Unbundling Air Pollution Concerns: A Closer Look at Socio-economic Factors

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1 Introduction

Air pollution has wide-ranging impacts on economic activity, human health and well-being, with accumulating evidence for India on the adverse implications (Kandlikar & Ramachandran, 2000; Balakrishnan et al., 2019; Spears et al., 2019). To cite from a recent tribunal order: “Violation of laid down air pollution levels resulting in large number of deaths and diseases needs to be addressed expeditiously” (para ix, Pg. 32, National Green Tribunal (NGT) order 21.08.2020) (NGT 2020a). The adverse impacts of air pollution are widespread on agricultural yields (Burney & Ramanathan, 2014; Gupta et al., 2017), labour productivity (Zivin & Neidell, 2012; Adhvaryu et al., 2016), cognitive functioning and health of children and older people (Power et al., 2011; Suglia et al., 2008; Jones, 2020), institutional functioning (Kountouris, 2020), increased healthcare costs and reduced profits to employers to name a few. The adverse health impacts from air pollution are a grave concern, especially for India, where air pollution has been on the rise for several decades now. We motivate the discussion by presenting here some data on air pollution and the health losses attributable to air pollution in India.

Air quality in Indian cities has been observed to be among the poorest in the world (WHO, 2018). Many Indian cities such as Kanpur, Varanasi, Faridabad, Delhi, Gaya, Patna, Lucknow, Muzzafarpur, Agra and Jaipur ranked among the top globally polluted cities in 2016. To motivate the discussion, we present some information on...
the air quality in India with the familiar index known as the air quality index (AQI). The air quality index AQI is a measure of the weighted values of various air pollutants (Central Pollution Control Board (CPCB), 2014) with a higher AQI denoting worse air quality (and vice versa). Figure 1 provides a snapshot of the extent to which this index (average of three months with the highest AQI in the year) has tended to exceed the limits for some cities during the three months with the highest AQIs in the year. A preliminary examination of the average AQI between May 2017 and March 2018 reveals that majority of the cities, namely 60%, have an AQI greater than the designated satisfactory limit which is set at 100.

The daily data indicates that in many cities, the AQI was beyond the satisfactory level for all the days in a month for several months during the year, indicating that the air quality was poor for a major part of the year (Fig. 2). This is a matter of grave concern as it indicates that the cities have been continually exposed to poor air quality for prolonged periods of time. For instance, by this measure, Delhi has consistently had air quality at worse than satisfactory levels for 5 months from

Fig. 1  Snapshot of AQI across some cities.
Source CPCB (n.d-a), APPCB (n.d.), KSPCB (n.d.), TNPCB (n.d.), MPCB (n.d.), CECB (n.d.), UPCB (n.d.), UPPCB (n.d.)

Fig. 2  Percentage of days where AQI exceeds the satisfactory limits in major cities.
Source CPCB (n.d-a), APPCB (n.d.), KSPCB (n.d.), TNPCB (n.d.), MPCB (n.d.), CECB (n.d.), UPCB (n.d.), UPPCB (n.d.)
November to March. Figure 2 captures the significant variation in the AQI across cities and seasonal variations in the air quality levels.

The relationship between air quality and health is well established, especially in relation to particulate matter (Johnson et al., 2011). We use particulate matter concentrations for the rest of our empirical analysis. Disability-adjusted life year (DALY)-based measurements are a convenient way of presenting the impact of air pollution on health. As Fig. 3 reveals, recent DALYs estimate (Balakrishnan et al., 2019) suggest that there is substantial variation across states in India. The columns represent DALYs attributable to overall air pollution (ambient particulate matter, household air pollution, ambient ozone pollution), while the orange and blue lines map DALYs attributable to household air pollution from exposure to PM$_{2.5}$ due to use of solid cooking fuels and the exposure to ambient particulate matter pollution based on PM$_{2.5}$ concentration level respectively. We note at the outset the importance of this differentiation between household and ambient pollution since policy instruments to deal with these two sources would be different. In terms of overall air pollution, Rajasthan, Uttar Pradesh, Haryana, Madhya Pradesh, Bihar and Chhattisgarh have some of the highest DALY rates per 1 lakh population. Uttar Pradesh, Haryana, Rajasthan, Bihar and Madhya Pradesh have high levels of DALYs attributable to both ambient and household pollutions, while DALYs for states like Delhi, Punjab and Maharashtra are primarily due to ambient pollution.

In addition to differentiation based on the source of pollution, air pollution can vary based on the kind of pollutant and also the economic activity that underlies the pollution source. Although the AQI is commonly used to obtain an idea of the air quality, it suffers from limitations as it masks concentration levels and movements in individual pollutants. Each pollutant originates from definite sources and has unique impacts, and accordingly, air pollution reduction policies and measures are needed.

**Fig. 3** DALY rate per 1 lakh population.
*Source* Based on data in (Balakrishnan et al., 2019); Data is for the year 2017 and has an uncertainty interval of 95%
For the rest of this paper, we therefore focus on individual pollutant concentrations. The ability to manage pollution effectively would depend on a host of interdependent factors, including supply-side and demand-side variables, and drivers that are technological, social or economic in nature. This study examines the relationship of PM$_{10}$ with income and other socio-economic factors at the state level and provides some policy insights that could be considered for addressing the air pollution concerns.$^1$

The paper is organized as follows. Section 2 contains the rationale and methods used in the analysis, Sect. 3 discusses some relevant insights from the literature, and Sect. 4 presents the results from an empirical analysis. Section 5 concludes with a discussion and suggestions based on potential synergies with the existing policies.

2 Rationale, Methods and Data

2.1 Rationale and Methods

The study examines the importance of socio-economic characteristics for air pollution management in cities and states in India, by analysing available data and information in the public domain. Three approaches are adopted to explore various dimensions of the problem, namely a desk review, a graphical analysis and an econometric exercise. We discuss these in some detail below.

2.1.1 Desk Review

A detailed literature review was carried out to understand the importance of various aspects of managing air pollution. These include studies concerning the types of air pollutants and their implications for health and socio-economic well-being, the sources of pollution and source apportionment studies that examine the causes and variations in these, the socio-economic determinants of air pollution and policies and instruments for managing air pollution. Both international literature and studies undertaken for India were consulted. Intensive efforts were also made to understand the data and information aspects of attempting an empirical exploration and its contextualization.

