The Urbanization-Migrant Labour-COVID-19 Trifecta: Regression Analysis and Policy Implications for Indian Urban Centres

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ABSTRACT

This study examines the complex relationship between urbanization, migrant labour and the spread of COVID-19 in India, highlighting the vulnerabilities faced by migrant labours during the pandemic. Rapid urbanization has changed the demographic and economic landscape of India, attracting millions of people to the urban areas which led to unplanned development, overpopulation and the emergence of informal settlements, which have increased inequality, put the urban poor at greater risk in times of crisis and COVID-19 has highlighted this vulnerability. Drawing from comprehensive datasets obtained from the Census of India, supplemented by information gathered from the official COVID-19 databases spanning various states, union territories, districts, and cities, the research investigates the nuanced relationships between urbanization patterns, migrant labour trends, and pandemic dynamics. Both descriptive and inferential statistics have been used to show the relationship between urbanization and COVID-19. The findings show that districts with higher urban populations, a greater number of towns, and a larger urban working population experienced higher COVID-19 prevalence. For validating the fact, both Poisson and Negative Binomial regression models were used among which, the Negative Binomial model was found to be more suitable due to its ability to handle overdispersion in the data. The study also reviews policy measures by Government of India like the One Nation One Ration (ONOR) scheme, Atmanirbhar Bharat Rozgar Yojana (ABRY) which aimed to support migrant workers during the pandemic. The analysis reveals the critical importance of policy interventions in addressing the challenges faced by urban migrant populations. The findings of this study can be used to inform policies and interventions to improve the urbanization and migrant labour scenario in India.

1. Introduction

Since the latter half of the twentieth century, the world has seen an unprecedented increase in urbanization. United Nation estimations from 2018 show that there has been an astounding 55.3% increase in the world's urban population. This trend will likely continue, with urban areas accounting for 68% of the world's population by 2050 (United Nations, 2018). Notably, Africa and Asia have contributed substantially more quickly to the growth of urban populations than other regions worldwide. India is the most populated country in Asia, falling only behind China. About 377.1 million people in India are urban dwellers, contributing to 31.16% of the country's total population (Sarkar, 2019, 2020; Sarkar & Lakshmana, 2024). The urban population in India is larger than the population of most countries around the world. Between 1901 and 2011, the percentage of the urban population living in metropolitan areas increased by over seven times, from 5.8% to 42.3%. The major reason behind it is the migration. The National Sample Survey (NSS) reports show that in the case of Delhi and Mumbai, 43% of their population is migrant, and a substantial portion of migrants are from less urbanized states like Bihar and Uttar Pradesh. Migrant labourers are attracted to metro areas because of the high concentration of job opportunities (Sarkar, 2019, 2020). However, most migrants from rural areas are generally absorbed in informal sectors. Approximately 67% of urban migrant labourers are absorbed in the informal sector (National Sample Survey Organisation, 2012).

In 2020, a debilitating and contagious virus known as coronavirus began spreading worldwide and was declared a pandemic by the World Health Organization (WHO) in March 2020. This was a challenge for the cities where unplanned and haphazard development was already a problem serving their population, and the pandemic worsened it. It showed that cities need to be better prepared for situations like this in the future. After the outbreak of COVID-19, the government implemented lockdowns all over the country, which created problems related to food, shelter, transportation and employment. This problem was specifically associated with the migrant population in the urban areas. Even after reaching the home, these migrant labourers were not accepted and considered as the spreaders of the disease. The two devastating waves of COVID-19 snatched many lives in India. The immediate impact of COVID-19 is over, but it heralds its existence at various times. This public health crisis left behind several questions associated with Indian Urbanization and the vulnerability of its labour force, as they are the most victimized section of society during this period. Many policies were implemented or strengthened regarding them. Against this background, the present study tried to show the relationship of COVID-19 with urbanization. Furthermore, the study raised concerns about the preparedness of urban areas to adapt to the new policies of migrant labourers in the urban areas.

1.1. Migrant Labourers in Urban India: How the COVID-19 Pandemic Increased Vulnerability?

The growth of the urban population, especially in metropolitan cities, is moulded by the migrant population. In India, around 450 million population are internal migrants (Census of India, 2011) (Sarkar, 2020). Among the internal migrants, 15.6 % are rural-urban migrants. There are two categories among them: one who migrates within the state and another who migrates across the state. As per the 2011 Census, there were 117.9 million inter-district migrants and 54.4 million inter-state migrants in India. Interstate migrants are mostly associated with low-paying and insecure jobs, such as manufacturing, construction, hospitality, transportation, and domestic work (Hannan & Hossain, 2021). The major factors contributing to their involvement in the informal economy are poor educational background, poverty, and seasonal stay in urban areas.

One of the major features of internal migration in India is its seasonality. According to Kesri and Bhagat (2013), 21 of every 1000 people in India are temporary or seasonal migrants, with Bihar having the largest share at 50 per 1000 (Keshri & Bhagat, 2013). The reason behind this is the seasonality of agriculture. A labour is required during different phases of crop production. Generally, most labourers are needed in rural India during the sowing and harvesting phases. Hence, during this time, the migrant labourers come back to their home places. These labourers are essential in both rural and urban areas as they involve various types of informal economic activities, agriculture, manufacturing, and construction, as well as in brick kilns and textiles (Deshingkar & Akter, 2009; Srivastava & Sutradhar, 2016). Short-term, seasonal, and circular migration is very common among society's lower and marginalised segments. The highest number of seasonal migrants is found among the Scheduled Tribe community (45 persons per 1000), followed by Scheduled Castes (25 persons per 1000). Long-term migrants are comparatively from rich and middle peasants, upper castes and those already in non-farm occupations in relatively developed regions (Keshri & Bhagat, 2012; Sharma, 2005).

