movement within cities returns to normal the levels of this pollutant should also rise. Several factors contribute to changes in the AOD, including burning fuels, road dust, biomass, waste, and industrial emissions. Meanwhile, electricity demand may be quite sensitive to the use of commercial spaces, potentially more so than the pollutant measures alone.

2.3 Remittance flow data

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[4] These data are available from https://posoco.in/reports/daily-reports/daily-reports/.

[5] In the POSOCO reports, the units of this variable are labelled MU (million units). This is equivalent to GWh.

[6] Because there are electricity shortages in India, even at the state level, energy consumption is not always equivalent to energy demanded: see Burlig, Jha, and Preonas (2019) for more details on shortages in the Indian wholesale electricity market.

In addition to these two indicator outcomes, we also obtained data on total daily domestic remittance flows from a large financial services company in India. This dataset captures financial activity conducted primarily by low-income workers in the informal sector, most of whom are migrants from other parts of India. These workers require the ability to transfer small amounts of cash to a remote bank account operated by family. Our dataset identifies millions of such transactions generated by more than 10 million unique migrants across India. We convert these data to US dollars using exchange rate data from https://fred.stlouisfed.org/series/DEXINUS. These data serve as a high-frequency indicator of economic activity, which is otherwise unavailable.

3 Empirical methods

In quantifying how electricity consumption and pollution have responded to India's COVID-19 lockdowns and subsequent loosening, it is important to adjust for confounding factors. For example, if we simply compare energy consumption and pollution concentrations in October 2019 (prior to the COVID-19 outbreak) and in March 2020 (the beginning of India's COVID-19 lockdown), this would conflate any impacts of COVID-19 with seasonality and overall trends.

In order to overcome these challenges, we use linear regression to construct a model of electricity consumption and pollution for each of India's states in the pre-COVID-19 period only (from the beginning of the sample through 24 March 2020). We then use this model to generate out-of-sample predictions of daily air quality and energy use for each state, during and after India's COVID-19 lockdown: from 25 March 2020 to 30 June 2020. This prediction serves as an estimate of what electricity use and air quality would have been in a business-as-usual scenario. To understand the impacts of COVID-19, we then compare this business-as-usual prediction with the observed data by estimating the prediction error: the difference between the predicted outcomes and the observed data. Finally, we summarise the impacts of the COVID-19 lockdown and identify recovery by calculating the median prediction errors in the lockdown period and the recovery period (01 July 2020 to 31 July 2020). This is broadly similar to the procedure employed by Burlig *et al.* (2020).[7]

Predicting business-as-usual: We begin by generating our model of electricity consumption and air quality in the business-as-usual world, using a regression capturing several factors that are highly predictive of both energy use and air quality. In particular, we estimate the following equation separately for each state, for the pre-COVID-19 period only:

$$Y_t = \beta \text{temperature}_t + \omega_t + \delta_t + \varepsilon_t \qquad (1)$$

where Y_t is energy consumption or pollution on date t, temperature_t is daily mean temperature, ω_t is a week-of-year fixed effect, δ_t is a cubic time trend, and ε_t is an error term. Estimating the model for each state separately is equivalent to interacting all terms in Equation (1) with a state fixed effect.

This is a relatively simple model, but captures several relevant features of the data generating process. First, we model the relationship between electricity/air quality and temperature. Temperature has been shown in prior research to have strong impacts on electricity (Auffhammer, Baylis, and Hausman, 2017; Davis and Gertler, 2015) and particulate matter (Tai, Mickley, and Jacob, 2010). Second, our model includes both week-of-year fixed effects and trends. By including week-of-year fixed effects, our model accounts for seasonal patterns, which are a key feature of both electricity use (Cicala, forthcoming) and air quality (Guttikunda and Gurjar, 2012). In addition, we use a cubic time trend to capture overall changes in electricity consumption and air quality over time. This is particularly important given the sharp increase in electricity consumption in India over time shown in Figure 2 above.