2.1.2 Descriptive and Graphical Analysis

Trends in air pollutant concentration levels are studied over time and across states to understand the patterns that emerge in the data through two-way tables and graphical

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$^1$Data on PM$_{2.5}$ is not available consistently at the same level of detail over time for all the cities/states. This is partially at least attributable to the fact that PM$_{2.5}$ monitoring was only started around 2009 and its coverage is being expanded.
representations. This facilitates an understanding of the heterogeneity across states in India and in the pollutant concentrations in these. An analysis of the changes in pollutant concentration levels of PM$_{10}$ and PM$_{2.5}$ pre- and post-COVID-19 pandemic control measures provides some insights on the potential for reduction in pollution levels. The income–pollution relationship is also examined in some detail with this approach, using state-level Gross State Domestic Product (GSDP) and PM$_{10}$ concentration as an indicator of air pollution.

### 2.1.3 Econometric Model

A rigorous econometric exercise is conducted to understand the associations between socio-economic characteristics of states and the observed pollution levels in terms of PM$_{10}$. A panel data regression model is used, with data for states pertaining to a period of 5 years. The rationale for the explanatory variables chosen for this estimation to understand the linkages with air pollution is briefly explained here.

**Urbanization**: Based on the existing understanding and evidence on urbanization, we introduce the share of urban population as a proportion of total population as an explanatory variable in our analysis, expecting an increase in urbanization to adversely impact emission levels of particulate matter.

**Income**: In the present study, we use the variable of total gross domestic product to capture the income effect with the expectation that there will be a positive relationship between income and pollutant concentrations given that the states in the Indian economy are various stages of development. India classified as a low middle-income country in global rankings.

**Industrialization**: The share of the secondary sector’s contribution in the total income or GSDP of the states is included in the analysis to capture its relationship with pollution concentration given that this has had a significant impact in other countries.

**Energy consumption**: Given that total energy consumption data at a sub-national level is not directly compiled by one source or method across states, we introduce per capita electricity consumption as a potential indicator that influences air pollution. On one hand, electricity being a source of clean energy should have a negative relationship with pollution, and India has initiated several programmes to encourage renewable energy, clean technology for coal-based power plants and even introduced a coal cess. However, since the bulk of India’s electricity production comes from coal, it is equally true that this could be a source of air pollution. Therefore, it is of interest to see how this variable behaves in the current context.

**Social Development**: States differ substantially in terms of outcomes on social sector indicators, depending on the indicator chosen. We use social sector expenditure to proxy for the impact of awareness and social development in general on outcomes observed with pollution. The expectation would be that of a negative relationship.

**Green Cover**: The analysis also uses the total forest cover of the state as a proportion of its total geographical area. This variable can play a crucial role in managing air pollution as the existing evidence seems to indicate.
2.2 Scale of Analysis

In India, there has so far been an emphasis on considering cities as the appropriate level of analysis for understanding the causes of and managing air pollution. This has its own merits in terms of the extent of population that is exposed, the concentration of pollutants observed in cities, the availability of data from monitoring sites in cities and the causes which conventionally have for the most part been associated with the growth of economic activities centred around cities. We conduct some analysis at the city level to illustrate a few points.

However, it is increasingly observed that for large parts of the country, air pollution is often contiguous across rural, peri-urban and urban areas and administrative boundaries defined by cities and states, as are some of the pollution sources which are distributed on the cities’ peripheries and hinterlands. Further, for economic decision-making, including setting targets for annual economic activity (production, logistics, etc.) and funding allocations, the state is the first level of decision-making, after the Centre. Given the spill overs across city boundaries, both the central planner and the state leadership can take care of inter-state externalities. The state in turn can take care of intra-state externalities and provide the requisite funds. At a practical level, most data on socio-economic characteristics is available consistently over time and across all states at the state level. For these reasons, we use the state as the preferred unit of analysis for most of our study.

It may be noted that the cities that we chose to examine are from the states of Delhi, Gujarat, Haryana, Maharashtra, Punjab, Rajasthan and Uttar Pradesh, which are among the most polluted. Most of these cities form part of the non-attainment cities listed under the National Clean Air Programme (NCAP) (more details are available in Sect. 3.3.1). Figure 4 contains the number of non-attainment cities under the NCAP in each state as represented by the area of the circle and totals up to 122 cities. Except for Delhi which is a city-state and Haryana, the majority of these cities are located in the states of Maharashtra, Uttar Pradesh, Andhra Pradesh, Punjab—all of which are part of the state-level analysis.

\[\text{Non-attainment cities refer to cities where the National Ambient Air Quality Standards (NAAQS) were exceeded and were identified based on 2011–2015 air quality data and the WHO air quality update of 2018 (MoEFCC 2019a).}\]
2.3 Variables and Data Sources

This study uses data for 32 states and union territories over a 5-year period from 2012–2013 to 2016–2017. Annual averages of PM$_{10}$ concentrations were obtained at the location level in every city from manual monitoring data under the National Ambient Air Quality Monitoring Programme (NAMP) from Central Pollution Control Board (CPCB) sources (n.d.-b). City-level and state-level averages were computed. Data on PM$_{10}$ annual averages was originally given based on the calendar year period. In order to facilitate comparison with other socio-economic variables, the corresponding financial years were identified. The choice of year was based on ensuring a maximum overlap in the number of months. For example, the calendar year of 2013 for PM$_{10}$ was matched with financial year 2013–14 and similarly identified for the other years. Real-time monitoring data across various pollutants- PM$_{10}$, PM$_{2.5}$, NO$_x$ and CO during the complete lockdown period in India due to the coronavirus pandemic was compiled from continuous ambient air quality monitoring stations (CPCB 2020).

Information on socio-economic variables was collected from various sources. Data on gross state domestic product (GSDP), per capita GSDP and value added from the secondary sector was based on Ministry of Statistics and Programme Implementation (MoSPI) data (MoSPI n.d.). Data on social sector expenditure was collected from reports on state finances (RBI 2019). Per capita electricity consumption data was collected from a Rajya Sabha Question answered by the Ministry of Power (2017). Proportion of urban population (projected) to total population was obtained from the estimates recently made available through the report of the technical group on population projections (MoHFW 2019). Ratio of total forest cover as a proportion of geographical area in the state was calculated from data sourced from the State of Forest reports given by the Forest Survey of India (2013, 2015, 2017, 2019). Total forest cover data is given at an interval of two years, so data for the years in between was interpolated on the assumption that the changes in the intervening period were uniformly distributed over time. Details of data sources and definitions are provided in Appendix A1.