There exists a gender disparity in the migrant labour force in India. The female migrant labourers are predominantly engaged in agricultural and allied activities. In contrast, male migrant workers engage in a more diversified range of activities, with most sectors having a population representation of less than 20% (Mazumdar et al., 2013; Mishra, 2021). However, the mobility rate has also increased among the females of the less developed states who work in the southern states, mainly to be absorbed in the export-processing zones and industries. The linguistic diversity of India was once considered a hindrance in terms of inter-state migration. Still, this factor is losing its importance as a barrier to work (Ministry of Finance, 2017). However, till now, migrant labourers have been exploited by local employers due to their inability to know the lingua franca of the destination region (Goswami, 2015; John et al., 2020). Another significant phenomenon that has affected labour in India is economic reform. Due to greater emphasis on the non-farm sector, the agricultural sector shrank. A substantial majority of farmer households cannot cover their consumption needs solely from agricultural earnings, which has led many farmers to wage labour (Mishra, 2020). Not only this, but a huge section of the labour force also did not benefit from economic reform as the growth of service sectors depends on highly skilled, educated people. This skill-based service sector growth generated an employment crisis in India as a substantial portion of labour needs to be more skilled and educated. They are absorbed in the informal economy. However, the scenario has changed in terms of the share of informal workers, where it is seen that the share of workers in the unorganized sector has decreased, and the proportion of informal workers in a formal economy has increased, maintaining an overall high percentage of informal workers.

Migrant workers frequently enter the labour market through labour contractors or familial networks, and some end up as victims of exploitative labour contracts tied to debts. These people may eventually become self-employed in the city's informal economy or work as manual labourers in construction-related industries. At least in part, social bonds based on caste, religion, ethnicity, language, and area tend to concentrate on migration movements. For instance, labour contractors frequently use connections outside work locations to deploy, oversee, and punish employees. The dynamics of migrant labourers denote their vulnerability including their uncertainty about work and the precarious nature of living in urban areas (Mishra, 2021).

2. Database and Methods

2.1. Data Sources

This study utilizes a comprehensive methodology to explore the factors affecting COVID-19 prevalence in 640 districts in India that were specifically chosen. India comprises 640 districts and a population of 1.2 billion, as per the 2011 census. The present study is based on secondary sources, primarily the Census of India, supplemented by information from the official COVID-19 databases at https://www.mohfw.gov.in/ and https://www.COVID19india.org/. The dataset spans from January 30, 2020, to January 8, 2024, capturing the distinctions of reported cases, active cases, recoveries, and deaths attributed to the virus.

2.2. Techniques

The study focuses on prevalence estimates of COVID-19, expressed as number of cases per 10,000 people. In addition, the case fatality rate (CFR) is calculated as the percentage of deaths relative to the control population, providing insight into the severity of the virus's impact. This dual approach combines the prevalence rate and CFR to provide a nuanced understanding of the epidemic dynamics in selected districts. The study adopts a two-pronged approach, including descriptive statistics and regression analysis, to analyze and interpret the data collected. Descriptive analysis summarises important COVID-19 data and provides a grassroots understanding of the trends and assumptions in the data. Subsequently, regression analysis, especially Poisson regression and Negative Binomial regression, is used to determine the relationship between the dependent variable (COVID cases per 10,000 population) and the set of independent variables.

The rationale for adopting regression models lies in their ability to provide a stepwise understanding of the impact of each variable. This method allows incremental contributions to be considered and allows researchers to identify the differential effects of urbanization, urban working population and number of towns on the spread of COVID-19 (González-Val & Sanz-Gracia, 2022). The stepwise approach also facilitates small comparisons between models, clarifying whether each successive model provides the explanatory power of the previous one.

2.3. Poisson Regression Model Equation

The Poisson regression model can be expressed as:

$$\log(\text{COVIDprevalenceper10000popu}) = \beta_o + \beta_1\,(\text{Urban}) + \beta_2\,(\text{NumberofTowns}) + \beta_3\,(\text{Urbanworkers})$$

Substituting the coefficients from the Poisson regression output:

$$\log(\text{COVIDprevalenceper10000popu}) = 0.0199 + 0.0210\,(\text{Urban}) + 0.0142\,(\text{NumberofTowns}) + 0.0178\,(\text{Urbanworkers})$$

2.4. Negative Binomial Regression Model Equation

The negative binomial regression model can be expressed similarly, but it includes an additional parameter (α) to account for overdispersion. The model equation is:

$$\log(\text{COVIDprevalenceper10000popu}) = \beta_o + \beta_1(\text{Urban}) + \beta_2(\text{NumberofTowns}) + \beta_3(\text{Urbanworkers})$$

Substituting the coefficients from the negative binomial regression output:

$$\log(\text{COVIDprevalenceper10000popu}) = -0.8020 + 0.0223\,(\text{Urban}) + 0.0262\,(\text{NumberofTowns}) + 0.0343\,(\text{Urbanworkers})$$

2.5. Interpretation of Equations

In both models, the coefficients (β_i) represent the change in the log of the COVID-19 prevalence rate per 10,000 population for a one-unit increase in the respective predictor variable, holding all other variables constant.

Urban: The percentage of the urban population.

Number of Towns: The count of towns.

Urban workers: The percentage of the working population in urban areas.

The constant term (β_o) represents the log of the expected COVID-19 prevalence when all predictor variables are zero.

2.6. Overdispersion in Negative Binomial Model

The negative binomial model includes a dispersion parameter (α), which is not explicitly shown in the equation above but is critical for adjusting the variance:

$$\text{Variance} = \mu + \alpha\mu^2$$

where (μ) is the mean of the dependent variable.

2.7. Model Selection

Based on the log-likelihood and handling of overdispersion, the negative binomial model is preferred as it provides a better fit and more reliable inferences in the presence of overdispersion (Berk & MacDonald, 2008).

3. Result and discussion

3.1. Details on covid-19 pandemic and labour migration scenario in India

The brutal reality of mismanaged urban growth, the intricacies of migrations and their vulnerability were starkly exposed with the advent of COVID-19 in India. The first case of India's 2019–20 coronavirus pandemic was reported on Jan 30, 2020, from the state of Kerala. The initial response to the pandemic was a sudden and harshly implemented lockdown, preceded by the Janta Curfew (one-day lockdown). While for the middle classes, it meant being confined to their houses and gradually transitioning to online ways of employment, communication, and entertainment, for the working classes, it was an abrupt interruption of earnings (Hannan & Hossain, 2021; Mishra, 2021). The pandemic exposed the flaws in India's labour migration system, emphasizing the urgent need for reform and strong support networks. India suffered from three phases of the COVID-19 pandemic.