Once we have estimated $\hat{\beta}$ and the vectors ω_t and δ_t, we generate predictions for each date in our sample, $\hat{Y}_t$, by simply plugging in observed values for temperature and time and turning on the relevant week-of-sample

[7] Here, we are using standard OLS regression in place of LASSO for the prediction step, because the data are more sparse. We also take medians rather than running a regression in the final step because we are not trying to control for time-varying fixed effects.

dummy. We compute prediction errors—the difference between actual behaviour and our estimate of business-as-usual behaviour—as $PE_t = Y_t - \hat{Y}_t$. We repeat this process for each state in our sample.

Quantifying COVID-19 impacts and recovery: With these prediction errors in hand, we estimate the effects of COVID-19 lockdown and quantify subsequent recovery by calculating the median prediction error within two periods: the COVID-19 lockdown period (25 March to 30 June) and a post-lockdown 'recovery' period (01 July to 30 July). We take median values rather than means because our predictions exhibit substantial noise and short-term spikes. Finally, we scale our results by normalising the median prediction error by the pre-COVID-19 period mean of the variable of interest.[8] Note that these scaled results can exceed 100%. This occurs when our predictions are particularly high relative to the observed outcome.

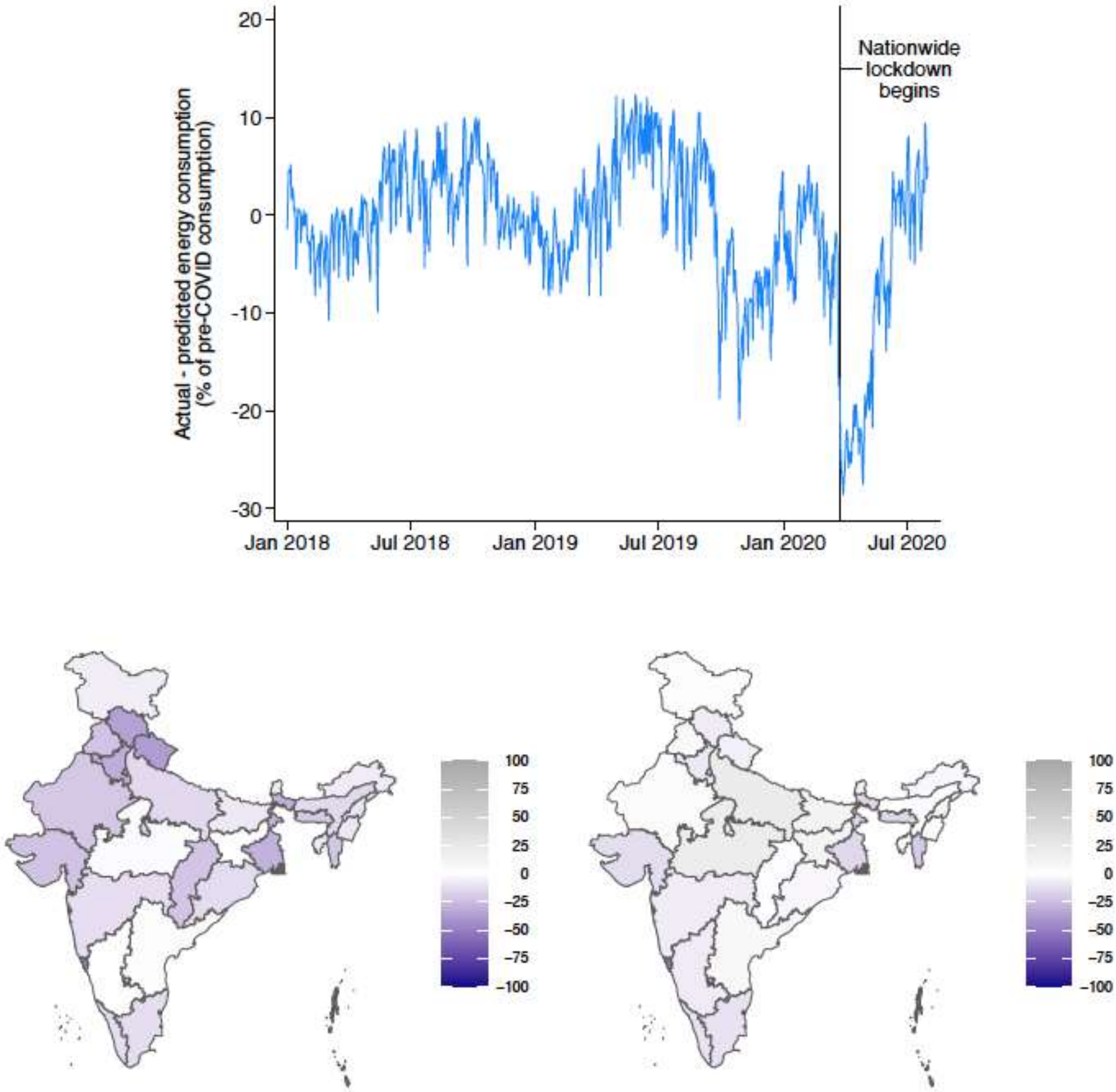
[8] When we compute state-wise estimates below, we scale the lockdown and post-lockdown period results by the average of the outcome in the corresponding date range prior to 2020. The national average plots are scaled by the average of the full pre-COVID-19 period.

