Institute for Economic Studies, Keio University

Keio-IES Discussion Paper Series

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5 January, 2021
DP2021-002
https://ies.keio.ac.jp/en/publications/13661/

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Acknowledgement : This work was supported by Grants-in-Aid for Scientific Research 18K01580 2018-2020.

The causal effects of long-term $PM_{2.5}$ exposure on COVID-19 in India

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Abstract

This study investigates the causal effects of long-term $PM_{2.5}$ exposure on COVID-19 deaths, fatality rates and cases in India by using an instrumental variables approach based on thermal inversion episodes. The estimation results indicate that a 1% increase in long-term exposure to $PM_{2.5}$ leads to an increase in COVID-19 deaths by 5.7 percentage points and an increase in the COVID-19 fatality rate by 0.027 percentage points, but this exposure is not necessarily correlated with COVID-19 cases. People with underlying health conditions such as respiratory illness caused by exposure to air pollution might have a higher risk of death following SARS-CoV-2 infection. This finding might also apply to other countries where high levels of air pollution are a critical issue in terms of development and public health.

JEL: Q53, I15, O13

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The causal effects of long-term $PM_{2.5}$ exposure on COVID-19 in India

1. Introduction

South Asia is at the epicenter of the global air pollution problem, which has become a silent killer in the contemporary world. About 91% of the population in this region lives in places where air quality fails to meet World Health Organization (WHO) guideline limits (WHO, 2005). Such contaminated air impairs the functions of the respiratory organs and can lead to lung cancer, obstructive pulmonary disease, and acute respiratory infections. Furthermore, ambient air pollution and household air pollution cause millions of deaths globally, including 4.2 million and 2.8 million deaths, respectively, in 2015 (Cohen et al., 2017). India is no exception and has recorded one of the highest levels of air pollution over the past decade. In addition to the severe environmental contamination caused by air pollution, the ongoing COVID-19 pandemic has created a dire situation in the country, which has seen one of the largest losses of life in the world along with a record economic collapse, with a GDP growth rate between −9.6% and −10.3% according to October 2020 projections of the World Bank and International Monetary Fund.

Although many scientific studies have confirmed the negative effects of air pollution on respiratory diseases, cardiovascular diseases, pregnancy outcomes, and neurocognitive diseases (e.g., Brook et al., 2004; Dominici et al., 2006; Puett et al., 2009; Wellenius, 2012; Di et al., 2017), evidence on how air pollution impacts health outcomes, especially in developing countries, remains scarce and has focused mainly on the effects of household air pollution (Duflo et al., 2008; Hanna et al., 2016; Balietti and Datta, 2017; Kurata et al., 2020[4]). Moreover,

4 Kurata et al. (2020) simultaneously consider both ambient and indoor air pollution to investigate their effects on child health outcomes in Bangladesh.

evidence obtained using causal inference frameworks that link ambient air pollution exposure with COVID-19 is similarly scarce in both developed and developing country contexts; two such studies focused on the US and the Netherlands, which are moderately polluted countries (Austin et al., 2020; Cole et al., 2020). Given these gaps in the literature, our study examines the case of India, one of the most polluted countries in the world in terms of air pollution exposure and also one of the countries most severely affected by the COVID-19 pandemic, in order to investigate associations between pollution and COVID-19. Specifically, we estimate the connection of long-term $PM_{2.5}$ exposure with COVID-19 deaths, fatality rates, and cases in India at the district level by using an instrumental variables (IV) approach based on thermal inversion episodes to represent exogenous variations in the level of $PM_{2.5}$. Thermal inversions are a meteorological phenomenon that worsens air quality levels. Exploiting long-term thermal inversion variations across districts in India, we find that those districts most severely affected by long-term exposure to $PM_{2.5}$ have an increase in COVID-19 deaths by 5.7 percentage points and an increase in the fatality rate by 0.027 percentage points, but this exposure is not necessarily correlated with COVID-19 cases. People with underlying health conditions such as respiratory illness caused by exposure to air pollution might have a higher risk of death following SARS-CoV-2 infection. Our findings might also apply to other countries where high levels of air pollution are a critical issue in terms of development and public health.

This paper contributes to the literature in the following ways. First, building on the first correlation study by Wu et al. (2020), this paper provides the first causal evidence in the context of a developing country where air pollution is a critical development and public health issue, linking exposure to air pollution with COVID-19 deaths, and the fatality rate, and cases. In the recent literature, (i) preliminary findings are based mostly on correlations, (ii) there are few investigations employing causal inference frameworks in either developed or developing country contexts, and (iii) causal inference studies have focused on only moderately polluted countries, such as the US and the Netherlands (Austin et al., 2020; Cole et al., 2020). Second, this paper examines the case of India to add to the body of evidence on long-term exposure to $PM_{2.5}$ in order to demonstrate external validity. The critical hypothesis behind this is that underlying health conditions such as respiratory illness caused by exposure to air pollution may increase the risk of death following SARS-CoV-2 infection. To test this hypothesis, it would be reasonable to use long-term exposure data, given that short-term exposure to air pollution does not immediately cause health disorders; put simply, accumulated exposure matters. The use of long-term $PM_{2.5}$ data would also be valid, particularly in the case of India, given that the mobility of people there is exceptionally low; for example, the urban-rural migration rate for working-age men between the ages of 25 and 49 years ranged from 4% to 5.4% in the period 1961–2001 (Munshi and Rosenzweig, 2016). This rate is critical for employing reduced-form econometric identification as our empirical strategy, which is an approach that depends on the reduced form regression model to regress COVID-19 indicators on the long-term lagged $PM_{2.5}$ data.

The remainder of the paper is structured as follows. Section 2 describes the data and methodology used. Section 3 discusses the main findings from the estimation results and the potential mechanisms. Section 4 concludes the paper and suggests future areas of research.

2. Background

This section provides background on air pollution in India (Section 2.1), the meteorological phenomenon known as thermal inversion that we rely on for identification in this study (Section 2.2), the COVID-19 pandemic in India (Section 2.3), and emerging studies linking COVID-19 cases, deaths, and fatality rates to air pollution exposure (Section 2.4).

