Trans. Inst. Indian Geographers
ISSN 0970-9851
Indexed in Scopus

COVID-19 contagion and its determinants across cities in India: An analysis of the spatially varying relationships during the early phase

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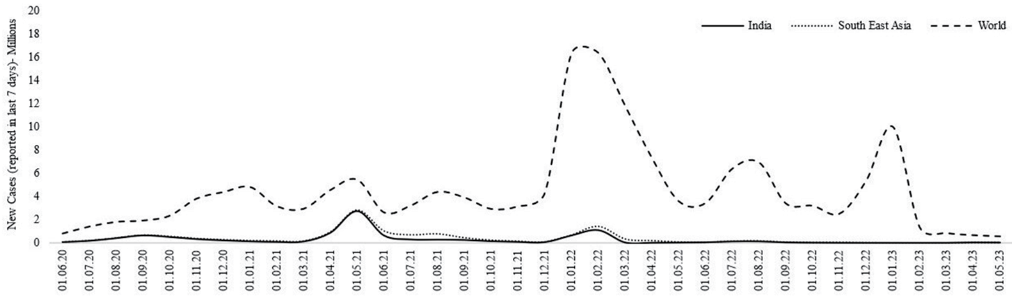
Abstract

Urban density and settings have proven to be a concern amid COVID-19, particularly in developing countries like India. This paper unveils its complex geographies with a focus on the 46 million-plus cities in India, across different phases of the pandemic. Multiple factors pertaining to density, transport, access to WaSH and so on, have been assumed to have an impact on the contagion spread, which has been tested with spatial models, employing both global (OLS) and local (GWR) approaches. Major findings suggest that while urban density can be a critical factor in the transmission of COVID-19, the nature of the relationship varies over time. Further, the spatial variability in the relationship flags the limited impact of uniform policy approaches, necessitating more place-specific measures to mitigate the spread of the contagion in densely populated cities.

Keywords: *COVID-19, density, geographically weighted regression, India, cities*

Introduction

The sudden spread of the COVID-19 virus in 2020 shocked the world and that is still reeling under its multidimensional impact. Although the cataclysm of the virus has had ramifications on everyone, it affected social, economic, and health groups differentially across space. The spatial trajectory of the COVID-19 pandemic, reveals that COVID-19 cases were higher in urban areas that are highly complex with diverse subpopulations and neighbourhoods. Based on past experiences, it is evident that when big cities face a pandemic that spreads rapidly within the community, human density and the urban setting has proven to be a matter of concern. Controlling the pandemic and recovery in such settings posed a challenge before the policymakers. In fast-paced and dense cities in most developing nations which are embedded in stark diversity and disparity, COVID-19 has further highlighted these vulnerabilities and also how policies have failed to effectively factor in spatial heterogeneity, hence becoming space-blind and uniform. This is an extended version of our paper published in Vol. 43 (No. 2) of Transactions (Yadav & Bhattacharjee, 2021b) where we tried exploring factors affecting COVID-19 cases and deaths in India. In this version, we have focussed on the transmission of the virus in the unlock phase 1 and the peak of the first and second phases of the pandemic that were critical. Furthermore, our research has also attempted to capture the



Source: Prepared by Authors based on data obtained from World Health Organisation

Fig. 1: Trend of New COVID-19 Cases in the Global, South East Asian, and Indian context