4 Results

We present the results in graphical form. For each of the primary indicators—electricity, AOD, and NO_2—we produce three plots: a time series of state-by-state prediction errors; a map of the median prediction error (scaled by the pre-COVID-19 indicator mean) for the COVID-19 lockdown period; and a map of the median prediction error (scaled by the pre-COVID-19 indicator mean) for the COVID-19 recovery period. Figures 3, 4, and 5 show our estimates for electricity, NO_2, and AOD respectively. For remittance flows, we only produce a time series, because we do not have state-by-state remittance flow data.

4.1 Electricity results

Figure 3: Electricity responses to COVID-19



Top panel: National average of prediction errors of electricity consumption, 2019–20, scaled by pre-COVID consumption. Bottom left panel: State-wise median prediction error, scaled by pre-COVID electricity use, COVID lockdown period. Bottom right panel: State-wise median prediction error, scaled by pre-COVID electricity use, recovery period.

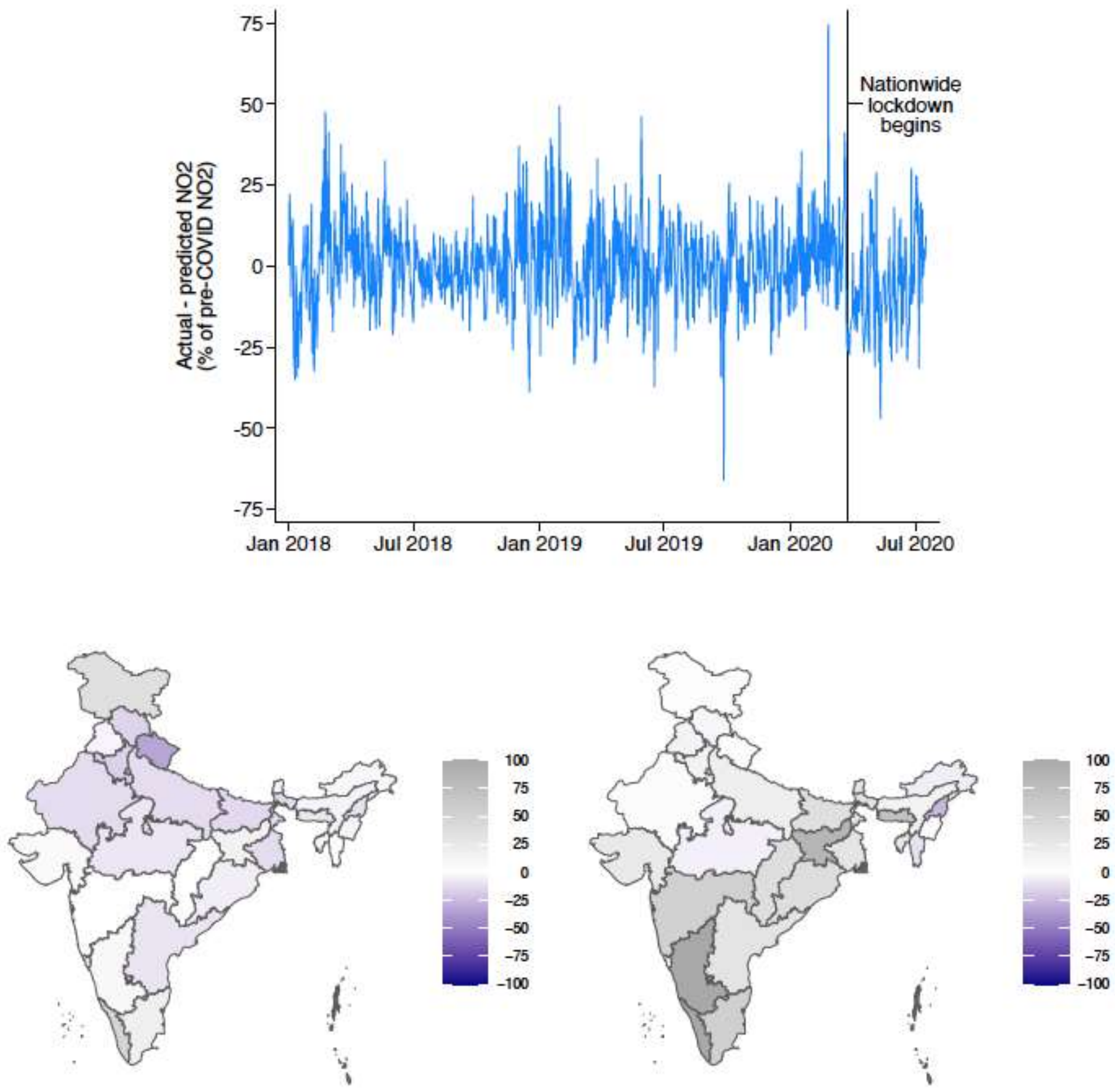
Indian electricity consumption declined sharply in response to the COVID-19 lockdowns. The top panel of Figure 3 shows a visible downturn in electricity consumption, which declined on average immediately after the lockdown began. At the national level, we see that electricity use is 13.0% lower during the lockdown period than the pre-2020 average energy use. However, there has been a significant recovery, with the month of July up by 3.0% relative to pre-2020 levels for the same period.