3.1.1. First wave in India

In the first wave, which extended from March 2020 to nearly the end of November 2020, the older population were at the highest risk category. This wave was characterised by a shortage of medicine, black marketing, and the unavailability of hospital beds. The Indian migrant workers were subjected to the most painful experiences during this phase as a nationwide lockdown was implemented on 24 March 2020, giving citizens only four hours' notice to react

(Ray & Subramanian, 2022). There were four phases of lockdowns from 24 March 2020 to 31 May 2020 (Phase 1: 24th March 2020 to 14 April 2020; Phase 2: 15th April 2020 to 3 May 2020, Phase 3: 4 May 2020 to 17 May 2020 and Phase 4: 18 May 2020 to 31 May 2020) to control the transmission of COVID-19. After that, several unlock phases were announced to restart the Indian economy. After the sudden announcement of lockdown, the migrant labourers who were absorbed in the big cities tried hard to come back to their homes. It led to the greatest exodus in India since the 1947 partition (Ellis-Petersen H & Chaurasia M., 2020). Due to the lack of transportation, they suffered the worst situation. The unavailability of food, loss of livelihood and uncertainty of future employment compelled them to go on the path of reverse migration. During this time, they suffered greatly, including a lack of food, healthcare facilities, and insufficient government assistance. Various dreadful incidents took place, for instance, accidents while walking along the railway tracks, lack of food and health care facilities, long trekking barefoot or even cycle/ rickshaw, and death of migrants during the journey due to lack of food. The pandemic's immediate repercussions included loss of jobs and earnings, non-payment of backlog wages, loss of consumption, and depletion of savings (Mishra, 2021). The exact number of returnees – was not available from government sources. However, as per data cited on 14 September 2020 by the Lok Sabha, it was about 10.5 million. The two most populous states that became the destination of many returnees were Uttar Pradesh and Bihar.

3.1.2. Second wave in India

The second wave of the pandemic began around 11 February 2021(Ranjan et al., 2021). The first and second wave in India lasted about 5 months. India saw extreme severity in this wave, and the daily cases rose in early March 2021. The second wave peaked in May (6th May, more than 414000 cases). It took around 36 days, from 80,000 COVID-19 cases on April 1 to more than 414,000 on May 6. However, the decline was also sharp and almost within the same period to reach its peak, it came back to similar numbers. The Ministry of Labor reports that during the second wave of COVID-19 in April and May of this year, about 5.15 lakh migrant workers left their places of employment and returned to their villages, as opposed to at least 1.14 crore during the first lockdown a year before (Joy, 2021). During this phase, the state governments imposed state-wide lockdowns. The states did not witness any extraordinary departure in the second wave compared to the first. The industries, manufacturing section, and public transportation were open during this phase, although there were restrictions. As the restrictions were partial and no nationwide lockdown was announced, many migrants stayed back in the cities while others left during the wave's early phase. But during this time, the labourers suffered different types of problems, e.g. not getting any work or no regular work, not having enough cash and ration, and difficulties getting vaccines and health care facilities.

3.1.3. Third wave in India

The problems faced by the migrants were more severe in the first wave compared to the second wave. The third pandemic wave in India lasted from January to March 2022, and breakthrough infections were common (Jayadevan et al., 2022). As of 19th July 2022, the day recorded 15,528, and the total number of active cases was 1,43,654. The third wave was characterized by fewer deaths and limited symptomatic patients, with lower casualties than the first and second waves. The study by Max Healthcare revealed that 60 % of COVID-19 deaths in the third wave occurred among the partially or completely unvaccinated (Business Standard, 2022). In this wave, only 23.4 % of patients required oxygen compared to 74 % during the second and 63 % during the first. As no nationwide lockdown was announced and some state-specific restrictions were implied, labourers were unaffected like the last two waves. In May 2023, the World Health Organisation announced that coronavirus was no longer a public health

emergency. However, since it arrived in India in 2020, it has always proved its presence by re-emerging at various times.

As of January 8, 2024, table 1 shows a comprehensive snapshot of the COVID-19 across various States and Union Territories in India. Maharashtra emerges as the epicentre with the highest total cases at 81,73,792, underscoring the significant impact of the virus in this state. Kerala and Karnataka follow closely, contributing to the regional variations in case numbers. Kerala has the highest COVID prevalence rate per 10,000 population (692), suggesting a concentrated virus spread in the state. Meanwhile, smaller regions like Dadra and Nagar Haveli Daman and Diu, Lakshadweep, Andaman and Nicobar exhibit lower prevalence rates. The distribution of active cases highlights the ongoing challenges faced by Kerala, Karnataka, and Maharashtra in managing the spread of the virus. The higher number of deaths in Maharashtra, Karnataka, and Kerala corresponds to their elevated total cases, indicating the severity of the impact. Discharge ratios, reflecting successful recoveries, generally remain high across most states, while Punjab, Uttarakhand, and Meghalaya show slightly lower ratios, suggesting potential complexities in the recovery process.

Table 1. COVID-19 Statistics in Indian States/UTs: total cases, prevalence, active cases, deaths, discharge ratio, and death ratio

