A Study of the Impact of Demographic and Socio-Economic Factors on the Spread of Covid-19 in India

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Abstract

The extent of spread of the novel coronavirus pandemic in India has been disproportionate across different regions. This paper attempts to investigate to what extent the spread of Covid-19 in Indian states and union territories is due to their respective demography, and social and economic conditions. This study is based on the premise that the demographic and socio-economic factors are responsible for the transmission of the coronavirus disease. Data of total Covid-19 cases from January 30, 2020 to October 24, 2020 for 35 states and union territories were analysed to determine whether population size, population density, literacy rate, population median age, headcount ratio in a region affect the proliferation of Covid-19. The study indicates that the factors considered are significant determinants of the increase in cases. The results of the paper will help the policymakers in strategizing policies to curb the spread of Covid-19 cases.

Keywords: Covid-19, Demographic Factors, India, Pandemic, Socio-economic

1. INTRODUCTION

The very first cases of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) were identified in China's Wuhan city of Hubei province in December 2019. Originated in China, the contagious virus spread to other parts of the world rapidly with people in Italy and few other European countries like Spain, France, witnessing early signs of the illness in their population in February 2020.In India, the first case of the infection was detected on January 30, 2020 in Kerala(Perappadan, 2020). Subsequently, World Health Organization (WHO) declared novel coronavirus disease 2019 (Covid-19) as a pandemic on March 11, 2020on concerns of alarming levels of spread and severity by the virus and further expectations of higher number of cases, deaths and affected countries going forward(WHO, 2020).

In view of increasing Covid-19 patients in most of the Indian regions, the Directorate General of Civil Aviation (DGCA), Government of India imposed travel restrictions on international flights on March 22, 2020(DGCA, 2020). Eventually, suspension of domestic travel operations was also imposed on March 24, 2020.

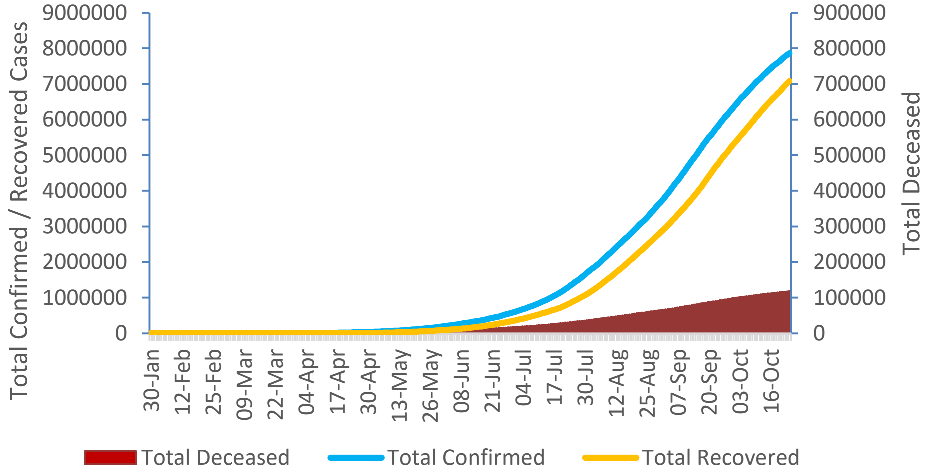
Despite several efforts by the Indian Government to inhibit the outbreak of the infectious virus by quarantining passengers coming across borders, restricting visas and social gatherings, closing international borders, encouraging social distancing and work from home policies and lastly, by imposing lockdowns in states and union territories with effect from March 25, 2020

(Ministry of Home Affairs), the cases rose to humongous levels. India is the second most affected country in the world having 7,863,993 cumulative cases with 117,984 deaths as on October 24, 2020. The USA is the only country surpassing the reported cases and death numbers with 8,863,808total cases and 230,478 deaths as on the given date.

In addition, as per the Worldometer website, the total reported case tally was just a little over 43 million along with approximately 1.16 million deaths worldwide until the given date (Worldometer, 2020).

The rising count of total cases and deaths along with number of active cases in India up to October 24, 2020 can be tracked in Fig. 1 below. The data of the confirmed, recovered and active cases along with death toll in India from January 30, 2020 to October 24, 2020 was taken from Covid19-India website (Covid19-India, 2020).