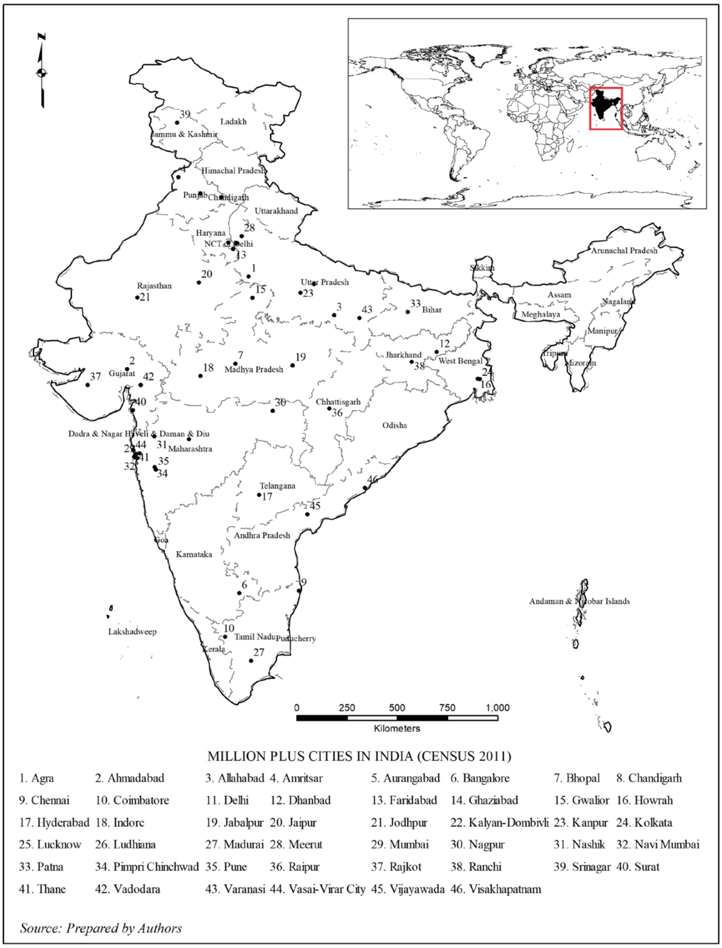
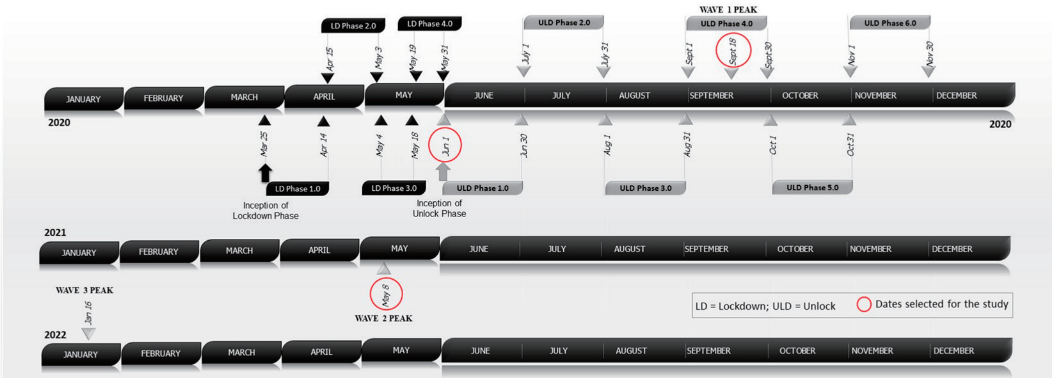


Fig. 2: Location of the study area



Source: Prepared by Authors based on information retrieved from Ministry of Home Affairs (MHA), Government of India.

Fig. 3: Timeline of Lockdown and Unlock Phases in India

spatial variation in the identified relationships between virus infection and determining factors.

If we look at the geographical spread of the contagion in the Global South, India recorded the highest share of cases among the South East Asian countries[1]. The South East Asian region accounted for as much as 51 percent of the global share of new COVID-19 cases during the peak of the second wave of the pandemic as of May 8th, 2021 (reported during the last 7 days[2]) and if we exclude India from the context, the global share of the South East Asian region drops to only 1.15 percent. This, points to the high incidence burden of the contagion in India, followed by Indonesia and Nepal, all of which had community transmission excluding Bhutan and Timor-Leste where sporadic cases were noted. At a global level throughout the pandemic, India has witnessed a high incidence of COVID-19 cases (Fig. 1), accounting for about 28 percent followed by 50 percent of the global share during the early phases of the pandemic in the peak of the first and second wave respectively and remained in the top three high-contagion countries besides the United States and Brazil.

The high incidence was witnessed in the beginning, primarily due to the unexpected spurt of the unknown virus, huge population size, density, and the skewed health infrastructure of the country. However, the relative share of the cases in India declined in subsequent phases, plausibly due to the rising awareness and mass vaccination drive[3]. Therefore, it is crucial to understand the nuances of the contagion from the

[1] One of the six WHO regions, the South East Asian region under the WHO framework consists of the countries of Bangladesh, Bhutan, India, Indonesia, Maldives, Myanmar, Nepal, Thailand, Timor-Leste, and Sri Lanka.