3 Key Insights from the Desk Review

3.1 Causes of Air Pollution

Causes of air pollution vary, depending upon the meteorological factors, geographical factors such as terrain and elevation, rural or urban nature of areas. At an over-arching level, the relationship between economic growth and pollution has been extensively researched, especially for developing countries. Evidence on the interaction between sub-categories of pollution, such as outdoor and indoor pollution, has also been mounting, with indoor air pollution being recognized as a major cause of ambient air pollution (Chafe et al., 2014). For instance, in India, as in several other developing
countries, cooking with biomass on cookstoves with inefficient combustion, has been seen as a prevalent concern for quite some time now (Bruce et al., 2000). Research on the adverse health impacts and ways to manage this pollution has increased exponentially over the last couple of decades (for instance, Zahnos et al., 2020; Lewis & Pattanayak, 2012, Hanna & Olivia, 2015). The Lancet Commission on pollution and health provides a recent assessment of the causes and implications of air pollution (Landrigan et al., 2017).

For a defined geographical area, how the sources contributing to air pollution in an area combine and evolve over time is important for understanding impacts and designing corrective measures. Information on the sources that contribute to air pollution over a demarcated area becomes a critical input in designing programmes and policies to control pollution. Source apportionment studies have therefore increasingly been recognized as an important step for designing contextually appropriate and cost-effective policies (Johnson et al., 2011). The variation in the sources and underlying causes contributing to air pollution is evident from studies conducted for Indian cities. This information is helpful in deciding which sectors need to be targeted for control measures. For example, transport, industry and dust from construction and roads contribute majorly to PM$_{10}$ and PM$_{2.5}$ pollution in Delhi (ARAI and TERI 2018) and to PM$_{2.5}$ pollution in Mumbai and Ahmedabad. Local sources of PM$_{2.5}$ pollution are important for Varanasi, including cooking, lighting and heating, apart from dust from roads and burning of open waste (Guttikunda et al., 2019; Dasgupta & Srikanth, 2020).

Across studies, it is observed that for most cities, air pollution was also clearly attributable to transboundary sources, beyond city boundaries. In the case of some cities, this has become an increasingly important factor, especially in the northern and western parts of the country. Airsheds with high pollutant concentration levels can stretch from within cities constituting an urban air shed, to cross parts of a state, covering both rural and urban areas such as in the Delhi NCR, and even cross-state boundaries as seen in the Indo-Gangetic Plain. This has in turn raised calls for an air shed management approach for controlling air pollution.

A common contributor to air pollution levels in many Indian cities is emissions from dust caused by varied sources like construction, roads etc., which has been observed in several developing countries (Johnson et al., 2011). As some evidence indicates, a way out is through encouraging vegetative cover (MoRTH, 2015; Johnson et al., 2011). For example, the Green Highways (Plantation and Maintenance) Policy of 2015 in India can potentially contribute to this purpose (MoRTH, 2015).

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3Sources of information: Delhi—ARAI and TERI (2018), year 2016; Mumbai and Ahmedabad—Ganguly et al. (2020), year 2018; Varanasi—Guttikunda et al. (2019), year 2015.

4https://www.worldbank.org/en/events/2019/10/21/air-quality-management-in-india-learning-from-international-experiences; https://www.downtoearth.org.in/news/air/join-the-dots-for-clean-air-67779.
3.2 **Socio-Economic Determinants of Air Pollution**

Various socio-economic determinants have been examined by scholars to enhance the understanding of the underlying associations with air pollution. Some socio-economic factors considered include population, population density, income and income proxies, energy efficiency and energy intensity-related measures, urbanization and built-up area, patterns of sectoral contribution to the national income, transportation and education-related indicators. Some key insights that are of relevance to India are discussed below.

3.2.1 **Population-Related Indicators: Population, Population Density, Urban Population and Urbanization**

Population and population density were seen to have a positive relationship with PM$_{2.5}$ in China’s case by some authors, for example (Luo et al., 2018; Ma et al., 2016). In the Indian case, population and pollution were seen to have positive relationships for SO$_2$, NO$_2$ and PM (Holian, 2014), while the relationship of population density and environmental productivity was negative for NO$_2$, SO$_2$ and PM (Managi & Jena, 2008).

Urban population is a critical factor in relation to air pollution and climate change, especially when taking into account the growing energy requirements in India (Imam & Banerjee, 2016). As per one study, the relationship of urban population with PM$_{2.5}$ was found to be U-shaped for India (Han et al., 2016). Scholars use different approaches for characterizing the causal relationship. Luo et al. (2018) and Managi and Jena (2008) consider urbanization as the share of urban population in total population, with the objective of capturing movement of people to urban areas, while Xu and Lin (2018) consider urbanization with the additional argument that movement to urban areas will also cause an increase in purchase of motor vehicles which would have impacts on pollution. Luo et al. (2018) find a negative relationship of urbanization with PM$_{2.5}$ concentrations and justify it saying that rural area’s energy consumption contributes a lot to PM$_{2.5}$ in China’s case. For India, Managi and Jena (2008) found a negative relationship with environmental productivity. Fang et al. (2015) construct an urbanization index for China with many factors including urban population, secondary sector contribution, private vehicles and area and found that it had a negative impact on air quality.

3.2.2 **Income and Income Proxies**

The relationship between income and pollution has been examined by many authors, particularly by exploring the concept of the Environmental Kuznets Curve (EKC) (e.g. (Grossman & Krueger, 1994). The EKC curve depicts the relationship between levels of environmental pollutant and income. The relationship is theoretically
hypothesized to be inverted U-shape, meaning that an increase in income leads to an increase in environmental pollutant until a point after which pollution is expected to decrease with an increase in income. Empirically, the inverted U-shape is contested and does not necessarily hold for all pollutants. While specifications have differed, most scholars have used a measure of gross domestic product (GDP) and/or consumption expenditure to capture income. Luo et al. (2018), Xu et al. (2016) and Managi and Jena (2008) consider per capita GDP guided by the EKC argument, while Holian (2014) considers two indicators, namely the district-level domestic product and the monthly consumption expenditure per capita, for measuring socio-economic development for India. Luo et al. (2018) find the relationship with income to be important, but opine that the nature of development, (namely the industrial sector’s contribution) is more important for the case of China, while Xu et al. (2016) find an inverted U-shaped EKC relationship between PM$_{2.5}$ and economic growth in China. Holian (2014) estimates the relationship between development (measured through income, income proxies and literacy rate) and air pollution (Particulate Matter, SO$_2$ and NO$_2$) for Indian cities between 2006 and 2011, controlling for various other socio-economic factors with a regression. They find that development is negatively related to PM and positively to NO$_2$, and that manufacturing-centric cities also have higher pollution. Managi and Jena (2008) examine the relationship between environmental productivity and income for NO$_2$, SO$_2$ and PM using regression methods for Indian states for the period 1991–2003. They find that environmental productivity falls more in states with higher income in relation to states with lower income after taking into account some socio-economic variables. Sinha and Bhattacharya (2017) undertook an EKC analysis for SO$_2$ emissions in India and found the conventional inverted U curve applicable in industrial areas, while Sinha and Bhatt (2017) found a N-shaped EKC curve for NO$_x$ in India.