State/UTs Name	Total Number of Covid-19 Cases	COVID prevalence per 10,000 population	Total Active cases	Deaths	Discharge Ratio (%)	Death Ratio
Maharashtra	81,73,792	817	882	1,48,571	98.17	1.82
Kerala	69,16,859	692	845	72,085	98.95	1.04
Karnataka	40,92,742	409	1,222	40,383	98.98	0.99
Tamil Nadu	36,11,393	361	184	38,086	98.94	1.05
Andhra Pradesh	23,40,909	234	85	14,733	99.37	0.63
Uttar Pradesh	21,45,564	215	21	23,718	98.89	1.11
West Bengal	21,26,744	213	189	21,556	98.98	1.01
Delhi	20,41,269	204	33	26,670	98.69	1.31
Odisha	13,48,494	135	79	9,215	99.31	0.68
Rajasthan	13,26,592	133	56	9,737	99.26	0.73
Gujarat	12,91,687	129	75	11,082	99.14	0.86
Chhattisgarh	11,87,920	119	125	14,193	98.79	1.19
Haryana	10,79,026	108	17	10,780	99.00	1.00
Madhya Pradesh	10,56,616	106	23	10,786	98.98	1.02
Bihar	8,55,308	86	18	12,315	98.56	1.44
Telengana	8,44,647	84	39	4,111	99.51	0.49
Punjab	7,93,694	79	11	20,571	97.41	2.59
Assam	7,46,177	75	51	8,036	98.92	1.08
Jammu & Kashmir	4,82,054	48	6	4,793	99.00	0.99
Uttarakhand	4,52,590	45	1	7,768	98.28	1.72
Jharkhand	4,43,853	44	0	5,337	98.80	1.20
Himachal Pradesh	3,22,955	32	6	4,246	98.68	1.31
Goa	2,63,550	26	46	4,014	98.46	1.52

Mizoram	2,39,562	24	0	734	99.69	0.31
Puducherry	1,77,638	18	7	1,982	98.88	1.12
Manipur	1,40,036	14	0	2,149	98.47	1.53
Tripura	1,08,500	11	4	943	99.13	0.87
Chandigarh	1,00,703	10	1	1,185	98.82	1.18
Meghalaya	96,990	10	0	1,628	98.32	1.68
Arunachal Pradesh	67,049	7	0	296	99.56	0.44
Sikkim	44,932	4	0	501	98.88	1.12
Nagaland	36,033	4	0	782	97.83	2.17
Ladakh	29,616	3	21	231	99.21	0.78
Dadra & Nagar Haveli & Daman and Diu	11,592	1	0	4	99.97	0.03
Lakshadweep	11,415	1	0	52	99.54	0.46
Andaman & Nicobar	10,766	1	0	129	98.80	1.20

Source: Authors' estimation from https://www.mapsofindia.com/coronavirus-updates-map.html

3.2. Analyzing covid-19 case distribution across urbanization levels in Indian districts

Significant insights into the mechanisms of the pandemic's transmission can be gained from examining how COVID-19 cases are distributed across various urbanization levels in Indian districts. The data set shows the quantity of COVID-19 instances reported in Indian districts according to the degree of urbanization. These districts are classified as mostly rural (with less than 20% urban population), moderately urbanized (with between 40% and 20% urban population), and highly urbanized (with more than 40 % urban population). The data indicates a strong relationship between the number of COVID-19 cases and urbanization. Highly Urbanized districts face a disproportionate share of Covid-19 cases (Table 2).

Table 2: Basic Descriptive Statistics of COVID-19 Case Distribution and Urbanization

District Level of Urbanization	Number of District	No of Registered COVID-19 cases	Percent Distribution of COVID-19 cases	Average no of COVID Cases/District	SD	CV
Highly Urbanized	122	14636255	46.75	119969.3	180236.1	150.24
Moderately urbanized	194	10296470	32.89	53074.59	106405.1	200.48
Predominantly Rural	324	6375354	20.36	19677.02	25874.87	131.50

Source: Authors' estimation from https://www.mohfw.gov.in/

Despite being the smallest group, highly urbanized districts are responsible for almost half of all COVID-19 occurrences. This disproportionate share suggests that urbanization is a major contributing factor to the COVID-19 epidemic. An average of 119,969.3 instances per district is noticeably higher than Moderately Urbanized districts (around 2.26 times higher) and Predominantly Rural districts (6.10 times higher). There is the greatest absolute dispersion in case numbers among all the categories, as indicated by the largest SD of 180,236.1. Some Highly Urbanized districts may have significantly more cases than usual, while others may have fewer.

Moderately urbanized districts account for approximately one-third of all districts and COVID-19 cases. Although much less than highly urbanized areas, the average number of cases per district (53,074.59) is still 2.70 times higher than that of predominantly rural districts. The SD of 106,405.1 is still rather high; however, it is lower than in highly urbanized areas. While not as severe as in Highly Urbanized zones, this shows significant absolute variability in case counts. The CV of 200.48 stands out as the highest among all categories. Certain Moderately Urbanized districts may have far larger case numbers than average, while others have much fewer case numbers, given the extraordinarily high relative variability. The discrepancy in urbanization levels within this category may be due to the differences in characteristics between districts, with some exhibiting characteristics resembling highly urbanized areas and others more rural.

Most districts are rural, although they account for the smallest proportion of COVID-19 cases. This inverse link strongly shows that COVID-19 distribution is less likely in remote locations due to lower population density and fewer international contacts. The average 19,677.02 cases per district is significantly lower than the other categories. The SD (25,874.87) and CV (131.50) are the lowest among all categories. Rural district case numbers are more closely distributed around the mean, as the lower standard deviation indicates. There is less extreme fluctuation, indicating more consistency in the variables influencing COVID-19 distribution. Interestingly, the CV of 131.50 indicates significant relative variability even with the lowest average. Compared to their average, certain rural areas have noticeably higher case counts; this could be because of things like being close to cities or having industrial zones that foster more social interaction.