[2] Since March 22, 2020, worldwide data has been collected by WHO region-specific dashboards, alongside aggregate count information directly reported to the WHO headquarters by the Member States. The WHO published COVID-19 Weekly Epidemiological Update based on the number of new cases reported every week.

[3] As per statistics of the World Health Organization, the share of people fully vaccinated in India was only 2.42-percent on May 8th, 2021, which increased to 46.6 percent during January 16th, 2022 and to 69.7 percent as on October 1st, 2022 and 87.81 percent as on May 1st, 2023. India is far ahead in the vaccination drive as compared to other South East Asian countries where the incidence burden was also high, namely Indonesia, Myanmar, Sri Lanka, and Nepal. However, Maldives, and Bhutan, predominantly due to the relatively less demographic size have reached the mass vaccination drive ahead of India.

spatial-temporal perspectives and the complex geographies. The study focuses on the 46 million-plus cities in India which were the hotspots of the transmission (Fig. 2), accounting for about 90 percent of the confirmed cases reported in India at the beginning of the unlock phase 1.0 (Fig. 3). There is limited literature on the Indian scenario because of the lack of reliable and consistent data on COVID-19 and real-time data for other relevant factors. Thus, as Smith *et al.* (2021) argues, understanding the factors that influence the ecology and epidemiology of COVID-19 is still much left to explore. Multiple combinations of factors have been hypothesized to have an impact on COVID-19 transmission (Cutrini & Salvati, 2021; Rios & Gianmoena, 2021; Yadav & Bhattacharjee, 2021b). This study identifies factors affecting the COVID-19 contagion in Indian cities and captures the spatially varying relationship between the determining factors and transmission cases in the early phases of the pandemic.

Theoretical context

We have followed the theoretical premise that density leads to closer contact and interaction among people, which makes them potential hotspots for the spread of COVID-19. At the million-plus cities level, we have tried to understand how density at the macro level is a significant predictor of COVID-19 transmission. The choice of the predictors has been based on existing studies. For example, Gao, *et al.* (2021) observed that activity density provides a general measure of the activity level in a region and their study on digital trace data of population activities in the United States stated it as a leading indicator associated with the contagion spread during the early stages. Olsen *et al.* (2020) developed a hierarchical model to understand COVID-19 contagion and severity in India in the early stages, at the district level using population density as a parameter. The non-pharmaceutical measures (lockdown and physical distancing) were argued as effective means to control the transmission, yet debatable. Wong and Li (2020) observe that the efficacy of such measures is partly constrained by the density factor and their study at the US county level has reflected on density as an effective predictor of COVID-19 infection. Further, a correlation between the spread and decay of COVID-19 with density has been noted across several cities in China, England, Germany, and Japan by Diao, *et al.*, (2021). Similar relationship has been found to be true both in the developed (Sutton, *et al.*, 2022; Martins-Filho, 2021) and the developing world (Rocklöv and Sjödin, 2020; Henderson, 2020) with regards to studies conducted in India, (Yadav and Bhattacharjee, 2020; Bhadra, *et al*, 2020; Arif and Sengupta, 2020) the early stages of the pandemic reflected a moderate association between population density and COVID-19 at different spatial scales. The common perception behind this pertains to the high risk associated with COVID-19 transmission in dense areas (Chan *et al.*, 2020) which are associated with early breakout due to increased contact rates in areas where density is high (Sy, *et al.*, 2021). The empirical evidence to support this theory is rare and offers mixed findings (Hamidi et.al., 2020) since studies have also noted an inverse relationship between density and COVID-19 incidence and mortality rates, attributed to the availability of improved healthcare infrastructure at high-density locations. Against this backdrop, we have attempted to assess the correspondence between density (population and employment) and COVID-19 transmission at the city level for different phases of the pandemic. Since this issue has policy implications, adopting a spatially specific approach may provide a roadmap toward mitigation of future pandemics.

Apart from density parameters, a significant positive correlation between economic size and confirmed cases of COVID-19 has been noted by Zhang, *et al.* (2020) across selected provinces in China. The country-level data repository from CSSE JHU (2021) has also reflected a positive association between GDP per capita and confirmed COVID-19 cases. Further, as Papandreou (2020) argues, connectivity factors have a direct impact on the pandemic spread and thus, large urban centres which are also international port cities have become hotspots of the pandemic. This is further validated by the study on air passenger traffic with COVID-19 incidence in China by Lau *et al.* (2020). Existing studies have reflected that, given the gene of the disease, dense and congested urban environments with high public transit usage have become acute vectors in contagion spread (Zhang, *et al.*, 2020; Chen, 2020; Meinsenzahi, 2020; Thakur, *et al.*, 2020).