3.2.3 Sectoral Contribution: Industrial Sector and Related Measures

The relationship between pollution and income is also conditional on how much that income is contributed to by various categories of economic activities, namely through primary, secondary and tertiary sectors. In relation to air pollution, both the composition and the size of the manufacturing sector are important considerations in determining the impacts (Cole, 2000). Some studies find that the tertiary sector can also contribute to air pollution (Luo et al., 2018), possibly due to factors like transportation (Xu et al., 2016). However, most scholars who have analysed the case of China find that a critical factor in relation to PM$_{2.5}$ pollution is the share and/or size of the industrial sector in the economy (Luo et al., 2018; Liu et al., 2019; Wang et al., 2018). The same holds true for India, with a positive relationship being observed between manufacturing sector and pollution (see Holian, 2014 for instance).
3.2.4 Energy-Related Indicators: Energy Intensity, Energy Efficiency, Electricity

Energy intensity and energy efficiency have been used to understand the implications for pollution in various ways. It has been used as a measure of technology, for instance (Xu & Lin, 2018). Most commonly, it has been calculated as a proportion of coal consumption and energy consumption in GDP, (Luo et al., 2018; Xu et al., 2016; Xu & Lin, 2018). Findings have varied. While Luo et al. (2018) find the relationship with energy intensity negatively significant for China, Xu et al. (2016) find a U-shaped relationship with PM$_{2.5}$. Beijing, in China, introduced subsidies and discounts for households to encourage movement to electricity or natural gas, along with incentives for greener transportation (Lu et al., 2020). China used technology to curb SO$_2$ and NO$_2$ pollution through installation of devices in coal and thermal power industries, along with financial incentives and penalties to industries and accountability of local political leaders (Lu et al., 2020; Guan et al., 2014).

In general, it has been observed that electricity consumption levels are closely associated with socio-economic development (Abdoli et al., 2015; Bayar, 2014; Sengupta, 2016). In India, the per capita electricity consumption is well below international standards, and hence, this is an important variable to plan for as it is associated with clean energy as well as overall well-being (Dasgupta & Chaudhuri, 2020). The per capita annual electric power consumption was 804.5 kwh per capita in 2014 in India, as compared to 3927 kwh per capita in China and 12,997.4 kwh per capita in USA (World Bank, 2019). SDG 7 encompasses the access to electricity as an essential part of affordable, sustainable and modern energy for all (UN, 2015).

3.2.5 Social Development Indicators: Education, Health

In studies for India, Managi and Jena (2008) and Holian (2014) consider education-related variables, namely those who have passed matriculation level schooling and literacy rate respectively. The former study suggests a positive relationship with environmental productivity caused possibly by increased awareness. The latter study indicates an inverted U-shaped relationship between education and pollution. In general, a case has also been made for having contextually appropriate pollution control policies at various local and regional levels. For example, China has had differential regional PM$_{2.5}$ pollution targets matching the developmental level of the area (Lu et al., 2020).

3.2.6 Forest Cover

Forest cover, in addition to contributing to carbon sequestration, can also help remove pollutants like SO$_2$, NO$_2$, PM$_{10}$ etc., from the air (Imam & Banerjee, 2016). Green spaces and vegetation around high pollution industrial areas, highways and other urban areas can help reduce dust and pollutant concentrations (MoRTH, 2015;
Johnson et al., 2011). India has various national and international commitments on forestry and green cover. The Nationally Determined Contribution (NDC) target is to create an additional carbon sink for 2.5–3 billion tons of carbon equivalent (GoI, 2015). Several states in the country have sizeable share of their land area under forests. In 2017–18, some of the states that had a high share of their geographical area under forests included Arunachal Pradesh, Mizoram and Meghalaya (FSI, 2019).

3.3 **Key Aspects of Some Recent Programmes and Initiatives**

3.3.1 **NCAP**

The National Clean Air Programme (NCAP) is the most comprehensive policy initiative in India for air quality management which was launched in 2019 and now covers 122 cities, described as the non-attainment cities (see Footnote 2, MoEFCC 2019a). Among noteworthy points for our analysis, the NCAP mentioned a goal of causing a 20–30% fall in PM$_{2.5}$ and PM$_{10}$ emissions by 2024. The cities included in the NCAP were to make city action plans with the National Green Tribunal requiring them to undertake carrying capacity assessments (NGT 2019b). As of now, carrying capacity and source apportionment studies in non-attainment cities have either been conducted or are in the process of being undertaken in 80 cities in 22 states (NGT 2020b). The city action plans for the most part comprise actions in relation to road dust, agricultural and waste burning, transportation and vehicular emissions, industrial emissions, construction, and use of domestic fuels. It is important to note that the NCAP recognizes that for many cities and states especially in the Indo-Gangetic plains, a significant part of the air pollution originates outside their boundaries, and hence, it is important to have comprehensive local and coordinated regional plans to tackle air pollution. An institutional and regulatory framework to facilitate matters is called for to introduce integrated DSM and SSM options. Further, guidelines and tool kits are required for ensuring reliable baseline and continuous monitoring and data collection. Initiatives for best practices documentation should be done and made available to all states drawing upon the experiences from both within and outside India.

3.3.2 **Funding Initiatives**

The 15th Finance Commission has provided funding through a grant of Rs. 4400 crores for the year 2020–21, for cities with population above a million for whom air pollution is a concern (GoI, 2019). The first instalment allows usage of funds to improve monitoring, infrastructure and capacities and to undertake source apportionment studies and so on. The disbursement of the second instalment of funds would be conditional on achieving improvements in air quality. In case there is failure to improve the air quality, this portion of the fund is to be redistributed among cities
which show improvements in air quality and to cities whose population is less than a million (GoI, 2019).