2.1. Air pollution in India

India has recorded one of the world's highest levels of air pollution over the past decade. India State-Level Disease Burden Initiative Child Mortality Collaborators (2020) suggest that air pollution contributes to 8.8% of the total deaths in India each year. Air pollution is also identified as one of the most severe risk factors for public health in India (ICMR et al., 2017). Around 1.04 million premature deaths and 31.4 million disability-adjusted life years (DALYs) are estimated to be attributable to household air pollution, whereas 627,000 premature deaths and nearly 17.8 million DALYs are attributable to ambient air pollution in the form of $PM_{2.5}$ (Balakrishnan et al., 2014). PM exposure levels in India are more than five times higher than those in the US (Greenstone and Hanna, 2014). Air pollution is not limited to urban areas but also affects rural areas owing to agricultural practices such as crop burning, emissions from heavy application of fertilizers, and biomass burning for indoor cooking.

A multiplicity of sources and geographical source regions, modes of exposure, and a range of impacts all add to the complexity of the air pollution problem in South Asia. Topographic characteristics also influence the spatial variations of air pollution. For example, air pollution can become trapped and stagnate relatively close to the ground across the Indo-Gangetic Plain owing to India's hilly and land-locked topography.

2.2. Thermal inversion

Thermal inversion is a meteorological phenomenon that occurs when a layer of warm air passes between two layers of cold air. The warm air traps the bottom layer of cold air, causing pollutants and particulates to concentrate near the Earth's surface (e.g., Jacobson, 2002). To date, few studies have used thermal inversion as an investigative tool. Some studies have proposed using thermal inversion conditional on weather-related variables for the instrument of air pollution. In the economics literature, Knittel et al. (2016) is one of the first studies to mention the relationship between thermal inversion and air pollution level, and Arceo-Gomez et al. (2016) use thermal inversion as an instrument for the concentration of air pollution.[5] Thermal inversions result from the combination of atmospheric forces and topographic characteristics. By controlling for their effects, thermal inversions can be considered exogenous phenomena that are suitable instruments for air pollution levels. That is, thermal inversions are highly correlated with levels of $PM_{2.5}$, affect outcome variables only through their effects on the level of $PM_{2.5}$ (in our case, COVID-19 indicators), and do not correlate with other omitted variables.

2.3. COVID-19 in India

Even as the rest of the world was beginning to feel the impact of the COVID-19 pandemic, few cases were observed in India until March 2020. The government was successful in keeping the virus out of the country by restricting international travel and isolating individual cases. Although this enabled India to buy some time and build the necessary internal response capacity, it soon became apparent that the challenges involved in preventing domestic transmission would be enormous. India has some of the largest population clusters in the world, making it an ideal breeding ground for a contagion, especially among the those most vulnerable, including slum dwellers and migrant workers.

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5 See also Jans et al. (2018), Sager (2019), Cui et al. (2019), Molina (2020), and Tsaneva and Balakrishnan (2020). As an alternative instrument, Deryugina et al. (2019) propose the use of changes in local wind direction to develop a new approach that uses machine learning techniques to estimate life-years lost due to air pollution exposure.

According to the Ministry of Health and Family Welfare, as of November 20, 2020, India had a total of 8,383,602 COVID-19 cases and 131,578 deaths, in line with the cumulative numbers reported by the COVID-19 India Dashboard (8,999,049 cases and 132,133 deaths). As of November 2020, the number of positive cases ranked second in the world according to Johns Hopkins University, despite the Indian government's relatively early decision to implement a nationwide lockdown of its 1.3 billion people at midnight on March 24, 2020, when the total reported cases had reached 568. Overcrowded cities and homes in the country are likely to have facilitated the spread of the virus. Governments debated how to balance saving lives with preserving livelihoods, concluding to ease lockdown restrictions in favor of returning people to work, which naturally led to a rapid increase in the number of positive cases and deaths. In addition, the relaxation of other restrictions also led to massive spikes in the number of cases across India. A sustained exponential increase in the number of positive cases continued until the end of September 2020, after which the curve mostly flattened (Appendix Figure 1).

Initially, cases and fatalities were observed mostly in urban centers such as Mumbai and Delhi, but subsequently became more prevalent across the entire country. Part of the massive spread of the contagion is attributable to the lockdown, which triggered a humanitarian crisis of unprecedented proportions. Fearing for their own survival, millions of migrant workers fled the city because of income loss, hunger, destitution, persecution from authorities policing containment, and fear of communities not maintaining social distancing (Sengupta and Jha, 2020). As they made their long trek home, the migrants carried the virus with them to rural areas. Lee et al. (2020) suggest that the initial wave of COVID-19 cases in India, Pakistan, and Bangladesh could be explained more readily by the mass migration from city centers to hometowns and rural areas driven by sudden job losses and the anticipation of India's lockdown restrictions.

2.4. Emerging studies linking COVID-19 to air pollution exposure

Evidence suggests that older adults, particularly those with severe underlying health conditions, might be at higher risk of severe COVID-19-related symptoms and death compared with younger people. According to medical data from China, approximately 80% of COVID-19 deaths occurred among adults over the age of 60 years, whereas only one (0.1%) death occurred in someone under the age of 19 years (CDC, 2020). However, there is still limited information regarding the risk factors for COVID-19 backed by scientific evidence, although many studies already underway are investigating these confounding factors. Among the various potential COVID-19 risk factors, medical specialists and researchers are focusing initially on respiratory ailments such as asthma and chronic lung disease. This is because, among those first hospitalized with COVID-19, the most frequently encountered complications were pneumonia, sepsis, respiratory failure, and acute respiratory distress syndrome. Various other risk factors for COVID-19 have since been identified, most of which remain under investigation.[6] The US Centers for Disease Control and Prevention (CDC) has published several potential risk factors in order to raise awareness and encourage precautionary behaviors. These underlying ailments include chronic lung disease, asthma, diabetes, and severe heart conditions.[7]

6 In addition to well-known breathing problems, blood clots pose a significant danger for COVID-19 patients. Clots cause patients with COVID-19 to have heart attacks and strokes, form rashes on their skin, and develop red, swollen wounds that resemble frostbite on their fingers and toes (Jose and Manuel, 2020).

7 The CDC also lists chronic kidney disease being treated with dialysis, severe obesity, age 65 years and older, living in a nursing home or long-term care facility, immunocompromised, and liver disease as underlying health conditions. For details, please see the following CDC webpage retrieved on April 27, 2020 (https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/groups-at-higher-risk.html).