Environmental factors have also been hypothesized as determinants of COVID-19 infection and deaths, although the literature is scarce, especially from the developing world. Setti, *et al.* (2020) provided the first evidence of a plausible linkage between air pollution levels and COVID-19 across Italian provinces. Since then, several epidemiological studies have noted a positive association between levels of air pollutants with COVID-19 incidence and deaths (Pluchino, *et al.*, 2021; Vasquez-Apestegui, 2021; Zoran, *et al.*, 2020; Bashir, *et al.*, 2020). In the Indian context, empirical observations are predilected more on fatalities rather than infections. Mele & Magazzino (2021) conducted a study of 25 Indian cities which reflected a significant causal link between PM2.5 concentrations and COVID-19 deaths. Another study on Mumbai city by Chattopadhyay & Shaw (2021) noted spatial hotspots of COVID-19 infections and fatalities at locations exposed to high levels of air pollution. The positive association between air pollutants and vulnerability to contagion has been attributed to decreased immune response facilitating viral penetration and replication (Bourdrel, *et al.*, 2021; Ali and Islam, 2020).

Studies have also noted institutional factors such as government effectiveness and city lockdown strategies in explaining variations in COVID-19 incidence (Yang, 2021; Maor & Howlett, 2020; Kumar & Nataraj, 2020). Additionally, the risk associated with getting infected by the contagion is far more acute in certain settings that provide a favorable environment for the virus spread. Accordingly, WHO (2020) has identified vulnerable groups who are most susceptible to infection in urban settings. Recent literature on COVID-19 has also highlighted the risk associated with slums and informal settlements (Espinosa *et al.*, 2021; Mishra, *et al.*, 2020; Corburn, *et al.*, 2020) and among migrant workers (Tagliacozzo, *et al.*, 2021; Fasani & Mazza, 2020; Koh, 2020). Yadav and Bhattacharjee (2021a) noted the spatial juxtaposition of vulnerable groups across high-risk contagion zones in Kolkata. Other studies (Das, *et al.*, 2021; Nath, *et al.*, 2021) discerned that high-risk clusters of COVID-19 overlap with localities consisting of a significant share