We examine sub-national heterogeneity in the bottom panels of Figure 3. We see declines in nearly all states during the lockdown period. The largest consumers in the pre-COVID-19 period—Maharashtra, Gujarat, Uttar Pradesh, Tamil Nadu, and Rajasthan—saw their consumption fall by 11.8%, 22.8%, 14.0%, 12.1%, and 21.0% respectively in the lockdown period relative to expectations. We see mixed recovery results for these states. Relative to the pre-COVID-19 period, consumption in Maharashtra, Gujarat, and Tamil Nadu remains depressed by 6.7%, 12.6%, and 10.8% respectively. Uttar Pradesh has more than recovered, consuming 21.9% more than expected in the pre-COVID-19 period. Rajasthan is also somewhat above expectations, at 5.0%.

This is consistent with India's manufacturing industry having been severely impacted by the pandemic and not yet returning to normal levels of activity. Uttar Pradesh and Rajasthan are much less industrialised than Gujarat and agriculture is the only sector of India's economy expected to grow, following a good monsoon season.

4.2 *NO_2* results

Figure 4: *NO_2* responses to COVID-19

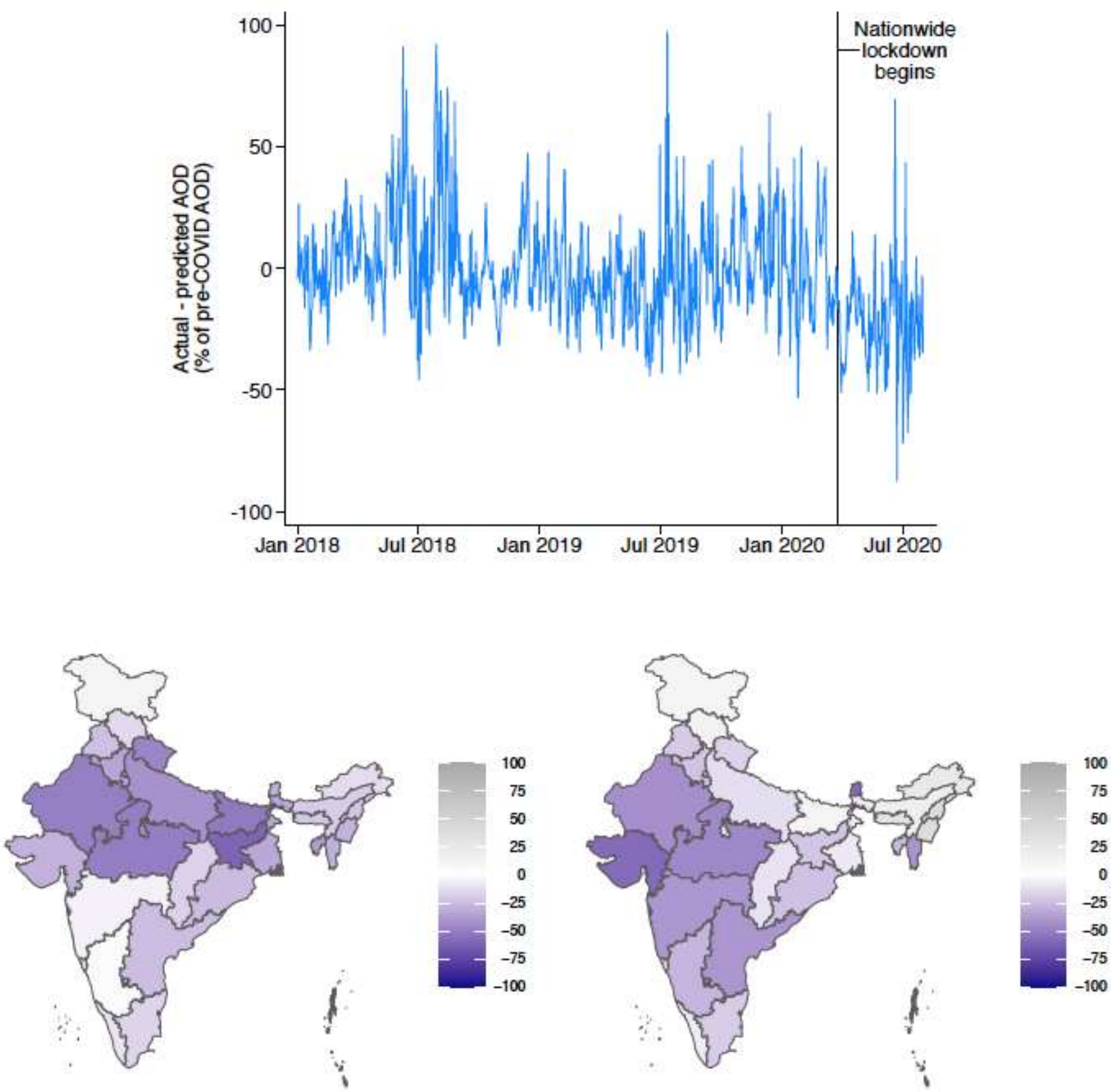