One of the first quantitative investigations into the role of pollution in this context comes from a correlation analysis in the US by Wu et al. (2020).[8] Surprisingly, their results indicate that only a 1-μg/m³ increase in $PM_{2.5}$ is associated with an 8% increase in the COVID-19 fatality rate. Their results were statistically significant and robust to secondary and sensitivity analyses. Although representing the first evidence establishing a link between air pollution and COVID-19 mortality, their study has potential estimation bias derived from endogeneity and omitted variables. Air pollution likely plays an important role, but it might be through a different mechanism, which could have very different policy implications. Likewise, most other studies focus on moderately polluted countries, such as the US, Netherland, Italy, Spain, France, and Germany (Andree, 2020; Conticini et al., 2020; Travaglio et al., 2020; Wu et al., 2020), and suggest a positive relationship between the air pollution and COVID-19. Given this gap, Yamada et al. (2020) examine the case of India, which is one of the most polluted countries in terms of ambient air pollution and household air pollution, and use district-level data to investigate links with the COVID-19 fatality rate. The results suggest a positive and statistically significant association between exposure to household air pollution and the COVID-19 fatality rate. However, the authors consider the estimation results as still premature, constrained by data availability and possible estimation bias. Although the above-mentioned studies are useful as preliminary estimates, they warrant more convincing and rigorous analysis beyond mere correlation. Unlike other studies, Austin et al. (2020) use wind direction as an instrument for $PM_{2.5}$ in order to establish causality, whereas Cole et al. (2020) use the long lag of air pollution

8 Ogen (2020) suggests a link between COVID-19 deaths and nitrogen dioxide (NO_2) levels, but that study does not control for any confounding factors.

and commuting times as their instruments. Although the validity of the instruments using long lag of air pollution and commuting times needs to be further clarified in terms of exclusion restrictions (e.g., longer commuting times may be correlated with the increase in number of COVID-19 infections), the wind direction instrument as employed by Deryugina et al. (2019) is promising.

3. Empirical strategy

3.1. Data

Table 1 presents the summary statistics for our sample. The details of each variable are described below. $PM_{2.5}$ and all other climate variables use the values at the geographical centroid of each district to reflect the representative value.

COVID-19

We compile the COVID-19 data as of November 1, 2020, including the number of cases and deaths by district based on the COVID-19 India Dashboard, a website that tracks the spread of COVID-19 in India. The COVID-19 India Dashboard collects data from multiple sources, including CSSE at Johns Hopkins University, Covid-19-India, reliable news sources, and government press releases.[9] We rely on this because the Ministry of Health and Family Welfare does not make public its district-level COVID-19 data. The data from the Dashboard and the Ministry are in close agreement, at least in terms of state-level COVID-19 indicators, with a correlation of 0.9993 for cases and 1.0 for deaths. A sustained exponential increase in the number

[9] Please see further details at the COVID-19 India Dashboard website (https://hisham2k9.pythonanywhere.com/aboutview).

of positive cases was observed until the end of September 2020. However, the curve has been mostly flat since then (Appendix Figure 1). All but three districts have had at least 1 case and 46 districts have not had any fatalities.

Although we use the best available COVID-19 data from India, there are ongoing discussions about their reliability. Some experts claim that the number of deaths is underreported, casting doubt on the strikingly low fatality rate (about 1.5 as of November 2020). Those experts suggest the following factors as contributing to the underreporting of the real number of COVID-19 deaths: fear of reporting, lack of timely access to health facilities, and cultural or religious cremation practices that limit the time available to perform autopsies for determining the cause of death. In contrast, others explain that India's low fatality rate is accurate, reflecting the reality of India's relatively young population. Still others (e.g., Philip et al., 2020) argue that India's fatality rate is, if anything, too high, and predict that India's fatality rate is actually much lower than that reported by the government.

$PM_{2.5}$

We use the mean value of $PM_{2.5}$ in each district from 2007 to 2016 to represent long-term exposure. The estimated $PM_{2.5}$ data is based on high-resolution satellite images captured by the Global Annual $PM_{2.5}$ Grids of MODIS, MISR, and the SeaWiFS Aerosol Optical Depth with GWR, v1 (1998–2016), which detail the annual concentrations (micrograms per cubic meter) of ground-level $PM_{2.5}$ with dust and sea salt removed. The resolution is per 0.01-degree grid cells (about 1 km^2). The simple two-way scatter plots show the positive correlations of the mean $PM_{2.5}$ from 2007 to 2016 with COVID-19 (Appendix Figure 2).

Thermal inversions

We generate data on thermal inversions by using the temperature data of the two different layers at 1000 hPa and 925 hPa (about 100 m and 750 m above sea level, respectively) from the NCEP/NCAR dataset, which has a resolution of 2.5° × 2.5° (roughly 250 × 250 km)[10]. These two pressure levels are the closest to the ground available in the NCEP/NCAR dataset. Thermal inversions occur when a layer of warm air passes between two layers of cold air. To derive the instrument for long-term exposure to $PM_{2.5}$, we first calculate the mean temperature of each pressure level for the 10 years from 2006 to 2017 by district. Then, we identify thermal inversions when the temperature difference D is negative by using the following formula: D = (temperature at 1000 hPa) – (temperature at 925 hPa). Here, we use the temperature data at midnight (00:00) in line with previous studies (Jans et al., 2018; Molina, 2020; Tsaneva and Balakrishnan, 2020) in order to hold the exogeneity because daytime temperatures are deemed to be more susceptible to economic activities.

Control variables

As additional controls, we use wind velocity, humidity, precipitation, temperature, humidity squared, and temperature squared in order to mitigate concerns about the exclusion restrictions of the IV approach given that they could potentially affect the occurrence of thermal inversions. The quadratic terms of humidity and temperature consider the potential nonlinearity between COVID-19 and explanatory variables. In each variable, we use either daily or monthly mean values to compute the mean yearly values of 2007–2016.