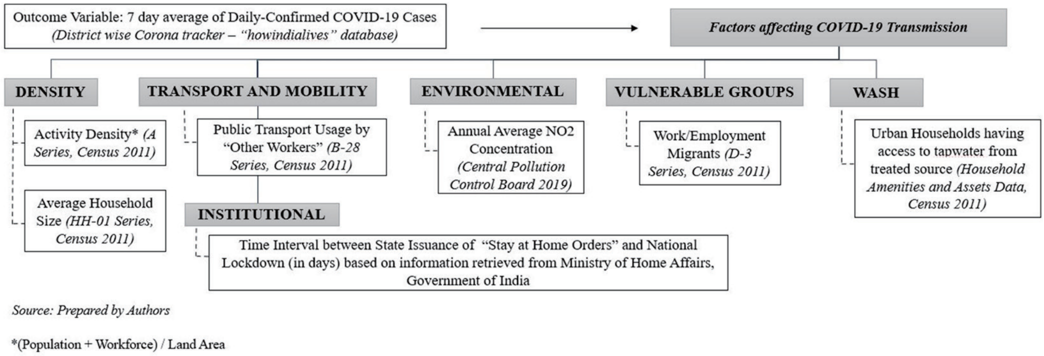


Fig. 4: Database used for the study with respective sources

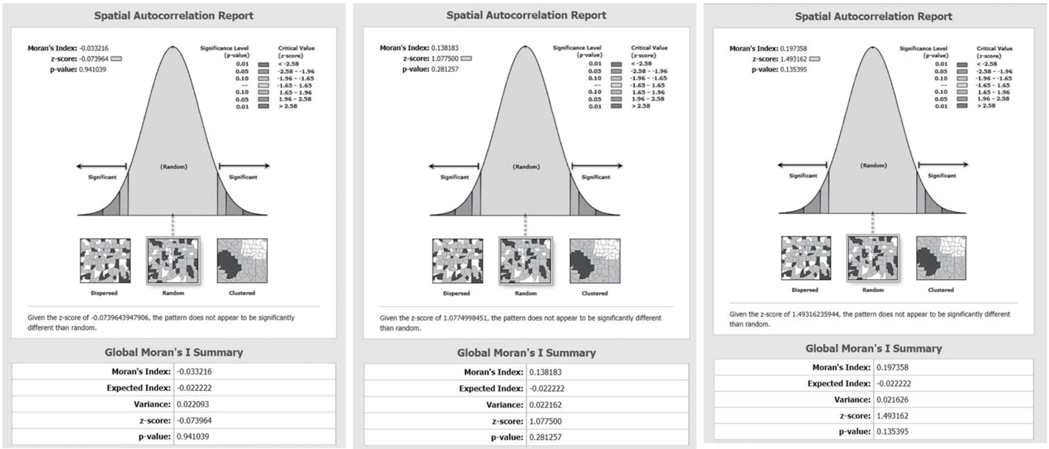
of slums and poor population. Similarly, Tubadji, *et al.*, (2021) observed how the geography of the pandemic in the UK is related to the geography of deprivation and inequalities that were incumbent in pre-COVID-19 times. The vulnerability factor is further accentuated by the skewed availability and accessibility to safe water, sanitation, and hygiene in these localities, thus rendering it difficult to follow COVID-19 protocols (Bhattacharjee, *et al.*, 2024). Hasan, *et al.* (2021) noted a significant spatial correspondence between the lack of access to water, sanitation, and hygiene (WaSH) facilities and virus transmission in the slums of Bangladesh. Against this backdrop, the selection of indicators on WaSH in the present study has been based on the interim guidance[4] on WaSH management during COVID-19. The selection of explanatory variables (Fig. 4) in this paper is based on the general understanding, theory, and existing literature on COVID-19 and our study captures the causality of the multiple factors to COVID-19 cases in Indian cities from the spatial-temporal approach. Besides, the spatially varying relationships between the transmission and determining factors are also noted. Our analysis is confined to the 1st and 2nd waves of the pandemic considering the severity of the virus in these phases, and the unlock phase 1.0 as implemented in India.

Empirical methods

The city is the unit of analysis. COVID-19 data is available at the district level, but many million-plus cities are also districts hence considered as a proxy to capture city-level transmission. The study attempts to cover different phases of the pandemic with high severity - the start of the unlock phase in India- 1st June 2020, the peak of the first wave- 18th September 2020, and the peak of the second wave- 8th May 2021 (Fig. 3). Further, it is worth noting that the unavailability of the required data at both spatial and temporal scales is a challenge. Therefore, we heavily relied on data sources that are widely used and comparable in the Indian context.

For the city-level analysis, drawing from the theoretical context and general understanding, multiple sets of indicators are selected as explanatory factors, each

[4] The interim guidance by WHO and UNICEF (2020) advocated for the provision of "safe water, sanitation, and waste management and hygienic conditions" for preventing the human-to-human transmission of the pathogen.



June 1st, 2020 September 18th. 2020 May 8th , 2021

Fig. 5: Spatial Autocorrelation Results for 1st June, 2020, 18th September 2020, and 8th May, 2021

of which falls in the broad category of density, institutional, transport/mobility, environment, vulnerable groups, and WASH parameters. Density has a varying effect on the pandemic spread in different geographies, and we attempt to test this hypothesis. During the COVID-19 pandemic, densities emerged as key drivers of the economy and posed major challenges given the nature of the virus. Therefore, density becomes the focus of our study. Figure 4 provides a detailed list of dependent and independent variables and their sources used in the study, along with the dependent variable COVID-19 infection[5].

Both global and local models are used for modeling spatial relations at the city level. Generally, Ordinary least square (OLS) is used to capture the relationships between the dependent and independent variables, wherein regression and its parameters remain the same over the geographic space. On the other hand, geographically weighted regression (GWR) captures local relationships that vary over space. GWR allows model coefficients to vary regionally, and regression run for each location (Mitchell & Griffin, 2021). We used GWR to explore city-level variations in the determining factors and the coefficient values mapped to represent this variation. This exercise has been done only for 1st June 2020 since the regression results are statistically suitable to run GWR compared to the other dates considered.