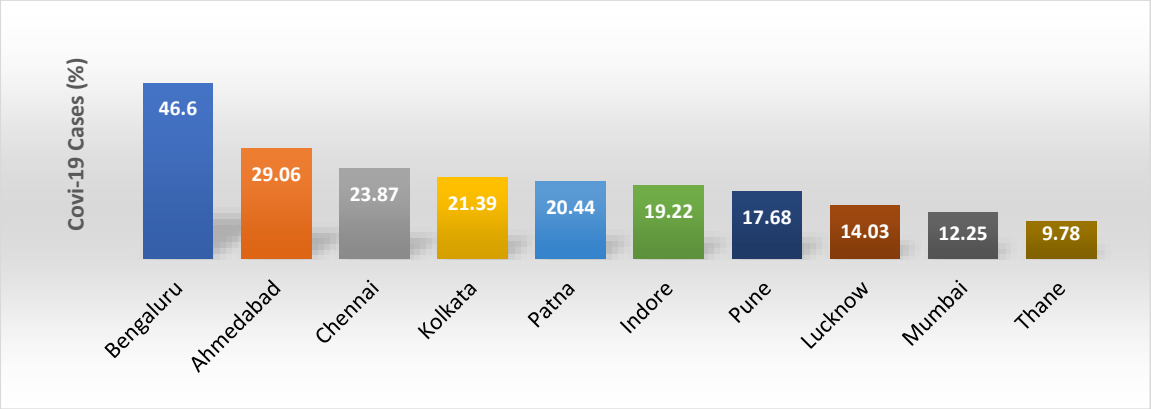
There could be several underlying reasons for the very strong association between the number of COVID-19 cases and the degree of urbanization, including greater population densities are typically found in highly urbanized areas, and these close quarters and congested living circumstances can contribute to the quick spread of infectious diseases like COVID-19. People commute to urban regions for work, education, and other reasons, which usually results in higher levels of mobility and linkage. The virus may spread through districts and regions more quickly as a result of this enhanced mobility. Urban locations typically have better access to healthcare infrastructure; however, this may not always be the case because of increased demand and possible resource pressure during a pandemic in highly urbanized districts. Socioeconomic conditions in cities can vary, with some groups living in congested, multigenerational houses or informal settlements where social distancing is difficult.

There may be differences in public understanding and adherence to health guidelines between urban and rural communities. Despite having more access to information, urban communities may suffer economic restrictions that make implementing lockdown measures difficult. Greater access to testing and reporting facilities is frequently correlated with testing and reporting in metropolitan areas, leading to a higher number of cases found. Due to limited testing options, underreporting may occur in rural areas.

3.3. COVID-19 prevalence in India's major metropolitan areas

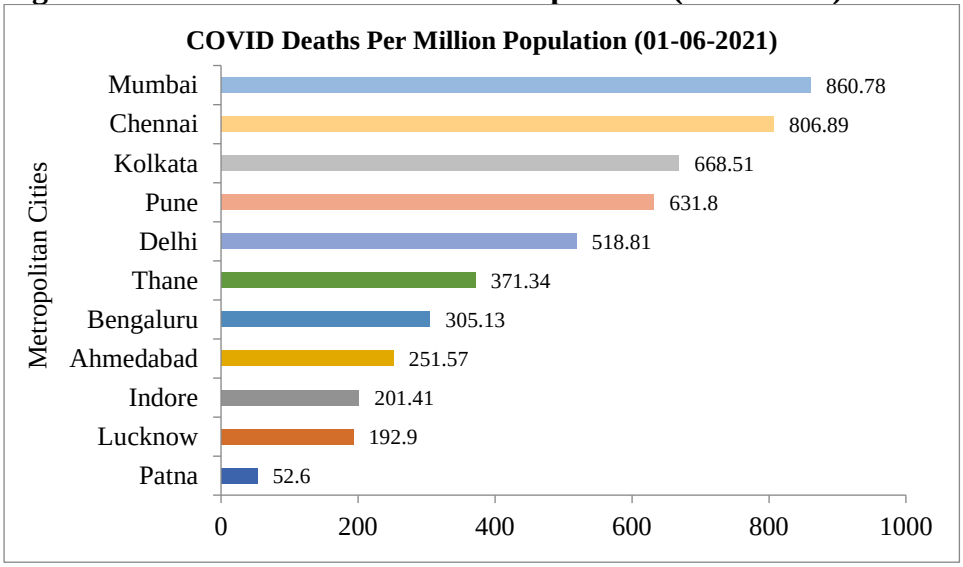
As of June 1, 2021, Bengaluru reported the highest COVID-19 cases among the listed cities at 46.6%, signifying a significant impact. Ahmedabad, Chennai, Kolkata, and Patna also exhibited substantial percentages, indicating notable prevalence. In contrast, Thane, Mumbai, Lucknow, and Indore showed lower percentages. These figures highlight regional disparities and suggest potential strain on healthcare resources in areas with higher case percentages. However, it's important to consider factors like population size and testing rates to understand comprehensively and note that the data represents a specific point during the pandemic (Figure 1).

Figure 1. Share of COVID Cases (%) in their Respective States (01-06-2021)



As of June 1, 2021, the data reveals varying COVID-19 mortality rates per million population across Indian cities (Figure 2). Mumbai, Chennai, Pune, Kolkata, and Delhi show higher rates, indicating a more pronounced impact. Factors such as population density and urbanization may contribute to these disparities. Cities like Patna and Bengaluru exhibit comparatively lower mortality rates. The analysis emphasizes the need for tailored strategies and resources based on regional dynamics for effective pandemic management.

Figure 2. COVID Deaths Per Million Population (01-06-2021)



3.4. COVID-19 Prevalence in India's Major Districts

Table 3 presents the COVID-19 prevalence per 10,000 population across various districts. Bangalore, Karnataka, has the highest prevalence, with 12,51,872 cases, translating to 125.19 cases per 10,000 population. Pune, Maharashtra, follows with 11,54,776 cases and a prevalence of 115.48 per 10,000 population. Mumbai City, Maharashtra, records 7,56,749 cases with a prevalence rate of 75.67. Thane, Maharashtra, has 6,10,128 cases and a prevalence of 61.01 per 10,000 population. Ernakulam, Kerala, has the lowest prevalence among the top five, with 6,02,800 cases and a rate of 60.28 per 10,000 population. These figures indicate a significant burden of COVID-19 in these districts, with Karnataka and Maharashtra showing particularly high prevalence rates, necessitating sustained public health efforts and resource allocation to manage and mitigate the spread of the virus.

Table 3. COVID-19 prevalence per 10,000 population, 2022

Top Rank	District	State	Total COVID-19 Cases	COVID prevalence per 10,000 population
1	Bangalore	Karnataka	12,51,872	125.19
2	Pune	Maharashtra	11,54,776	115.48
3	Mumbai City	Maharashtra	7,56,749	75.67
4	Thane	Maharashtra	6,10,128	61.01
5	Ernakulam	Kerala	6,02,800	60.28

Source: Authors' estimation from https://www.mohfw.gov.in/

Table 4 provides the COVID-19 case fatality rates (CFR) for various top five districts. Darbhanga in Bihar has the highest CFR at 3.38 %, indicating a significant impact of the virus in this district. In Maharashtra, Nanded follows with a CFR of 2.94 %, Kolhapur at 2.83 %, Aurangabad at 2.74 %, and Sangli 2.68 %. These values highlight the concerning fatality rates in these areas, particularly within Maharashtra, which has four districts in the top five. The relatively high CFRs suggest challenges in healthcare responses and the need for improved medical interventions and public health measures in these regions.