Wind velocity data are from ERA5, the fifth-generation ECMWF reanalysis dataset on global climate and weather for the past 4 to 7 decades. The data values show the wind velocity at a height of 10 m above the surface of the Earth with a resolution 0.5° × 0.5°. Humidity data

10 The use of NCEP/NCAR data is supported by past literature to provide consistent best-estimate of weather at grid-level (e.g., Garg et al. 2018; Hansen-Leiws, 2018; Tsaneva and Balakrishnan, 2020). With the resolution of NCEP/NCAR at 2.5°×2.5°, the variation is deemed to be large enough to use it as the instrument for PM2.5.

are from the NCEP/NCAR dataset Reanalysis 1: Surface, which is a grid-level dataset from near the surface level (0.995 sigma level) with a resolution 2.5° × 2.5°. Precipitation and temperature data are from the Terrestrial Air Temperature and Terrestrial Precipitation of Version 5.01 Gridded Monthly Time Series 1900–2017; both of these datasets are interpolated and documented by Kenji Matsuura and Cort J. Willmott from the University of Delaware (e.g., Willmott and Matsuura, 1995). The monthly averages of station temperature (degrees) and precipitation (mm) are interpolated to a latitude/longitude grid with a resolution of 0.5° × 0.5°.

Table 1: Summary statistics

	Obs	Mean	Std. Dev.	Min	Max
Fatality rate from COVID-19	636	0.01	0.01	0	0.06
Number of deaths from COVID-19 per km^2	639	0.30	5.38	0	133.96
Number of cases from COVID-19 per km^2	639	11.80	141.96	0	3354.86
$PM_{2.5}$, 2007–2016 (average, $\mu g/m^3$)	640	40.51	20.52	2.8	100.6
Thermal inversion dummy, 2007–2016 (average)	640	0.11	0.31	0	1
Wind velocity, 2007–2016 (average, meter per second)	640	2.52	0.62	1.43	5.61
Humidity, 2007–2016 (average, %)	640	62.11	13.32	29.32	90.16
Precipitation, 2007–2016 (monthly average, mm)	637	112.76	60.18	9.1	381.4
Temperature, 2007–2016 (monthly average, degree)	637	24.39	4.52	-3.1	29.2
$Humidity^2$, 2007–2016 (average, %)	640	4655.03	1680.85	986.68	8738.33
$Temperature^2$, 2007–2016 (monthly average, degree)	640	617.98	260.16	0.33	983.70

Source: COVID-19 India Dashboard, NASA, NCEP/NCAR, ERA5, NCEP/NCAR Reanalysis 1: Surface, Terrestrial Air Temperature and Terrestrial Precipitation of Version 5.01

Note: COVID-19 indicators are as of November 11, 2020.

3.2. Methods

We conducted our analysis at the district level, using the 640 administrative districts surveyed in the 2011 Census of India. An econometric analysis employing concentration of $PM_{2.5}$ as a primary regressor is limited for multiple reasons: (i) the non-random spatial and inter-temporal variations of $PM_{2.5}$; (ii) endogeneity, such as individuals and households living in areas with cleaner air possibly having different unobservable socio-economic characteristics compared with their counterparts living in more polluted areas; and (iii) measurement errors such as ambient particles captured by satellite images and air pollution observation stations. To address these issues, we use the following two-stage identification formula.

$$\mathrm{COVID}_{dt} = a + bPM_{2.5_{dT}} + d\sigma_{dT} + f_s + \mu_{dT}$$

$$PM_{2.5_{dT}} = e + fINVERSION_{dT} + f_s + \varphi_{dT}$$

Here, COVID_{dt} is the number of COVID-19 cases or deaths in district d at time t (as of November 1, 2020); $PM_{2.5_{dT}}$ is the mean exposure level to $PM_{2.5}$ during time period T (2007–2016); σ_{dT} is a vector of district-specific climate indicators, including temperature, temperature^2, precipitation, wind velocity, humidity, and humidity^2; f_s is state-fixed effects to control for the time-invariant state-level heterogeneity such as state-level containment policies against COVID-19; and μ_{dT} (φ_{dT} in the first stage) is the error term. This identification strategy relies on the spatial variation of $PM_{2.5}$ across districts, which are not fully controlled by state fixed effects (see Appendix Table 1). For the instrument of $PM_{2.5}$, we use the inversion dummy, $INVERSION_{dT}$. Importantly, we build the inversion data using the values at midnight in order to hold the exogeneity given that inversion episodes based on daytime temperatures are susceptible to economic activities. The weather-related controls are also important to assure that the exclusion restriction holds, given that the weather controls may independently affect health outcomes, such as the link between temperature and mortality (Deschenes and Greenstone, 2011).

4. Results and discussion

4.1. Estimating the causal effects of long-term $PM_{2.5}$ exposure on COVID-19

Table 3 presents the relationship between long-term $PM_{2.5}$ exposure and COVID-19 based on an IV approach. As previously discussed, we use the IV approach to mitigate the estimation biases from endogeneity and measurement errors. The first-stage estimation results show a strong link between the thermal inversion instrument and the levels of $PM_{2.5}$ in Table 2. Also, based on the conventional threshold for the weak instrument test formalized by Staiger and Stock (1997), the Kleibergen-Paap (2006) rk statistic has sufficient values across all the specifications in Table 3.

Table 2: First-stage estimation results

	(1)	(2)	(3)
	Mean $PM_{2.5}$, 2007–2016 (log)		
Mean thermal inversions dummy, 2007–2016	0.378***	0.223***	0.144***
	(0.0426)	(0.0415)	(0.0335)
Controls		√	√
State fixed effects			√
Observations	640	637	637
R-squared	0.078	0.586	0.766

Source: NASA, NCEP/NCAR, ERA5, NCEP/NCAR Reanalysis 1: Surface, Terrestrial Air Temperature and Terrestrial Precipitation of Version 5.01
Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Estimations are based on a robust variance estimator.

As shown in columns 1 to 6 in Table 3, exposure to $PM_{2.5}$ is positively correlated with COVID-19 deaths, the fatality rate and cases. The statistical relationships are robust for deaths and the fatality rate at the 1% significance level (columns 1 to 4), but COVID-19 cases are not necessarily significant (columns 5 and 6). Variations in the levels of $PM_{2.5}$ could be proxied in part by state fixed effects. However, the results in columns 2, 4, and 6, which reflect the added state fixed effects and controls, do not reveal any significant change in magnitude and p-values from the results without state fixed effects in columns 1, 3, and 5.