We estimated several models using the exploratory approach (Fig. 4) and concluded that a small set of variables explain significant variation in virus transmission. In this paper, we have given the final model results that include seven variables having consistent and statistically significant relationship to the outcome variable at different times. Multiple regression models were checked to meet

[5] The seven-day average of the daily-confirmed cases around the selected days: 1st June 2020, 18th September 2020, and 8th May 2021 have been calculated. We have taken the cases per lakh population as our outcome variable. The choice of our outcome variable as the seven-day average of the daily-confirmed cases has drawn from the weekly epidemiology reports of WHO (2020) and OECD (2020).

their assumptions, for example, significance and sign of coefficients. To verify the normal distribution of the residuals, we did Jarque-Bera test. Furthermore, regression model checked for heteroscedasticity and multicollinearity. Finally, Moran's I test for spatial autocorrelation of the residuals show the hypothesis residuals are distributed randomly in the space cannot be rejected for all models (Fig. 5). It is worth noting that spatial data rarely meet all these assumptions, so we modified our model wherever these assumptions were not met.

Results and discussion

OLS findings at the million plus cities level

The explanatory variables selected for OLS regression models in the study explain about 51 percent to around 66 percent of the variation in the weekly average of daily confirmed COVID-19 cases reported in the 46 million-plus cities of India during the period considered (Table 1). As of 1st June 2020, our findings reveal a positive association between activity density and COVID-19 transmission. This positive association may be supported by observations in existing studies (Chan *et al.*, 2020; Diao, *et al.*, 2021; Sutton, *et al.*, 2022) that larger cities with higher densities tend to have higher transmission rates due to increased contact rates among individuals. This is because higher contact rates in settings like public transport and workplaces not only facilitate virus spread, but implementing effective distancing measures also becomes challenging, contributing to higher transmission rates as compared to less densely populated areas. However, during the peak of the first and second wave, our findings have not reflected any significant association between activity density and COVID-19 transmission. This trend might be due to the other factors like better healthcare infrastructure, awareness, and higher connectivity in big cities that facilitated rapid testing and early detection to contain the spread of the contagion. Also, economies of density facilitate e-commerce coupled with "work from home" option that minimizes the risk of getting infected. As of 1st June 2020, other significant predictors are usage of public transport by other workers[6] and the time gap between state issuance of "stay at home" orders and nationwide lockdown. By the peak of the first wave, other factors like living conditions and air quality become more paramount. Thus, as of 1st June 2020, our first model reflected that the share of public transport use by other workers bears a strong positive association with COVID-19 transmission, as undoubtedly, public transport systems are super-spreaders of the contagion. Studies viewing public transport systems as a vector in the Indian context are rather limited, especially because of an early lockdown. However, several guidelines which were issued by the MoHFW, Government of India from time to time regarding the complete shutdown of public transport systems like buses, local trains, and metro rails followed by their phase-wise resumption and capping

[6] A person, who has been engaged in some economic activity during the last year of the reference period but not as a cultivator or agricultural labourer or worker in the Household Industry. The type of workers that come under this category includes all government servants, municipal employees, teachers, factory workers, plantation workers, those engaged in trade, commerce, business, transport, banking, mining, construction, political or social work, priests, entertainment artists, etc. All those workers other than cultivators or agricultural labourers, or household industry workers are 'Other Workers'. (Census of India, 2011)

Table 1: Summary of OLS Results

Variables	1st June, 2020		18th September, 2020		8th May, 2021		
Daily confirmed cases per lakh populations (outcome variable)	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	VIF
Activity density in persons per km2	0.002	3.03*	-0.01	-1.69	-0.002	-1.97	1.2
Average household size	1.95	1.53	-3.83	-0.41	47.458	2.32*	1.7
Share of public transport usage by "other workers"	0.444	6.28*	1.168	2.29*	0.822	0.72	1.8
Time interval (in days) between state issuance of stay-at-home orders and complete nationwide lockdown	-0.492	-3.53*	-1.49	-1.48	0.827	0.37	1.2
Annual average NO_2 concentration	-0.005	-0.12	0.648	2.08*	1.42	2.04*	1.4
Work/employment migrants	0.203	1.5	2.266	2.33*	1.058	0.48	1.6
Urban households having access to tapwater from treated source	0.007	0.01	0.256	0.82	0.334	0.48	1.5
Intercept	-14.15	-1.78	4.357	0.07	290.84	2.28	-----
Adjusted R^2	0.66		0.51		0.29		