Table 4. COVID-19 case fatality rate among the districts, 2022

Top Rank	District	State	COVID-19 Case fatality rate (%)
1	Darbhanga	Bihar	3.38
2	Nanded	Maharashtra	2.94
3	Kolhapur	Maharashtra	2.83
4	Aurangabad	Maharashtra	2.74
5	Sangli	Maharashtra	2.68

Source: Authors' estimation from https://www.mohfw.gov.in/

Table 5 shows the COVID-19 recovery rates for the top districts. Bangalore, Karnataka, leads with a 98.2% recovery rate. Pune, Maharashtra, follows with 98.0%, while Thane, Maharashtra, has 97.9%. Mumbai City and Ernakulam, Kerala, both have a recovery rate of 96.9%. These high recovery rates, ranging from 96.9% to 98.2%, reflect effective healthcare management and public health policies in these districts.

Table 5. COVID-19 recovery rate among the districts, 2022

Top Rank	District	State	COVID-19 recovery rate
1	Bangalore	Karnataka	98.2
2	Pune	Maharashtra	98.0
3	Mumbai City	Maharashtra	96.9
4	Thane	Maharashtra	97.9
5	Ernakulam	Kerala	96.9

Source: Authors' estimation from https://www.mohfw.gov.in/

3.5 Regression Models

The analysis of the Poisson and negative binomial regression models for predicting COVID-19 prevalence per 10,000 population, based on urbanization, number of towns, and urban workers, reveals several important insights.

3.5.1. Poisson Regression Model

The Poisson regression model shows significant coefficients for all the predictors, indicating that urbanization, the number of towns, and the number of urban workers are positively

associated with COVID-19 prevalence. Specifically, the coefficients are 0.021 for urbanization, 0.014 for the number of towns, and 0.018 for urban workers, all with p-values less than 0.001. However, the log-likelihood of -2985.7 and a likelihood ratio chi-squared statistic of 1836.7 ($p < 0.000$ suggest that while the model fits reasonably well, it may not capture all the nuances in the data.

3.5.2. Negative Binomial Regression Model

The negative binomial regression model also shows significant coefficients for all the predictors, with values slightly higher than those in the Poisson model: 0.022 for urbanization, 0.026 for the number of towns, and 0.034 for urban workers, all with p-values less than 0.003. The log-likelihood of -1551.6 and a likelihood ratio chi-squared statistic of 278.58 ($p < 0.0000$) indicate a better fit than the Poisson model. Moreover, the significant dispersion parameter ($\alpha = 0.918\backslash$), $p < 0.001$) confirms the presence of overdispersion, meaning that the variance exceeds the mean in the data.

Table 6 presents results from Poisson and Negative Binomial regressions analyzing the impact of urban factors on COVID-19 prevalence per 10,000 population. All predictors (Urban Population percentage, Number of Towns, and Urban Workers percentage are highly significant in both models. The coefficients are larger in the Negative Binomial model, indicating stronger associations when overdispersion is considered. The Poisson model has a higher Pseudo R-squared (0.23 vs. 0.08), suggesting it explains more variance. Overall, urban characteristics significantly predict COVID-19 prevalence, with potentially stronger effects in the Negative Binomial model.

Table 6. Estimation of regression models

Variables	**Poisson Regression**		**Negative Binominal Regression**	
Dependent Variable: COVID-19 prevalence per 10,000 population				
	Coefficient	Std. error	Coefficient	Std. error
Urban Population %	0.021***	0.0006	0.022***	0.002
No of Towns	0.012***	0.0005	0.026***	0.003
Urban workers %	0.017***	0.0035	0.034***	0.011
Constant	0.019	0.126	-0.802**	0.39
Number of observations	636		636	
Number of variables	3		3	
Pseudo R squared	0.23		0.08	

**Statistically significant at the 5% level. ***Statistically significant at the 1% level.

4. Discussion and Policy suggestions

4.1. Is poisson regression or negative binomial regression better for modeling covid-19 prevalence?

The key difference between the two models is their handling of overdispersion (Ibarra-Espinosa et al., 2022). The Poisson model assumes that the mean and variance of the dependent variable are equal, which is not the case here. This leads to underestimated standard errors and potentially misleading inferences. In contrast, the negative binomial model accounts for overdispersion, providing more accurate standard errors and p-values (Ver Hoef & Boveng, 2007). Given these points, the negative binomial regression model is recommended. It fits the data better, as indicated by a higher log-likelihood, and appropriately addresses the overdispersion present in the data, leading to more reliable estimates and inferences. Therefore, the negative binomial regression model is the superior choice for modelling COVID-19

prevalence per 10,000 population based on urbanization, the number of towns, and urban workers.

Based on the analysis of the Poisson and negative binomial regression models for predicting COVID-19 prevalence per 10,000 population, the negative binomial regression model is the more suitable choice. The key reason for this is the presence of overdispersion in the data, which is indicated by the negative binomial model's significant dispersion parameter (α). Overdispersion occurs when the variance of the dependent variable exceeds its mean, which can lead to underestimated standard errors and misleading p-values in a Poisson model.

The negative binomial regression model accounts for this overdispersion, providing more accurate standard errors and p-values. Additionally, the model fit statistics indicate a better fit for the negative binomial model, with a significantly higher log-likelihood (-1551.6) than the Poisson model (-2985.7). While the Poisson model's pseudo R^2 is higher, this metric can be misleading in overdispersion and does not necessarily indicate a better model. Therefore, considering the improved handling of overdispersion and the better overall model fit, the negative binomial regression model is more appropriate for analyzing COVID-19 prevalence per 10,000 population based on urbanization, number of towns, and urban workers.