In India, the estimation results indicated that a 1% increase in long-term exposure to $PM_{2.5}$ leads to an increase in COVID-19 deaths by 5.7 percentage points (column 2) and an increase in the COVID-19 fatality rate by 0.027 percentage points (column 4), but this exposure is not necessarily correlated with COVID-19 cases (column 6). These results imply that people with underlying health disorders such as respiratory illness caused by exposure to air pollution might have a higher risk of death following SARS-CoV-2 infection. However, the increase in COVID-19 cases in India might also be explained more readily by other factors.[11]

11 For example, Austin et al. (2020) show that recent $PM_{2.5}$ levels are associated with the incidence of COVID-19 in the US. Lee et al. (2020) suggest that the initial increase in cases in India, roughly by the second quarter of 2020, is partly explained by mass migration from city centers to hometowns and rural areas due to job losses and anticipation of lockdowns.

Table 3: Effects of exposure to $PM_{2.5}$ on COVID-19

	(1)	(2)	(3)	(4)	(5)	(6)
	COVID-19 deaths		COVID-19 fatality rate		COVID-19 cases	
	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS	IV/2SLS
Mean $PM_{2.5}$, 2007–2016 (log)	4.350***	5.710***	0.0182***	0.0267***	0.871	1.258
	(1.185)	(1.771)	(0.00659)	(0.0102)	(0.692)	(1.035)
Control variables	√	√	√	√	√	√
State fixed effects		√		√		√
Kleibergen-Paap (2006) rk statistic	19.2	15.2	28.0	18.6	28.0	18.6
Observations	593	593	635	635	635	635

Source: COVID-19 India Dashboard, NASA, NCEP/NCAR, ERA5, NCEP/NCAR Reanalysis 1: Surface, Terrestrial Air Temperature and Terrestrial Precipitation of Version 5.01
Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses. Estimations are based on a robust variance estimator. "COVID-19 deaths" in columns 1 and 2 denotes the number of deaths from COVID-19 per km^2 in the log term. "COVID-19 cases" in columns 5 and 6 denotes the number of COVID-19 cases per km^2 in the log term.

4.2. Robustness test: Exclusion of Delhi, Assam, and Goa

To check the robustness of the estimation results shown in Table 3, we run the same specifications using the IV approach while excluding about 5%–10% of the observations, which include the three states with the largest number of attritions of COVID-19 cases (i.e., Delhi, Assam, and Goa). As shown in Appendix Table 2, those states have many cases that cannot be assigned to a specific district within the state. The estimation results are robust for columns 1 and 2, which employ COVID-19 deaths and the fatality rate, respectively, as the dependent variable, but not for column 3, which uses COVID-19 cases as the outcome. Column 3 in Table 4 shows that a 1% increase in long-term exposure to $PM_{2.5}$ increases the number of COVID-19 cases by 2.2 percentage points at the 10% significance level. Also, it is worth noting that all the results indicate larger coefficients of mean $PM_{2.5}$ in 2007–2016 compared with that shown in Table 3, implying that the elasticity of COVID-19 to $PM_{2.5}$ exposure in Delhi, Assam, and Goa is relatively small compared with other states.

Table 4: Effects of exposure to $PM_{2.5}$ on COVID-19, excluding Delhi, Assam and Goa

	(1)	(2)	(3)
	COVID-19 deaths	COVID-19 fatality rate	COVID-19 cases
	IV/2SLS	IV/2SLS	IV/2SLS
Mean $PM_{2.5}$, 2007–2016 (log)	6.090***	0.0379***	2.203*
	(1.784)	(0.0129)	(1.200)
Control variables	√	√	√
State fixed effects	√	√	√
Excluding Delhi, Assam, and Goa	√	√	√
Kleibergen-Paap (2006) rk statistic	15.6	14.0	14.0

Observations	563	597	597

Source: COVID-19 India Dashboard, NASA, NCEP/NCAR, ERA5, NCEP/NCAR Reanalysis 1: Surface, Terrestrial Air Temperature and Terrestrial Precipitation of Version 5.01
Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses. Estimations are based on a robust variance estimator. "COVID-19 deaths" in columns 1 and 2 denotes the number of deaths from COVID-19 per km^2 in the log term. "COVID-19 cases" in columns 5 and 6 denotes the number of COVID-19 cases per km^2 in the log term.

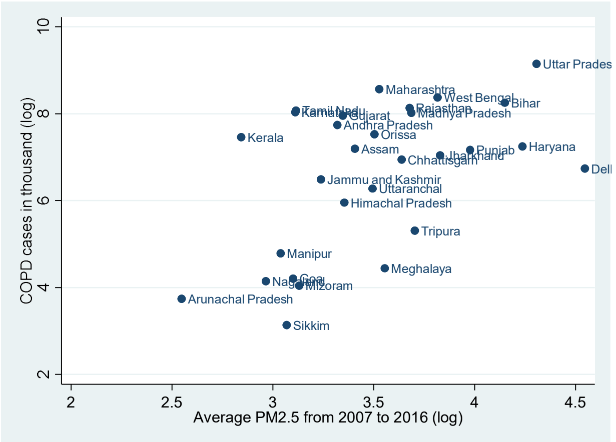
4.3. Discussions of the mechanism: The link between exposure to $PM_{2.5}$ and COVID-19

Exposure to air pollution adversely affects one's respiratory and cardiovascular systems. This impact could exacerbate the severity of COVID-19 symptoms and may increase the risk of fatality in COVID-19 patients. In the case of India, this possibility is based on long-term exposure to toxic $PM_{2.5}$. It has been reported that the risk of severe COVID-19 increases with age (e.g., 8 out of 10 COVID-19 deaths reported in the US have been in adults aged 65 years and older, according to the CDC). As new studies emerge and our understanding progresses day by day, we are learning about other risk factors that might increase the severity of COVID-19. The CDC has suggested that adults of any age with the following conditions are at increased risk of severe COVID-19: chronic obstructive pulmonary disease (COPD), cancer, chronic kidney disease, and heart conditions, among others.[12] Furthermore, the CDC has also noted that adults of any age with underlying conditions, such as asthma, cerebrovascular disease, and cystic fibrosis, might also be at increased risk for severe COVID-19.