The Ministry of Environment and Climate Change (MoEFCC) is to provide around Rs.10 crores in funds for cities with population of more than a million and above a specified PM$_{10}$ standard of 90 µg/m$^3$. This fund is for the purpose of building capacities and various pollution-reducing measures in these cities; while for cities with lesser population, funding of Rs. 10 lakhs for each city (if population is less than 5 lakhs) or Rs. 20 lakhs for each city (if population is between 5 and 10 lakhs) is to be given (MoEFCC, 2019b).

### 3.3.3 Role of the National Green Tribunal

The role of the courts in protecting the environment has been much discussed in the Indian context. Specifically, with regard to air pollution management, significant orders have been passed by the NGT, starting from 2018. Recent ones include orders passed by the Tribunal dated 16.01.2019, 15.03.2019, 06.08.2019, 20.11.2019, 11.03.2020 and the latest, 21.08.2020. The enforcement of the principle of sustainable development and the Public Trust doctrine and the interests of public health have been emphasized in these orders. The CPCB has been regularly reporting on the status, (latest dated 18.08.2020) and the NGT has provided directions, including in its most recent order dated 21.08.2020. Directions have been provided to various state governments and agencies accordingly, with regard to preparing and executing action plans for controlling air pollution. These have included functioning of monitoring stations, undertaking source apportionment and carrying capacity studies, review of master plans in the light of such studies, development of action plans and graded response action plans and emergency response systems, information on execution of action plans and reduction in pollution loads if any, and evaluation of the existing air quality monitoring systems.

### 3.3.4 Energy Sector

On the energy front, the Indian government has various programmes which link up well with increasing electricity access and improving energy efficiency, and these should be integrated to the extent feasible. These range from permits for energy efficiency under the PAT programme for energy-intensive industries to subsidies for LED bulbs under the Ujjwala programme for households, to renewable energy certificates-based trading for the renewables sector. With regard to directly impacting air pollution, an emissions trading scheme is being piloted in the state of Gujarat (GPCB, 2019). However, most of these schemes and programmes operate under independent targets and mandates, and as of date, there has been some emphasis on measuring the potential and actual impacts in terms of greenhouse gas emissions. The same holds true for programmes across sectors that seek to incentivize the use of e-vehicles for transportation, or the targets fixed under various national
missions. A range of initiatives to strengthen the infrastructure in the power sector, increase competition in the electricity sector, establishment of power exchanges and trading forums, evolution of legal and institutional frameworks (Electricity Act, 2003, the Energy Conservation Act, 2001, Integrated Energy Policy (IEP), 2005 and the National Mission for Enhanced Energy Efficiency (NMEEE), 2008) have worked well alongside the demand-side initiatives mentioned above (PAT, UJALA, ECBC, Star Ratings, etc.) in ensuring electricity access alongside promoting energy efficiency and clean energy. There are important lessons to be learnt here on introducing complementary regulatory and market mechanisms for effectively managing air pollution.

In fact, research indicates that India has been reasonably successful in reducing energy intensity of its GDP and achieving energy savings. Going forward, India may be able to achieve relatively high growth rates transitioning to a middle-income country while maintaining per capita electricity consumption at about 50% of the levels observed among developed countries currently (Dasgupta & Chaudhuri, 2020). This should be expected to have beneficial implications for air pollution, even given a high growth rate and a growing population.

4 Findings from Data Analysis

The initial discussion on AQI in Sect. 1 provides a glimpse into the substantial differences in air pollution levels across cities and states in India. As set out in Sect. 2, we conduct a set of empirical exercises to further probe the issue, drawing upon some of the insights from the desk review highlighted in Sect. 3. The findings from the empirical analysis are presented below.

4.1 Trends in Air Pollution

Mapping AQI and DALY values across states in Sect. 1 provided a glimpse into the variation that exists across cities and states both in relation to levels of pollution and exposure to pollution. We examine in more detail the data by first mapping the trends in PM$_{10}$ over the last few years, just short of a decade, from 2011–2012 to 2018–2019.

Figure 5 plots the annual average PM$_{10}$ concentration over the years for different states. Most of the states have consistently exceeded the NAAQS. NAAQS for PM$_{10}$ is 60ug/m$^3$ (CPCB, 2009). We compute the exceedance factor for these states. The exceedance factor ratio is obtained by dividing the annual average pollutant concentrations by the respective pollutant standards. Ratio values between 1 and 1.5 are categorized as "high pollution", and ratio values above 1.5 are categorized as "critical pollution" (CPCB, 2016). The calculations for 2018–19 indicate that 88% of states fall under the categories of "high pollution" and "critical pollution". Delhi has
consistently had the highest exceedance factor value in comparison with the other
states during these 8 years with the ratio within the range of 3.6–4.6. There are
only a few states, such as Kerala, Puducherry and Sikkim that have consistently not
exceeded the NAAQS in any year.

Combining the PM$_{10}$ data across regions and comparing the concentration levels
across these regions, Fig. 6 reveals substantial differences between regions, with the
north and east regions consistently having higher pollution in comparison with the
other regions. The southern region experiences relatively lower pollution in compar-
ision with the other regions, since it does not exceed the NAAQS for most of the
years. The North East has the second lowest pollution out of all the regions over the
period, since it only slightly exceeds the NAAQS in most years.

The comparison across states confirms the significant heterogeneity in pollutant
concentrations that exists between various states, traceable for the most part to various
economic and social conditions in the state. The current COVID-19 situation has
proved to be a great leveller with concentration levels coming down across regions,
due to the restrictions placed on economic activities, including lockdowns. This in
turn has provided an opportunity to understand the potential for reducing pollution
across India. We next examine this contrasting situation.

### 4.2 Air Quality During COVID-19 Lockdown Period

In order to control the spread of the coronavirus, the Indian government imposed
varying degrees of restrictions on economic activities over different phases of lock-
down and unlock of the economy. The most stringent measures were imposed during
a four-week period from March to April covering transportation, manufacturing and
construction, followed by a gradual easing of restrictions in stages each lasting for a
few weeks at a time. It is reasonable to presume that the halting of activities in major
sectors of the economy would lead to reduction in pollution attributable to these
activities. A comparison of the levels of pollution with and without such restrictions on economic activities can help to infer the extent to which interventions targeted at these sectors can lead to the abatement of pollution.