**Statistically significant at 5 percent*
Source: Based on Authors calculations

on passenger capacity do support our findings. Few studies across metropolitan cities in India have found a consistent increase and spatial spread of the contagion with the phase-wise resumption of public transport, (Naveen & Gurtoo, 2022; Yadav & Bhattacharjee, 2021a; Sharma, 2020; Thomas, et. al., 2021). However, the existing studies lack empirical evidence on the same, and our study is an attempt in this direction. A negative association was noted between the time interval of state issuance of stay-at-home orders and the complete nationwide lockdown of the transmission. The common perception is that the states which imposed stay-at-home orders much before the nationwide lockdown have been more effective in controlling the spread of the contagion, as delayed response in some cases had led to fatal outbreaks, especially in the large cities.

By the peak of the first wave, other factors like the share of work/employment migrants to the total migrants[7] showed a strong positive association with COVID-19 transmission. This may partly be due to the "Shramik Special" trains carrying stranded work migrants to their hometowns since the beginning of the unlock phase 1.0, which inevitably led to the spread of the contagion. Other significant factors which have yielded positive association with COVID-19 transmission during the first wave are the

[7] In the Census of India, migration data is collected by birth place and by place of last residence. Further, the Census of India also captures the reasons for migration. The following reasons for migration from place of last residence are captured: Work/Employment, Business, Education, Marriage, moved after birth, moved with household and any other. The Census of India defines a work/employment migrant as a person who has moved either temporarily or permanently from one location to another within the country in search of employment or work opportunities. This movement could be within the same state, between states, or from rural to urban areas.

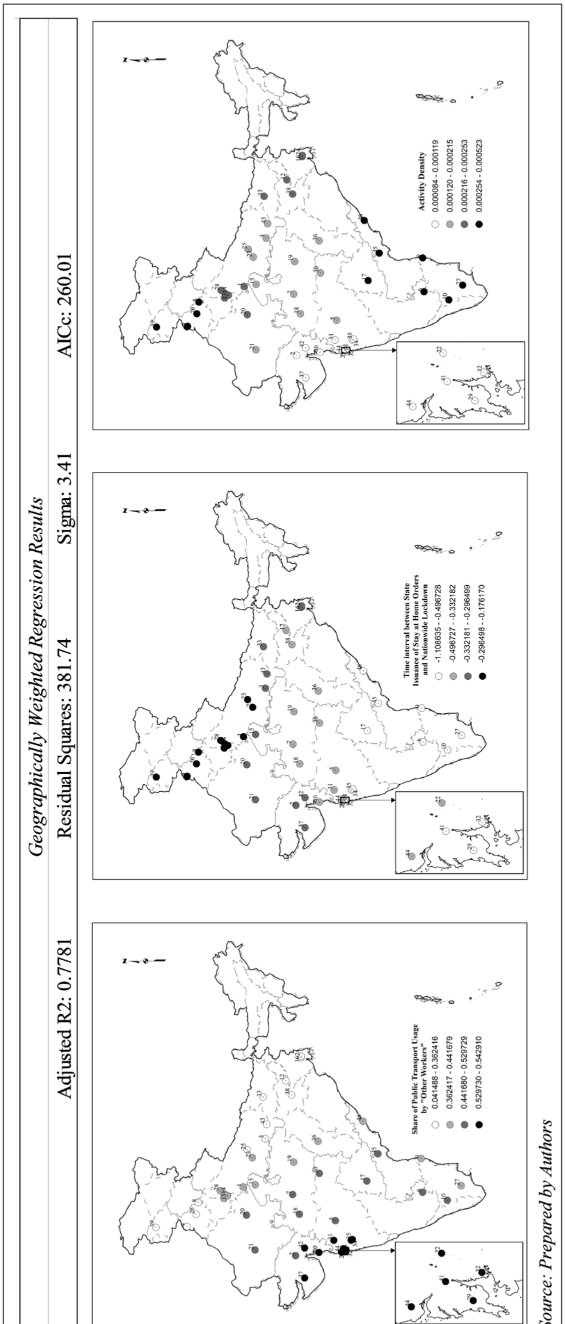


Fig. 6: Spatial distribution of exploratory variables in the GWR model (1st June 2020)
Source: Prepared by authors