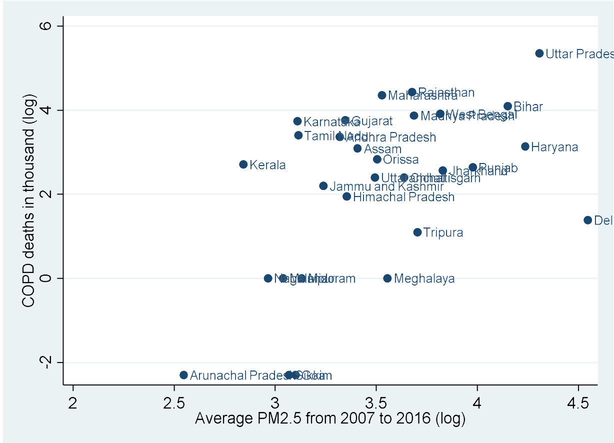
12 Based on information published on the CDC website, retrieved November 17, 2020 (https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-with-medical-conditions.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fneed-extra-precautions%2Fgroups-at-higher-risk.html).

Of these (possible) underlying conditions, we test the relationship between the level of $PM_{2.5}$ and respiratory diseases, that is, the cases of COPD and asthma and their related deaths estimated from the Global Burden of Disease Study 1990–2016 by Salvi et al. (2018). COPD is a group of diseases that cause breathing-related issues along with symptoms such as frequent coughing or wheezing, shortness of breath, and difficulty in taking a deep breath. Similarly, asthma causes repeated wheezing episodes, breathlessness, chest tightness, and nighttime or early morning coughing. In the case of India, the two-way scatter plots in Figure 1 show strong positive correlations (ranging from 0.49 to 0.52) between the mean level of $PM_{2.5}$ in 2007–2016 and the incidence of COPD, asthma, and their related deaths for each state in India in 2016. The positive relationship between exposure to air pollution and onset of chronic respiratory disease is inconclusive (Shin et al., 2020), but this link would be plausible in many cases, as other studies have suggested (e.g., Andersen et al., 2012; Hendryx et al., 2019; Schraufnagel et al., 2019). This implies that exposure to $PM_{2.5}$ might impair or worsen respiratory functions. Those who reside in areas with high levels of $PM_{2.5}$ might have a higher risk of death following SARS-CoV-2 infection, which is consistent with our estimation results (Table 3).

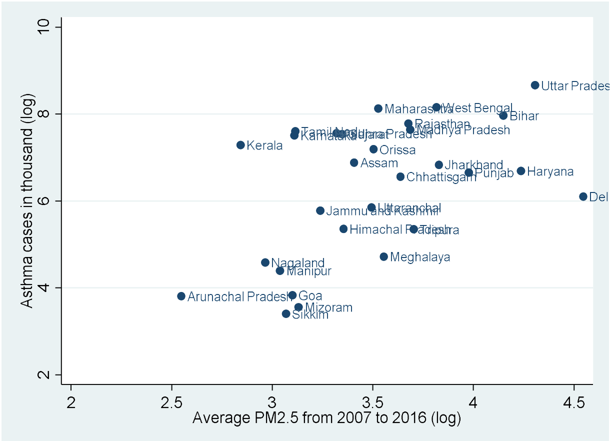
Figure 1: Correlation between mean $PM_{2.5}$ levels in 2007–2016 and respiratory diseases in each state in India in 2016



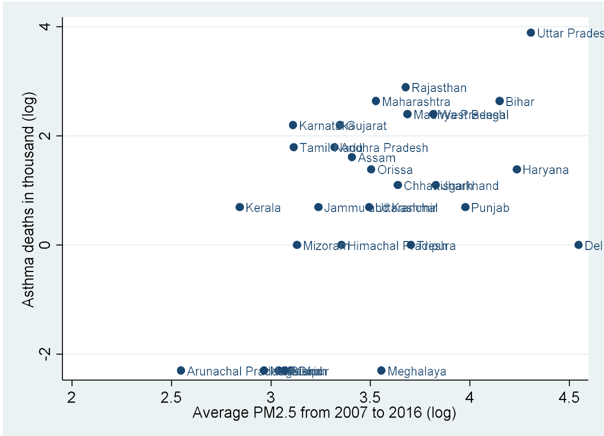
Panel A: COPD cases



Panel B: COPD deaths



Panel C: Asthma cases



Panel D: Asthma deaths

Source: Author's compilation based on data from NASA and the Global Burden of Disease Study 1990–2016 by Salvi et al. (2018).
Note: COPD, asthma, and $PM_{2.5}$ data are plotted as log values. COPD and asthma cases and deaths are shown in units of one thousand, and $PM_{2.5}$ is shown in units of $\mu g/m^3$.

The potential mechanism of the link between exposure to air pollution and incidence of COVID-19 remains to be clarified. Thus far, only a few studies have shown a positive causal link between these phenomena, in the Netherlands and the US (Austin et al., 2020; Cole et al., 2020), where recorded air pollution levels are modest compared with those in India according to WHO standards. However, the number of fatalities is increasing worldwide. Austin et al. (2020) use wind direction as an instrument for $PM_{2.5}$, whereas Cole et al. (2020) use the long lag of air pollution and commuting times as their instruments. The wind direction instrument has also been employed by Deryugina et al. (2019), but its validity would need to be clarified further in terms of exclusion restriction (e.g., longer commuting times might also be correlated with the increased number of COVID-19 infections). Even if the two studies by Austin et al. (2020) and Cole et al. (2020) are scientifically verified through a peer-review process, it would still be crucial to confirm their external validity and ascertain precisely why air pollution leads to an increase in the number of COVID-19 cases. For example, does a higher level of air pollution prolong the time the virus remains airborne, or are there any other mechanisms? This is an open policy question that should be addressed to save lives. At present, policies designed to limit the spread of COVID-19, including a phased approach of gradually increasing the capacity limit of restaurants and bars, rely on the assumption that COVID-19 is not airborne—that is, that 6 feet (~2 m) of social distancing would be sufficient to prevent transmission. The principal stance of the WHO is that COVID-19 is not airborne and is instead spread primarily from person to person through small droplets from the nose or mouth.[13] These droplets are relatively heavy, do not

[13] According to the latest scientific brief by WHO (2020), (i) airborne transmission of SARS-CoV-2, the virus that causes COVID-19, can occur during medical procedures that generate aerosols; and (ii) the WHO, together with the scientific community, has been actively discussing and evaluating whether SARS-CoV-2 might also spread through aerosols in the absence of aerosol generating procedures in indoor settings with poor ventilation.

travel very far, and quickly fall to the ground. Future studies could examine this conventional wisdom to determine what additional measures to take to potentially mitigate the catastrophic damage from the ongoing crisis.