Researchers have noted that pollution across various cities changed markedly during the first phase of near complete lockdown (Dasgupta & Srikanth, 2020; Sharma et al., 2020; ICIMOD, 2020). Building on these earlier analyses, for the present exercise, we select a few cities which are representative of some of the highly polluted cities located within some of the most polluted states in India, for which there was comparable and consistent data publicly available. The cities included in the analysis are: Delhi, Ahmedabad, Gurugram, Hisar, Chandrapur, Mumbai, Jalandhar, Jaipur, Ghaziabad and Varanasi in the states of Delhi, Gujarat, Haryana, Maharashtra, Punjab, Rajasthan, Punjab, Rajasthan and Uttar Pradesh, respectively. Most of these cities come under the NCAP and are classified as non-attainment cities. As noted in Dasgupta and Srikanth (2020), a comparison of the daily concentrations of pollutants such as PM$_{10}$, NO$_x$, PM$_{2.5}$ and CO over the lockdown period with corresponding levels during the same period in the previous year reveals that there are marked declines in the levels of most pollutants.

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5 Real-time monitoring data obtained from continuous ambient air quality monitoring stations from CPCB: https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing.
### Table 1 Change in pollutant concentrations between 2020 and 2019 (March–April).

| Name of state | Name of city   | PM10 | PM2.5 | NOx /NO2 | CO |
|---------------|----------------|------|-------|----------|----|
| Delhi         | Delhi          |      |       |          |    |
| Gujarat       | Ahmedabad      |      |       |          |    |
| Haryana       | Gurugram       |      |       |          |    |
| Haryana       | Hisar          |      |       |          |    |
| Maharashtra   | Chandrapur      |      |       |          |    |
| Maharashtra   | Mumbai         |      |       |          |    |
| Punjab        | Jalandhar      |      |       |          |    |
| Rajasthan     | Jaipur         |      |       |          |    |
| Uttar Pradesh | Ghaziabad      |      |       |          |    |
| Uttar Pradesh | Varanasi       |      |       |          |    |

Source: Authors’ calculations based on data from CPCB (2020).

Note: Data for Jalandhar on NOx corresponds to NO₂ data; Legend: Decrease in concentration levels are represented in green, increases in red.

For this analysis, we consider in particular the data on PM₁₀ and PM₂.₅ concentrations. The percentage change in PM₁₀ indicates a decrease from 11 to 68%. PM₂.₅ values across most cities except Mumbai also decreased, with percentage decreases over the previous year values ranging from 6 to 63%. Table 1 summarizes the change in pollutant concentration levels between COVID-19 and pre-COVID-19 levels in the previous year. The data is suggestive of the extent to which a decrease in pollution is possible in most cities, especially for PM₁₀ and PM₂.₅ if sources of pollution (i.e. pollution contributing economic activities) were adequately managed.

### 4.3 Policy Instruments for the Pollution–Income Relationship

We examine the relationship between income and pollution with state-level data on GSDP and particulate matter. Figure 7 represents annual per capita GSDP on the x-axis and annual average concentrations of PM₁₀ on the y-axis. The red lines separate the states into four quadrants. The horizontal line depicts the all-India average per capita GSDP, while the vertical line represents the NAAQS annual standards for PM₁₀, which is at 60 µg/m³. We also examine the relationship between total GSDP and PM₁₀. Expectedly five heavily populated but larger states shift from the left income quadrant to the right, into the higher GSDP group of states. Controlling for population has the advantage of linking more directly with development, since most policy measures and financing to support programmes for development consider population to be an important criterion for decision-making.

Air pollution has differential impacts in different states. Irrespective of whether one considers the total or the per capita income levels, only five states have pollution...
below the prescribed limit as per this particular indicator. These are the states of Sikkim, Puducherry, Kerala, Mizoram and Manipur. In general, among states in the upper right-hand quadrant which have high pollution and income levels, the scatter is skewed towards pollution, with the exception of two (Chhattisgarh and Goa), and a cluster of four states which hover around the cut-offs. These states are the ones which enjoy more privileged positions in terms of their income levels. High income states that have options to generate surpluses should actively consider introducing selective instruments such as taxes on pollution-generating activities. The introduction of permits trading for specific sectors would also be appropriate such as for the energy sector, setting up cross-boundary trading mechanisms. Gujarat has started a pilot, and this could provide valuable insights on developing a robust permits trading system.

The upper left quadrant has states which are heavily populated and in some instances also are not the typical high-income states (for instance, Rajasthan), challenging the standard idea of the positive relationship between income and pollution, even when considered in terms of the total GSDP. These are the states that need to be supported with direct funding (such as fiscal transfers) to support developmental programmes that facilitate the decoupling of economic growth with air pollution.
A targeted subsidy on green infrastructure would encourage investment in greener alternatives and move the states on a more sustainable growth pathway.

There is an urgent need for source apportionment studies in states with high pollution levels, and to that extent, the policy focus (NCAP, NGT) on such studies for the non-attainment cities (NACs) is welcome. A focus on specific cities however alone may not suffice where transboundary pollution sources are significant such as for states like Delhi. Many of these states are also clustered, and it may be feasible to have common regional regulatory bodies. States that have high per capita incomes may be well placed to raise some resources on their own through innovative market-based instruments. While command and control type of instruments which prescribe technology and performance standards are necessary and must be coupled with fines and penalties associated with non-compliance, market-based economic instruments have to be actively considered. Delhi, Haryana, Uttarakhand and Chandigarh belong to the northern region, and similarly, Maharashtra, Gujarat and Goa are all states in the western region. Many cities in these regions like Mumbai, Ahmedabad and Delhi have pollution sources outside their boundaries, which can also be governed better with the presence of a common regional regulatory body. The regulator can take into account the damage caused by the particular state on its neighbouring states and decide on fines and penalties proportional to the total social cost of such negative externalities. For instance, if spatial heterogeneity is addressed through the use of an emissions trading scheme, the cost of the permit must be high enough to encourage abatement and adoption of cleaner technology in the region and the incentivization accordingly designed.

States with air quality that falls within the limit and per capita incomes lower than average need to be supported actively with funding to ensure green growth. Handholding is necessary to ensure that these states can lead the way in sustainable development. A nation-wide enforceable tax or permits system encourage states with high income and pollution levels to abate, while utilizing the additional revenue to facilitate cleaner development in these low-income states. States with air quality better than the standard and per capita incomes higher than average (e.g. Kerala, Sikkim, Puducherry) must be incentivized to retain their position.