4.2. Policy reforms for pandemic preparedness and resilience

The above result clearly shows that urbanization positively correlates with COVID-19 prevalence. In order to address these issues and enhance preparedness and resilience, it is necessary to make changes to current policies and implement new ones. The government of India took several short-term actions to control rapid COVID-19 and mitigate problems related to mobility, food supply, and employment. As discussed earlier, the most prominent sufferers of COVID-19-induced lockdown were the migrant labourers. The government also focused on long-term policies to reduce their economic and social vulnerability and made significant changes.

4.3. Short-term actions

India's sudden, strict lockdown in March 2020 left millions of migrant workers stranded in cities without work or means to return home. Facing desperation, many undertook difficult journeys on foot. This mass exodus, particularly to poor states like Uttar Pradesh and Bihar, remains a dark chapter in post-independence India. Recognizing this hardship, the government launched financial assistance programs and special Shramik trains and buses to facilitate free travel for over 9 million migrants. The government allocated another Rs. 10 billion (US$ 134 million) for migrant welfare under the PM-CARES fund. Each state received a minimum of Rs. 1 billion (US$ 13.4 million), with additional grants based on population and COVID-19 cases. The effectiveness of these programs is still being assessed. Shramik special trains and buses were launched to help stranded migrants reach their hometowns. Initially, migrants were charged fares, leading to political controversy. The Supreme Court intervened, making travel free for migrants. Over 9 million migrants used these services, with 6 million transported by trains. However, the effectiveness of these initiatives remains under scrutiny.

4.4. Long term actions

To overcome the COVID problem in a real sense and increase preparedness, the government of India either launched or modified a set of long-term policies so that this kind of chaos can be avoided in the future. The most significant ones are discussed below.

I. One Nation One Ration Card (ONORC)

The One Nation One Ration Card (ONORC) initiative was introduced under the National Food Security Act (NFSA) 2013. It allows eligible cardholders to access food grains from any Fair Price Shop (FPS) nationwide. It was initially tested in four states, i.e., Andhra Pradesh,

Telangana, Maharastra and Gujrat 2019. However, the scheme gained significance during the COVID-19 pandemic for its potential to assist those migrant labourers who had lost their livelihoods and either returned to their hometowns or got stuck in their working places. As part of the COVID-19 economic relief package, the government aimed to implement ONORC nationwide by March 2021, aligning with the technology-driven reforms of the Aatma Nirbhar Bharat Abhiyan. The Supreme Court of India also directed the implementation of ONORC by July 31, 2021 (Rathore & Raj, 2022). And by August 31, 2021, the scheme was operational in most states and Union Territories, except Assam and Chhattisgarh. The ONORC scheme facilitated over 300 million transactions between April 2020 and July 2021, with monthly interstate transactions increasing significantly. In December 2021, monthly interstate transactions surged 38 times compared to April 2020, reaching 813,000. Intradistrict transactions were predominant, exceeding 130 million in 2021 (Rathore & Raj, 2022; A. Sharma, 2021).

Although the concept aimed to address the challenges migrants face during the lockdown, implementation hurdles such as technological constraints and resistance from some states have limited its effectiveness (Joshi et al., 2016). Technological constraints such as a lack of digital awareness among both the beneficiaries and distributors and difficulties in implementing biometric authentication hindered the smooth execution of the ONORC scheme. Data synchronization problems were also prominent due to the unavailability of real-time updates across diverse state databases. Political resistance from some states is another reason that negatively impacted the scheme. Finally, it remained ineffective, especially among the migrant workers, because many migrants hesitated to use the scheme even when all benefits were accessible due to their preference for their families in the village to consume ration. Moreover, news and cases of data theft and misuse of information made the labourers sceptical about the Scheme. All these challenges leave many migrant workers without access to subsidized food grains, emphasizing the need to overcome implementation barriers (Bhandari, 2020).

II. Atmanirbhar Bharat Rozgar Yojana (ABRY)

Aiming to address the impact of the COVID-19 pandemic on job opportunities, ABRY was introduced to ease the financial burden on employees of low-income categories. The scheme commenced on October 1, 2020, and accepted registrations for eligible employers and new employees until June 30, 2021. Employees earning a monthly wage below Rs. 15,000 and not previously employed in an establishment registered with the Employees' Provident Fund Organization (EPFO) before October 1, 2020, can avail themselves of the scheme's benefits. Additionally, EPF members with a Universal Account Number (UAN) earning less than Rs. 15,000 per month, who left employment during the pandemic from March 1, 2020, to September 30, 2020, and did not rejoin an EPF-covered establishment by September 30, 2020, are also eligible.

The government provides a subsidy for two years from the registration date. It created about 39.51 lakh new job opportunities by crediting Rs.2583 crores in EPF accounts (Kamal & Kumbhar, 2023). However, the slow formalization process and the predominantly formal sector-focused benefits left a considerable segment of the migrant workforce unaddressed. Bridging this gap requires a significant approach that recognizes the unique challenges of the informal sector in India.

III. Pradhan Mantri Garib Kalyan Yojana (PMGKY)

Pradhan Mantri Garib Kalyan Yojana (PMGKY) was introduced as a relief package to address the impact of the COVID-19 pandemic. The scheme was valid from March to May 2020 and involved the government paying 24% of monthly wages into EPF accounts for employees earning below Rs. 15,000 per month in establishments with up to 100 employees. The scheme