5. Conclusion

In addition to the severe environmental contamination caused by air pollution, the ongoing COVID-19 pandemic has created a dire situation in India, which has seen one of the largest losses of life worldwide along with a record economic collapse. Despite the urgent need to address issues related to development and public health, evidence on how ambient air pollution impacts health outcomes is still scarce, especially in developing countries. A few emerging causal studies linking air pollution exposure and COVID-19 have focused on only moderately polluted countries. Given these gaps, this study sought to investigate the causal effects of long-term $PM_{2.5}$ exposure on COVID-19 cases, deaths, and fatality rates in India by using an IV approach based on thermal inversion episodes.

The estimation results indicate that a 1% increase in long-term exposure to $PM_{2.5}$ leads to an increase in COVID-19 deaths by 5.7 percentage points and an increase in the COVID-19 fatality rate by 0.027 percentage points, but this exposure is not necessarily correlated with COVID-19 cases. These results imply that people with underlying health conditions such as respiratory illness caused by exposure to air pollution might have a higher risk of death followingSARS-CoV-2 infection. The two-way scatter plots in Figure 1 show a strong positive correlation between the mean level of $PM_{2.5}$ in 2007–2016 and the incidence of COPD and asthma and their related deaths in each state in India in 2016. Although the positive relationship between exposure to air pollution and onset of chronic respiratory disease is inconclusive (Shin et al., 2020), this link would be plausible in many cases, as other studies have suggested (e.g., Andersen et al., 2012; Hendryx et al., 2019; Schraufnagel et al., 2019). This implies that exposure to $PM_{2.5}$ might impair or worsen respiratory functions. Those who reside in areas with high levels of $PM_{2.5}$ might have a risk of death following SARS-CoV-2 infection.

These findings could have profound implications for governments as they decide whether to ease lockdowns and how to deal with the aftermath of the COVID-19 pandemic. A scientific consensus seems to be emerging that improving air quality may play an important role in overcoming or at least reducing the impacts of the pandemic. Although at an early stage, research implies that pollution must be limited as much as possible when lockdowns are lifted in order to minimize the impact of subsequent waves of infections. These emerging findings also afford us an opportunity to not only enforce existing air pollution regulations to protect human health (both during and after COVID-19), but also increase investments, implement policy reforms, and enhance institutional capacity to improve air quality management on a more urgent basis. Countries could promote cleaner fuels and adopt more environmentally friendly transportation and energy technologies. For example, India could prioritize air pollution and strengthen its capacity to manage air quality based on a broader state and multi-jurisdictional airshed approach.

Acknowledgements: We are thankful for comments from the seminar participants at the World Bank and Nagoya University. This work also benefitted from a series of rich discussions held in connection with a flagship air pollution study of the South Asia region jointly conducted by the World Bank and the International Institute for Applied Systems Analysis (IIASA). Accordingly, we thank Markus Amann and his team at IIASA, Maureen Cropper, Yongjoon Park, Jostein Nygard, and Michael Toman. Hans Timmer and Karin Shepardson kindly provided

suggestions, especially from policy perspectives.

Funding: This work was supported by JSPS (Japan Society for the Promotion of Science) KAKENHI (Grant Numbers 18K01580 and 19K13712) and the Keio Gijuku Academic Development Funds.

Declaration of Interests: Authors do not have any conflicts of interest.

Contributor Roles Taxonomy (CRediT) Author Statement:

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Muthukumara Mani: Writing - Review

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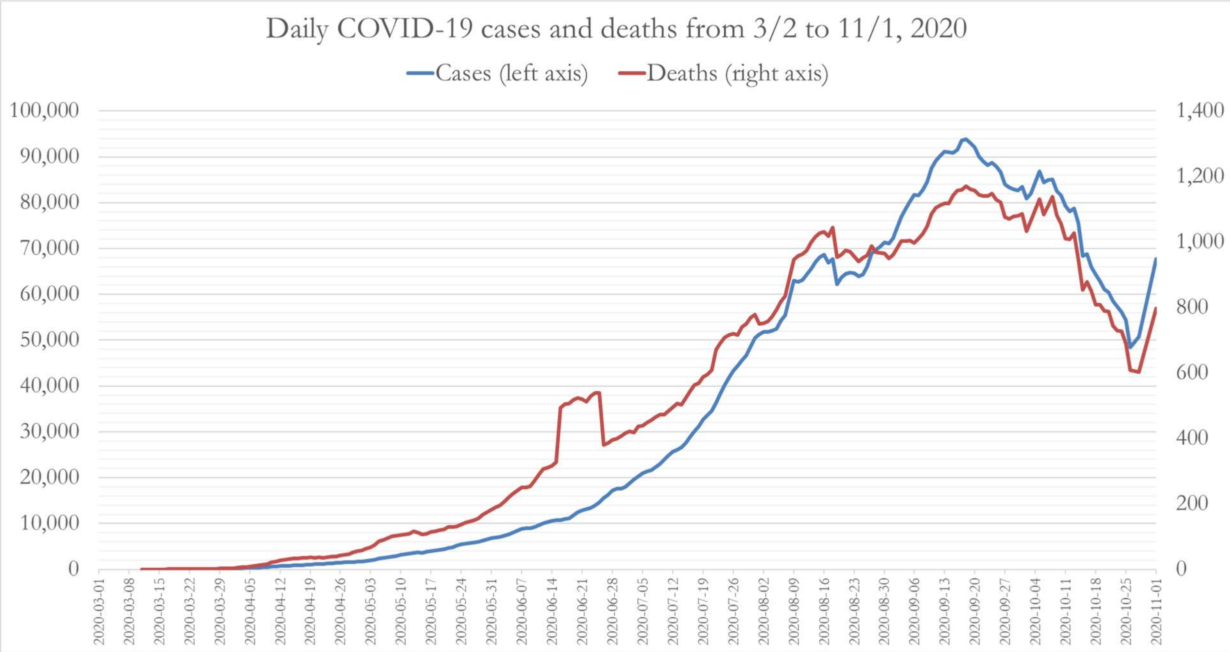
Appendix