Top panel: National average of prediction errors of NO_2 consumption, 2019–20, scaled by pre-COVID NO_2. Bottom left panel: State-wise median prediction error, scaled by pre-COVID NO_2, COVID lockdown period. Bottom right panel: State-wise median prediction error, scaled by pre-COVID NO_2, recovery period.

We next estimate impacts for NO_2. Overall, we find that our prediction errors are somewhat noisier for NO_2 than for electricity. However, we still observe that prediction errors of NO_2 concentrations are 8.4% lower than the average pre-COVID-19 concentrations in the lockdown period. NO_2 concentrations have largely recovered to trend—if anything, average NO_2 usage is 19.7% higher than predicted in July.[9] We present the national average time series of prediction errors (scaled by the mean pre-COVID-19 NO_2 concentration) in the top panel of Figure 4. In the bottom panels of Figure 4, we turn to heterogeneity by state. We find that most of the reductions in NO_2 during the lockdown period occur in northern (and typically polluted) states. Rajasthan, Uttar Pradesh, Bihar, Delhi, and Madhya Pradesh saw reductions of 13.1%, 12.8%, 13.7%, 23.4%, and 9.0% respectively during the lockdown period. NO_2 vales generally recovered across the country in July, though Delhi remained 10.8% below expectations during the recovery period.