### 4.4 Socio-economic Determinants of PM$_{10}$ Pollution

To probe the role played by various socio-economic factors, an econometric analysis was conducted. A panel dataset was compiled with data for 32 states and union territories, for a period of 5 years from 2012–13 to 2016–17. Apart from PM$_{10}$ concentrations, the factors considered were income (gross state domestic product), urbanization, (proportion of urban population to total population), energy (per capita electricity consumption), secondary sector contribution (share of secondary sector in GSDP), social development (proxied by social sector expenditure), green cover (share of forest cover in geographical area of state) and transportation (total number of registered motor vehicles).
The number of observations varies from 142 to 160 across variables. While there is substantial variation across states in PM$_{10}$ levels, within-state variation is much lower. Per capita electricity consumption increases over time in most states and also varies substantially across states. The share of forest cover in the geographical area also varies widely over states, but not much over time.

Expectedly, there is significant (5%) and positive correlation of PM$_{10}$ with GSDP, social sector expenditure, transportation and significant negative correlation of PM$_{10}$ with the share of forest cover. Correlations among the regressors were also significant in certain cases. The transportation variable is very highly and significantly correlated with GSDP and was therefore dropped from the analysis. Among the other variables, there are correlations though the coefficients are not high, such as between GSDP and the share of the secondary sector’s contribution or between per capita electricity consumption and urbanization. The secondary sector GSDP is not significantly correlated with GSDP but is correlated with per capita electricity consumption. This is probably explained by the fact that India’s economic transition was to move directly from agriculture to services. Social sector expenditure is significantly correlated with GSDP and with the share of forest cover in the state.

Statistical tests on alternative specifications were run to select the most appropriate regression model for the dataset, between random effects, fixed effects and pooled OLS options. The estimates from the selected specifications are presented in Table 2. The BP-LM test suggested that random effects were more appropriate than pooled OLS (Chi value: 202.34, $p = 0.00$), while the Hausman test indicated use of a random effects model rather than a fixed effect model (Chi value: 2.47, $p = 0.65$). Table 2 reports two specifications, both having PM$_{10}$ concentration levels as the dependent variable.

Specification 1 is the estimation with all the variables. The coefficients suggest that these are all correctly signed as per expectations, with income, urbanization, share of the secondary sector having a positive impact on PM$_{10}$ pollution, while electricity consumption and forest cover have a negative impact on PM$_{10}$ levels. Unfortunately though, given the correlations among the regressors, the significance levels for some variables are low. This prompted a re-estimation of the model by dropping some of the variables based on the correlation matrix. Several alternative estimations were done. It was interesting to note that the results across alternative estimations were fairly consistent with regard to two key variables, namely share of forest cover and per capita electricity consumption. The results after dropping social sector expenditure and share of secondary sector due to their high correlations with GSDP and per capita electricity consumption, respectively, are reported in specification 2. This specification meets the criteria for a good specification. In specifications 1 and 2, per capita electricity consumption and share of forest cover in the geographical area of the state are significant explanatory variables. Per capita electricity consumption is negatively related with PM$_{10}$ suggesting that ceteris paribus, increases in per capita electricity consumption are associated with a fall in PM$_{10}$. This is in line with the reasoning that electricity is a cleaner fuel. Although ideally one would like to control for the source of power, there are data limitations in conducting such an analysis. Diagnostics suggest that the growth rate of non-fossil installed capacity has been
Table 2  Regression estimates- Socio-economic determinants of PM$_{10}$ pollution

| Estimation variable | Independent variables                              | No of obs | Estimated coefficient |
|---------------------|---------------------------------------------------|-----------|-----------------------|
| Estimation 1: PM$_{10}$ | ln(GSDP)                                           | 135       | 8.4 (9.46)            |
|                     | Per capita electricity consumption                 | 135       | (−0.02** (0.01)       |
|                     | Proportion of urban population to total population | 135       | 10.98 (73.2)          |
|                     | Social sector expenditure                          | 135       | (−1.05e − 6 (2.50e-06) |
|                     | Share of secondary sector in GSDP                  | 135       | 4.46 (45.87)          |
|                     | Share of total forest cover in geographical area   | 135       | (−82.53* (42.62)      |
| Estimation 2: PM$_{10}$ | ln(GSDP)                                           | 140       | 5.22 (6.47)           |
|                     | Per capita electricity consumption                 | 140       | (−0.02** (0.01)       |
|                     | Proportion of urban population to total population | 140       | 5.09 (56.58)          |
|                     | Share of total forest cover in geographical area   | 140       | (−91.39*** (31.59)    |

Note  All regressions are run with a constant term. ***Significant at 1% level, **Significant at 5% level; *Significant at 10% level. Robust standard errors given in parentheses

higher than fossil during this period. An increase in forest cover area in relation to the geographical area of the state causes a decrease in PM$_{10}$ concentration, which is consistent with the understanding that forests can play an important role in air pollution management.

A principal component analysis leads to three components with eigenvalues of 2.64, 1.62 and 0.99, significant at the 5% level. Component 1 and 2 cumulatively account for 71% of the variation with component 1 explaining 44% of the variation. 87% of the variation is cumulatively explained when component 3 is added. The principal components or eigenvectors suggest that the most important variables for component 1 were GSDP, proportion of forest cover in geographical area for the state, with social sector expenditure playing a limited role. For component 2, major drivers were per capita electricity consumption and the secondary sector’s contribution to GSDP. For component 3, urban population as a proportion of total population was a major contributor with the share of the secondary sector in GSDP contributing to a limited extent.

The results clearly indicate the importance of the share of forest cover and per capita electricity consumption as determinants of PM$_{10}$ concentration levels.
5 Conclusion

When policies are in place, the most important determinant of whether action proposed will be implemented successfully lies in the ground realities. This means that all actors need to be on-boarded: state and non-state. Supply-side measures supported by public sector resources alone cannot solve the problem, nor can a sole focus on technology-driven big ticket solutions. An understanding of the socio-economic determinants and explicitly factoring these implies that the demand-side measures can be brought into play.

There is a need to generate more information and fill the data and research gaps that persist. More research is required to map and evaluate the full impacts of air pollution in India and the costs to the economy. While efforts to expand monitoring stations in cities are ongoing, these need to be set up in rural and peri-urban areas as well. It is perhaps time to also integrate across sectors and define policies to incentivize air pollution management, and to measure, monitor and evaluate over time the success in terms of reduced air pollution outcomes. The use of population as a criterion for determining eligibility for funding air pollution reduction (as in the Finance Commission grant) or the extent of funding might disadvantage cities with severe pollution problems but with lower population, and there is a need to research on how best to incorporate relevant socio-economic factors that could influence the city and the state’s ability to tackle air pollution. For instance, 76 out of the 122 non-attainment cities have population below a million.