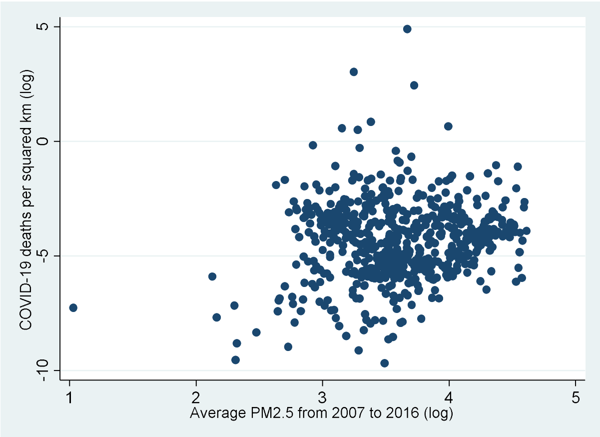
Appendix Figure 1: Daily COVID-19 cases and deaths



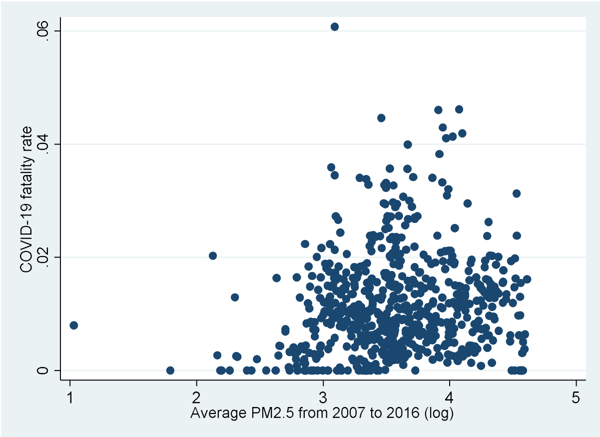
Source: COVID-19 India Dashboard

Note: Ten-day moving average. The correlation between cases and deaths is 0.9439.

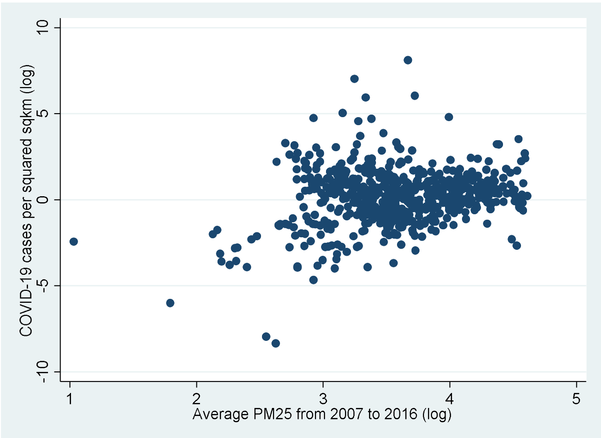
Appendix Figure 2: Correlations between COVID-19 indicators and mean $PM_{2.5}$ from 2007 to 2016



Panel A: COVID-19 deaths per km^2 (log)



Panel B: COVID-19 fatality rate



Panel C: COVID-19 cases per km^2 (log)

Source: COVID-19 India Dashboard and NASA

Appendix Table 1: Summary statistics of mean $PM_{2.5}$ from 2007 to 2016 by state/territory

State/Territory	Mean	S.D.	Min	Max
Delhi	94.3	2.8	89	97.3
Uttar Pradesh	74.2	13.9	43.3	100.6
Haryana	69.1	13.9	47.1	93.9
Bihar	63.4	6.9	50	76.9
Chandigarh	54.2	.	54.2	54.2
Punjab	53.4	4.6	42.3	62.9
Jharkhand	46.0	4.8	37.8	54.1
West Bengal	45.4	5.6	36.2	55.6
Tripura	40.6	5.3	35.3	47.1
Madhya Pradesh	39.9	9.1	29.7	73.3
Rajasthan	39.5	12.4	22.3	73.7
Chhattisgarh	38.0	7.2	26.9	52.6
Meghalaya	35.0	6.0	27.8	42.8
Maharashtra	34.0	3.9	24.2	41.3
Odisha	33.2	4.1	25.5	38.6
Uttarakhand	32.9	15.8	15.3	58.2
Assam	30.2	5.8	20.1	41.9
Himachal Pradesh	28.6	12.1	10	42.9
Gujarat	28.4	4.8	18.9	36.2
Andhra Pradesh	27.6	2.5	23	32.8
Dadra & Nagar Ha	26.3	.	26.3	26.3
Jammu and Kashmir	25.5	8.5	2.8	38.8
Daman & Diu	24.7	2.1	23.2	26.2
Puducherry	24.2	4.8	18.6	29.4
Mizoram	22.9	3.5	18.6	28.5
Tamil Nadu	22.5	3.2	13.9	26.6
Karnataka	22.4	3.7	16.7	30.4
Goa	22.2	1.1	21.4	23
Sikkim	21.5	5.3	13.8	25.3
Manipur	20.9	2.3	17.4	25
Nagaland	19.4	2.1	16.4	22
Kerala	17.2	1.4	14.9	19.6
Lakshadweep	13.8	.	13.8	13.8
Arunachal Pradesh	12.8	3.7	6	18.7
Andaman & Nicobar	8.8	4.4	4.1	12.8

Source: NASA

Appendix Table 2: COVID-19 cases that cannot be assigned to specific districts in India

State / Territory	Cases	Deaths	Note
Delhi	391,582	6,561	Unknown
Assam	94,863	245	Unknown
Goa	37,389	417	Unknown
Odisha	7,508	0	State Pool
Andaman & Nicobar Islands	4,288	60	Unknown
Andhra Pradesh	2,461	0	Other State
Maharashtra	2,172	147	Other State
Manipur	2,074	2	CAPF Personnel
Sikkim	1,949	66	Unknown
Tamil Nadu	1,907	2	Airport Quarantine
Manipur	1,744	32	Unknown
Telangana	496	1,311	Unknown
Andhra Pradesh	434	0	Foreign Evacuees
Tamil Nadu	428	0	Railway Quarantine
Chhattisgarh	255	32	Other State
Telangana	250	0	Other State
Goa	200	1	Other State
Rajasthan	189	39	Other State
Gujarat	162	3	Other State
Rajasthan	85	0	BSF Camp
West Bengal	66	3	Other State
Rajasthan	61	0	Evacuees
Karnataka	36	3	Other State
Telangana	33	0	Foreign Evacuees
Assam	13	0	Airport Quarantine
Rajasthan	2	0	Italians
Assam	1	0	Other State
Tamil Nadu	0	3	Other State
Ladakh	0	2	Unknown

Source: COVID-19 India Dashboard