4.3 AOD results

Figure 5: AOD responses to COVID-19



[9] Differences between state outcomes as measured by changes in electricity consumption versus changes in NO_2 are not necessarily surprising, since these measures are responsive to different types of economic activity.

Top panel: National average of prediction errors of AOD consumption, 2019–20, scaled by pre-COVID AOD. Bottom left panel: State-wise median prediction error, scaled by pre-COVID AOD, COVID lockdown period. Bottom right panel: State-wise median prediction error, scaled by pre-COVID AOD, recovery period.

We next show results for AOD, a broader indicator of air quality. Note that AOD is much more variable than either electricity or NO_2 and is therefore much harder to predict. On average, we find that air quality in India has improved during the COVID-19 lockdowns, with a reduction in AOD of 25.8% relative to baseline levels. We also find evidence of incomplete recovery, with levels still depressed by 17.2% in July. We show the overall time series in the top panel of Figure 5.

In the bottom panels, we again examine heterogeneity across locations. While we find that nearly all states saw a reduction in AOD during the lockdown period, the intensity of the decline varies across space. India's northern region is typically its most polluted. We find that states in the north such as Madhya Pradesh, Rajasthan, Bihar, and Delhi saw air quality increase substantially during the lockdown period, with reductions in AOD of 50.3%,49.9%, 52.2%, and 38.4% respectively.

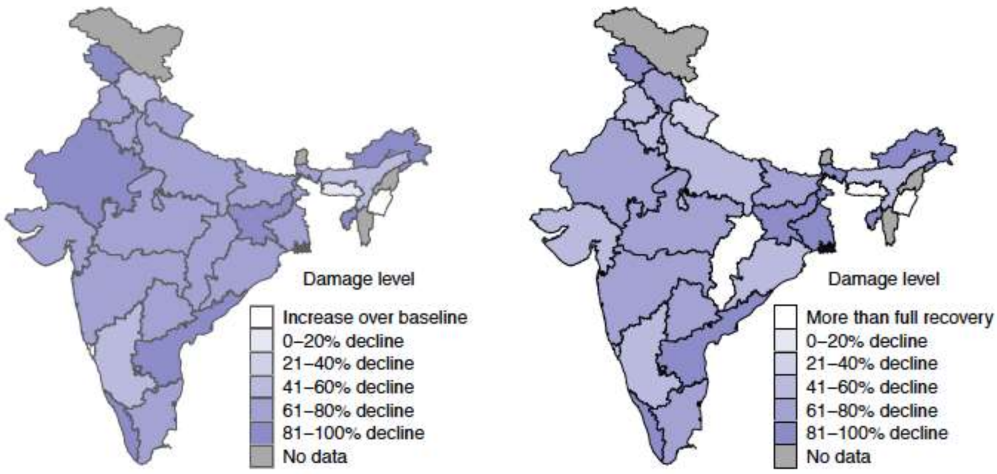
During the recovery period in July, however, we find that the spatial pattern has changed. In July, Bihar had an AOD that was 11.6% above expectations; Uttar Pradesh and Delhi both recovered partially, with recovery period estimates of 12.4% and 20.1% below expectations respectively. Other states have got worse. Notably, Gujarat, 29.4% below expectations in the lockdown period, fell to 58.2% below expectations in July. Andhra Pradesh worsened too, falling from 24.6% below expectations to 40.5% below expectations.

4.4 Remittance results

Finally, we use our remittance flow data to examine how an important economic indicator responded to COVID-19. We first estimate the average daily remittance transfer made over the period from 01 April 2019 to 29 February 2020 for every state. We compare this number to the average daily transfer made during the COVID-19 lockdowns (01 April through 30 June 2020) and to the average daily transfer in our recovery period (01 July to 26 July).[10] The difference between daily transfers over the baseline, lockdown, and post-lockdown periods tells us about the magnitude of the economic shock and the degree of recovery.

Figure 6 shows a dramatic decline in remittance flows during the lockdown period. Importantly, there was little evidence of recovery even by the end of July. This suggests that, even though some formal sector economic activity may have restarted, low-income migrant workers—who form a crucial part of India's informal sector—remain worse off than before the pandemic.