While the government’s role is critical in ensuring that the right policies are in place and public investment takes place in enabling the policies, environmental stewardship lies with all actors in the economy. In fact, it is the citizens who have to demand action from each other and the state to manage air pollution for their health and well-being. This requires adequate information and communication, which moves the science and technology (physical and social) from the domain of experts to that of citizens. Air pollution has relationships with many Sustainable Development Goals and is directly mentioned in Sustainable Development Goal 3 (Good health and well-being) in relation to reducing diseases and deaths caused through hazardous quality of air and in Goal 11 (Sustainable Cities and communities) in relation to decreasing the cities’ adverse environmental impact per capita due to air quality. There is much that can be done in this regard to nudge behaviour in the right direction.

There is scope for addressing air pollution through enhanced cooperation among actors and across states in the country. In November 2019, the AQI in Delhi increased to severe levels repeatedly, leading popular media to report it as an air emergency. This corresponded to a period when the stubble burning was reducing in neighbouring states, while Delhi and surrounding areas continued to suffer from the accumulated stock of pollutants from this source along with other causes of air pollution. While wind speed and direction maybe beyond immediate control, institutional structures that support regional cooperation in a connected economy can play a major role.
While drawing up city action plans is a very welcome step, the role of small towns, peri-urban areas and rural areas in terms of understanding the sources of air pollution and designing policy for undertaking abatement measures needs to be paid more attention. An airshed management approach is called for. This approach was followed in Beijing through planning, monitoring and defining unified targets for contiguous areas. Typically, resources at the state level tend to be allocated across sectors and programmes based on sectoral priorities and targets. Environmental concerns may or may not find a place in these allocation decisions unless it is explicitly mandated. These mandates in the Indian federal system have tended to emanate from the Centre, whether in terms of target requirements or in terms of funds devolved for meeting specific targets. An exception in recent times has been the devolution of funds on the forestry head through fiscal transfers by the 14th and 15th Finance Commissions as part of the horizontal devolution. Studies reveal that when funds compensate for fiscal disability arising from environmental conservation (forests in this case), these do not guarantee fund flows to the sector in question (Dasgupta and Srikanth, 2021). Formal agreements, institutional structures and policies at sub-national levels, are called for to tackle abatement across state boundaries that are beneficial either to one or more states.

Our findings indicate that policies that tap into synergies between air pollution reduction and climate mitigation can have a substantial impact on particulate matter-related pollution. Expanding green cover and ensuring access to higher consumption of clean energy have the most significant impacts on air pollution. When these goals are pursued, it helps in achieving multiple SDGs as well as the commitments made under India’s NDCs. The co-benefits of climate mitigation policies have substantial and significant impact for India. Economic instruments that exploit the synergies would be best placed to serve both interests.

Legislative and regulatory mechanisms need to be put in place so that a range of mechanisms at sub-national level can be conceptualized for supporting the cause. While some may require public support such as in procuring products based on energy-efficient technologies or pollution abatement technologies from the private sector, others may call for outright public investment in clean investment such as in infrastructure and renewable power generation. Experience from other countries suggests that economic instruments can be effective in controlling pollution. The role of fiscal and non-fiscal instruments, market and non-market instruments has to be acknowledged and mainstreamed.

Behavioural change among consumers and producers for a more sustainable lifestyle can blend well with the air pollution management strategy. Communications, outreach and knowledge management are important components for impacting air pollution. Reaching communities actively through risk-based communications for instance has not been pursued thus far. Over-dependence on government agencies and courts has created a narrative where the consumer consumes, the producer produces, and it becomes solely the public sector (agencies) responsibility to do the clean-up primarily through command and control-type approaches, supported by imposition of fines and penalties and levying compensation for environmental degradation. There is a need to move away from this conventional typecast, where
Air pollution management continues to be largely framed in terms of an unavoidable consequence of economic growth, attributable to urbanization and industrialization.

Air pollution management needs to be pursued as a priority for achieving sustainable development, with integrated management across sectors and spatial dimensions. Technological solutions will work best only when policies factor in the socio-economic determinants and both the supply side and the demand side are taken care of through appropriate market and non-market instruments.

Appendix: Data Sources and Definitions

| Variable | Data source | Unit of measurement | Definition |
|----------|-------------|---------------------|------------|
| PM$_{10}$ | Manual monitoring data under national ambient air quality monitoring programme from CPCB (n.d-b.) | $\mu$g/m$^3$ | – |
| PM$_{10}$, PM$_{2.5}$, CO, NO$_x$ | Real-time data under continuous ambient air quality monitoring stations from CPCB (2020) | PM$_{10}$ and PM$_{2.5}$: $\mu$g/m$^3$, CO: mg/m$^3$; NO$_x$: ppb | – |
| Air quality index | Air quality data from CPCB, (n.d.-a), state pollution control boards for Andhra Pradesh, Karnataka, Tamil Nadu, Maharashtra, Chhattisgarh, Uttarakhand, Uttar Pradesh | ratio | The air quality index (AQI) is a measure of the weighted values of various air pollutants (CPCB 2014) with a higher AQI denoting worse air quality (and vice versa) |
| Gross state domestic product | Constant prices, base year 2011–12. Data collected from MoSPI (n.d.) website | INR lakh | – |
| Per capita gross state domestic product | | INR | – |
| Gross state value added from secondary sector | | INR lakh | Secondary sector includes value added from manufacturing, electricity, water supply, gas and other utility services and construction (MoSPI n.d.) |

(continued)
| Variable                                           | Data source                                          | Unit of measurement | Definition                                                                                                                                 |
|----------------------------------------------------|------------------------------------------------------|---------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| Social sector expenditure                         | Reports on state finances (RBI 2019)                 | INR lakh            | Social sector expenditure includes expenditure on “social services, rural development, and food storage and warehousing” (RBI 2019)      |
| Per capita electricity consumption                | Rajya Sabha question answered by MoP (2017)         | kwh                 | “Per capita consumption = (gross energy generation + net import)/mid-year population” (MoP 2017)                                           |
| Proportion of urban population (projected) to total population | As on 1st March, as estimated in the report of the technical group on population projections (MoHFW 2019) | Ratio               | –                                                                                                                                         |
| Total forest cover/geographical area              | State of forest reports, FSI (2013,2015,2017,2019)   | Ratio (variables measured in km²) | Forest cover: “all lands more than one hectare in area with a tree canopy of more than 10%, irrespective of land use, ownership and legal status” (FSI 2017) |

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