usage of public transport by other workers and NO_2 concentration. Past studies on the association between air pollution and COVID-19 infections have reflected on increased vulnerability to virus transmission owing to exposure to an environment saturated with high levels of SO_2, NO_2, and PM10 (Ali and Islam, 2020; Bourdrel, et. al, 2021). A study conducted by Chattopadhyay and Shaw (2021) in Mumbai city also noted a similar trend and a significant positive association between pollution levels and COVID-19 infection in certain suburban wards of the city. Our results also substantiate these findings with a positive association between the annual average concentration of NO_2 and COVID-19 transmission across million-plus cities which are associated with extremely high NO_2 levels accounting for as high as 75 ug/cubic m of annual average NO_2 concentration (CPCB, 2019).

Similarly, during the peak of the second wave, a significant positive association has been noted between the annual average concentration of NO_2 and COVID-19 transmission. The other significant variables noted during this phase are the average household size, which reiterates the impact of density as an influential determinant of COVID-19 transmission. This is particularly because the household size is high in the slums and squatter settlements in big cities of India which increases the risk of transmission when one member of the household is infected since the COVID-19 protocols of social distancing and isolation are too difficult to be practiced in such vulnerable and congested settings.

Evidence of spatial variability in local relationships

In addition to the global models for understanding spatial relations at the city level, we have used geographically weighted regression (GWR) to capture local relationships that vary over space (Fig. 6). GWR results for 1st June 2020 are retained and mapped since significant test results have been obtained only for this phase. The association between the activity density and COVID-19 transmission is relatively strong in Srinagar, Amritsar, Ludhiana, and Chandigarh in the northern states and Hyderabad, Vishakhapatnam, Vijayawada, Bangalore, Chennai, Coimbatore, and Madurai, cities located in the southern states. Further, regarding public transport usage, the association is relatively strong in most of the cities located in the Mumbai and Pune metropolitan regions in Maharashtra and Rajkot, Vadodara, and Surat in Gujarat. These areas have a highly developed public transport system[8] with the suburban and metro railway that caters to the mobility needs of a large section of commuters for their work-related trips. Finally, about the time interval factor, the association has been relatively strong in the cities located in the northern states of Jammu and Kashmir, Punjab, Delhi, Haryana, and Uttar Pradesh. These are some of the early affected states having the first cases detected during the initial week of March. However, they had a delayed response in undertaking non-pharmaceutical measures (Kumar and Nataraj, 2020), which has plausibly led to higher infection in the million-plus cities located in these states.

[8] Public transport constitutes nearly 40 percent of the modal share of work trips by “Other Workers” in most of the million plus cities as per Census 2011.

Concluding remarks

Urban density and setting have proven to be a concern amid the COVID-19 pandemic, particularly for developing countries like India. On the one hand, with the inception of the outbreak, cities prepared themselves to control the transmission of the virus, and on the other, their resilience towards other aspects became weaker. In such a scenario, cities suffered from multidimensional vulnerabilities and a crippling economy. During each phase of the pandemic in India, new concerns about the handling of the situation came to the fore. It was soon realized that the non-pharmaceutical responses such as lockdowns, and isolation, which were adopted to control the pandemic, unfortunately, does not prove to be an effective strategy in the medium and the long term. Besides, it had a differential impact on the heterogeneous regions and society. The initial focus to control the contagion remained no longer the priority as the need shifted to dealing with multidimensional issues such as improving healthcare infrastructure, rising unemployment, creating livelihood opportunities, and enhancing the resilience of multiple aspects of vulnerabilities that came to the fore. Therefore, how to control the pandemic and recovery in such complex and diverse settings posed a major challenge to policymakers. Similarly, the preparedness for future ones also becomes central to policy orientation.

Studies such as this become critical for a better understanding of the pandemic, particularly at different spatial and temporal scales. Countries like India with huge diversity and disparity further necessitated such attempts. We hope this would contribute to the global, national, and regional efforts to understand the spatiality of COVID-19 and offer insights at a specific geographical level for targeted interventions (control and recovery), particularly for urban density. Our findings reiterate that density matters, and how we manage density matters the most. Besides, the role played by other factors also varied across time and space. This study flags the limited impact of uniform policy approaches, necessitating more place-specific measures for short, medium, and long-term impacts.

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