Figure 6: Changes in daily remittance transfers relative to a baseline average over the period April 2019 through February 2020



[10] Data availability considerations force us to use dates that are slightly different from the periods covered by our pollution and electricity data, which start at 25 March for the lockdown period and end at 30 July for the recovery period.

Left panel: State-wise change in daily transfers during the COVID lockdown period. Right panel: State-wise change in daily transfers for 01–26 July 2020.

5 Conclusion

We show that both air pollution and electricity consumption can be used to derive important insights into economic activity following the outbreak of the coronavirus pandemic. Across four measures—electricity, NO_2, AOD, and remittance flows—there is evidence of a widespread economic downturn across the country, immediately following the lockdowns in response to COVID-19. More than a month after the end of the lockdown, several areas remain subdued, with lower than usual electricity consumption concentrated in the industrial states of Gujarat and Maharashtra. In a more positive sign, NO_2—a pollutant associated with transportation fuels—has returned to near-normal levels in much of the country, suggesting that vehicular mobility may have increased. Of course, increased mobility is also likely to be associated with a greater spread of the disease, a question that lies outside the immediate scope of this paper. Remittance flows remained substantially depressed at the end of July.

We have focused in this paper on data from India and restricted ourselves to state-level variation. In principle, our work could be easily replicated for other countries and for finer geographic regions, especially if using publicly available satellite data. In large parts of the developing world, economic data is even harder to come by than in India. As national policymakers and international aid organisations think about where to target scarce funding, this type of analysis might help shed light on which regions, countries, or states require the most assistance.

References

Auffhammer, M., Baylis, P., and Hausman, C.H. (2017) 'Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States' [English], National Academy of Sciences Section: Social Sciences, Proceedings of the National Academy of Sciences, February.

Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2017) 'Weather, climate change and death in India', unpublished.

Burke, M. (2020) 'COVID-19 reduces economic activity, which reduces pollution, which saves lives'. URL: http://www.g-feed.com/2020/03/covid-19-reduces-economic-activity.html

Burlig, F., Jha, A., and Preonas, L. (2019) 'Blackouts in the developing world: the role of wholesale electricity markets', Mimeo.

Burlig, F., Knittel, C.R., Rapson, D., Reguant, M., and Wolfram, C. (2020) 'Machine Learning from Schools about Energy Efficiency', *Journal of the Association of Environmental and Resource Economists*, https://doi.org/10.1086/710606.

Chay, K.Y., and Greenstone, M. (2003) 'The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession', *Quarterly Journal of Economics* 118(3), pp. 1121–67.

Chen, W., Chen, X., Hsieh, C.-T., and Song, Z. (2019) 'A Forensic Examination of China's National Accounts' [English], *Brookings Papers on Economic Activity* 2019(1), pp. 77–141.

Cicala, S. (forthcoming) 'Imperfect markets versus imperfect regulation in US electricity generation', *American Economic Review*.

Davis, L.W., and Gertler, P.J. (2015) 'Contribution of air conditioning adoption to future energy use under global warming' [English], *National Academy of Sciences Section: Social Sciences, Proceedings of the National Academy of Sciences* 112(19), pp. 5962–67.

Guttikunda, S.K., and Gurjar, R.R. (2012) 'Role of meteorology in seasonality of air pollution in megacity Delhi, India' [English], *Environmental Monitoring and Assessment* 184(5), pp. 3199–211.

Hale, T., Angrist, N., Cameron-Blake, E., Hallas, L., Kira, B., Majumdar, S., Petherick, A., Phillips, T., Tatlow, H., and Webster, S. (2020) 'Oxford COVID-19 Government Response Tracker'.

Lyu, C., Wang, K., Zhang, F., and Zhang, X. (2018) 'GDP management to meet or beat growth targets' [English], *Journal of Accounting and Economics* 66(1), pp. 318–38.

Tai, A.P.K., Mickley, L.J., and Jacob, D.J. (2010) 'Correlations between fine particulate matter (PM2.5) and meteorological variables in the United States: implications for the sensitivity of PM2.5 to climate change' [English], *Atmospheric Environment* 44(32), pp. 3976–84.

Acknowledgements

We thank Geet Chawla, Claire Fan, Garrison Schlauch, and Kaixin Wang for their excellent research assistance. All remaining errors are our own.

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