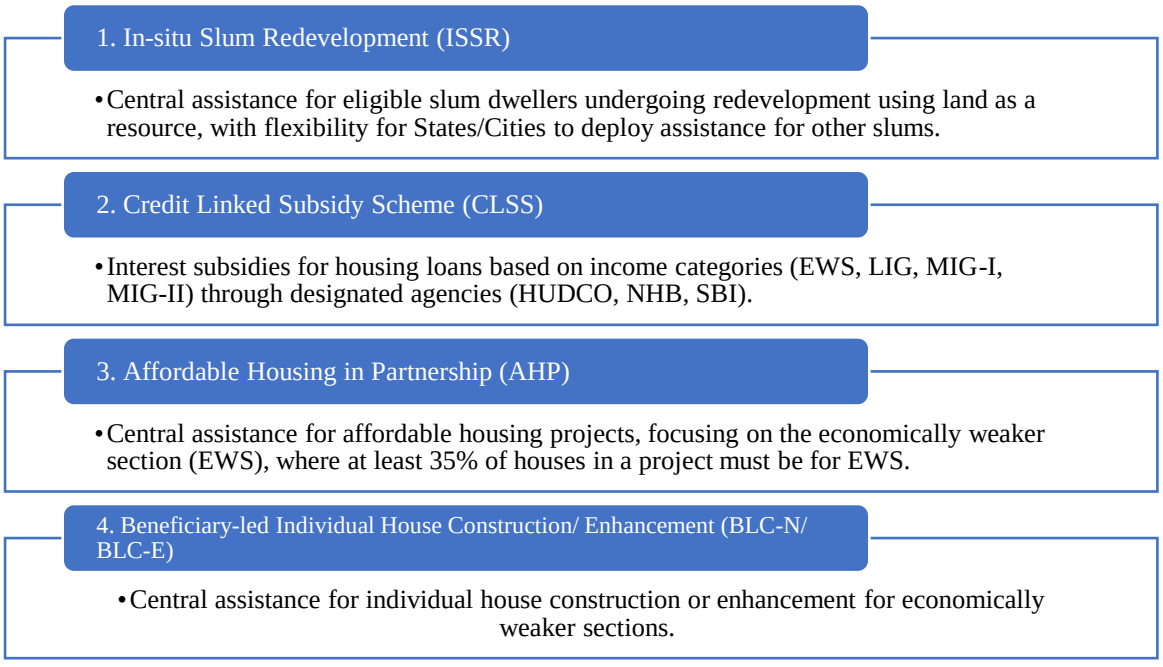
aims to provide immediate financial relief and support to affected employees, such as migrant labourers, during the specified period. The benefits of Rs.2567 crores were credited to retain 38.91 lakh low-wage employees(Kamal & Kumbhar, 2023). However, challenges in identifying and reaching all eligible beneficiaries, especially those in the informal sector, were difficult, reducing the scheme's impact (Pal et al., 2021).

IV. PMSVA Nidhi Scheme

The Ministry of Housing and Urban Affairs launched the PM Street Vendor's AtmaNirbhar Nidhi (PM SVANidhi) on June 01, 2020, to provide affordable working capital loans to street vendors affected by the Covid-19 lockdown, enabling them to restart their livelihoods. Under the scheme, street vendors can access loans of up to Rs. 10,000, which are repayable in monthly instalments over one year. There are no penalties for early loan repayment. The scheme encourages digital transactions by offering monthly cash-back incentives of up to Rs. 100. Vendors can request a credit limit escalation upon timely or early loan repayment. However, challenges such as lack of awareness, cumbersome documentation procedures, and limited financial literacy among target beneficiaries have limited the scheme's reach (Malhotra and Baag, 2022). Strengthening awareness campaigns, simplifying procedures, and offering financial literacy programs are crucial for enhancing the scheme's impact (Chowdhary, 2021).

V. The Pradhan Mantri Awas Yojana-Urban (PMAY-U)

The Pradhan Mantri Awas Yojana-Urban (PMAY-U), initiated in June 2015, is a flagship program by the Government of India under the Ministry of Housing and Urban Affairs (MoHUA). It aims to provide weather-resistant houses to eligible beneficiaries in urban areas through various verticals. The verticals include:



The scheme aims to address housing needs and contribute to socio-economic development, emphasizing completing ongoing projects and fostering a holistic approach to urban housing. The scheme, covering all urban areas, was extended until December 2024 (except CLSS), focusing on completing sanctioned houses by March 2022.

5. Conclusion

The study's findings show that highly urbanized districts, which are fewer in number, accounted for nearly half of the total COVID-19 cases. The unsustainable urbanization in the

global south is already an alarming issue due to high population density, poor housing conditions, and lack of safe drinking water, sanitation and healthcare facilities. As a result, the cities have become the bombs of spreading diseases. The state-level variations also prove this fact. The states like Maharashtra, Karnataka and Kerala became epicentres with the highest total cases and prevalence rates. Cities like Bengaluru, Chennai, and Mumbai showed higher COVID-19 mortality rates per million population.

Furthermore, Poisson and Negative Binomial regression models were used to validate the fact. However, the Negative Binomial model was more suitable due to its ability to handle overdispersion in the data. In this model, urbanization, the number of towns, and the urban worker population were positively associated with COVID-19 prevalence. This study also unearthed the vulnerability of labour in the urban centres of India. It reviewed how the sudden lockdown due to COVID-19 massively shattered their lives. Studying the internal migration dynamics also proves the pandemic opened the already existing long-term problems of the internal migrant labour force in India, which doesn't have a proper database, proper legal system of recruitment, impact of caste, gender and language biasedness, role middleman and exploitation.

Additionally, it showed how the government's initial response could have been more responsible. The sudden lockdown without securing the earnings of the daily wage earners, physical torture during the exodus, and no arrangement of healthcare and food facilities created chaos. However, the government took measures in the latter half to keep the situation steady. Subsequently, the government took long-term measures like ONORC, Atmanirbhar Bharat Rozgar Yojana (ABRY) and Pradhan Mantri Garib Kalyan Yojana (PMGKY). However, these policies faced challenges like a need for digital awareness, technological constraints, and the need to address informal sectors properly. Based on these findings, sustainable urban development is the only solution to this problem. For this purpose, several steps should be taken. Firstly, there should be a campaign for labourers to promote digital literacy. It will help them in various ways, such as knowing their rights, fair wages, and legal protection. In this regard, the Government should also work on the digital divide, which is very prominent in rural and urban areas. Subsequently, there should be a ground reality check of implementing the rural development programmes. More focus should be given to skill development and the establishment of sources of employment in rural areas so that rural-to-urban migration can be reduced. It will reduce the major problems of urban areas, such as high population density, housing problems, and the provision of healthcare facilities, sanitation, education, and employment. Also, the focus should be on the informal sector-based approach, simplification of the documentation process, and greater inter-state and centre-state cooperation for overcoming political resistance. The urban centres should take lessons from COVID-19 into disaster preparedness plans for better future resilience.

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