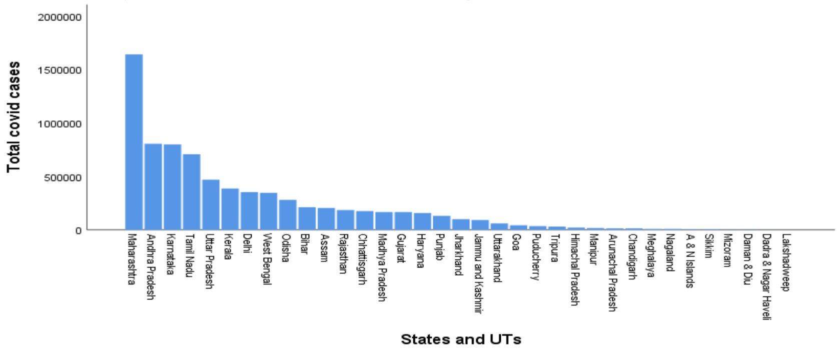
Figure 1: Chart of variation in confirmed cases, active cases and death toll with time in India



Source: Covid19-India.org

The distribution of total confirmed cases in various states and union territories (UTs) of India until October 24, 2020 is shown in Fig. 2 below.

Figure 2: State-wise distribution of Covid-19 cases in India



Source: Covid19-India.org

The five most affected and least affected regions of India until October 24, 2020 is shown in Tab. 1 below.

Table 1: Top five and bottom five regions in terms of Covid-19 cases in India

Top Five Regions	Total Cases	Bottom Five Regions	Total Cases
Maharashtra	1,638,961	Sikkim	3,770
Andhra Pradesh	804,026	Mizoram	2,389
Karnataka	798,378	Daman & Diu	1,655
Tamil Nadu	706,136	Dadra & Nagar Haveli	834
Uttar Pradesh	468,238	Lakshadweep	0

Source: Covid19-India.org

As evident from Fig. 2 and Tab. 1, the officially registered cases across Indian states varied to a great extent owing to the nation's size and diversity. For instance, Maharashtra reported the highest number of cases in the country at 1,638,961 while its neighboring state, Gujarat, documented 166,254 cases. Basis this irregular spatial distribution, various states have been analysed and classified into severe, moderate and controlled categories (Ghosh, Ghosh, & Chakraborty, 2020). The uneven spread of novel coronavirus infection within the country has been investigated in this empirical study based on the premise that the socio-economic and demographic factors are responsible for the transmission of the coronavirus disease. It has been previously demonstrated that demographics, average household and business size, air quality and care home tradition are significant determinants of uneven mortality rate of the coronavirus in some adversely affected regions of European Union countries (Kapitsinis, 2020). The role of demographic composition of a population in spread and mortality rate due toSARS-CoV-2has been emphasized in a previous study, wherein it has been observed that case fatality rate was higher in countries with older populations versus younger populations (Dowd, et al., 2020). The importance of underlying socioeconomic factors resulting into inconsistent trajectory of Covid 19 transmission has also been discussed in a few studies along with considering environmental risk factors(Luo, Yan, & McClure, 2020);(Sarkar & Chouhan, 2020).Sarkar & Chouhan derived a socio-environmental vulnerability index based on selection of 16 indicators to study district level vulnerability towards Covid-19 in India. They found the existence of spatial variability in vulnerability based on the aforementioned factors.

Further, the crucial role of climatic variables(Wu, et al., 2020); (Menebo, 2020); (Gupta, Banerjee, & Das, 2020), cultural differences(Bruns, Kraguljac, & Bruns, 2020) and psychological reactions (Taylor, Landry, Paluszek, & Asmundson, 2020);(Dryhurst, et al., 2020)can never be ruled out in the transmission of the disease.

2. METHODOLOGY

1.1 Data collection

State-wise data of total confirmed Covid 19 cases in India was retrieved from the Covid19-India website. The primary source of data for various variables considered for studying socio-economic and demographic impact on spread of novel coronavirus was the census website (Census-India) and www.data.gov.in.As the census data is collected every 10 years, the recent data of 2011 has been used in this study. The following variables have been selected and studied based on the latest information available for all the 35 states and UTs.

1. **Population Density:** The population density (measured as persons/sq. km.) is a potential determinant of registered Covid-19 cases as it may have an impact on diffusion of the novel coronavirus infection. The above proposition has also been supported in a previous study, whereby it states that the degree of transmission of the disease is strongly correlated with the population density of a region (Stojkoski, Utkovski, Jolakoski, Tevdovski, & Kocarev, 2020).
2. **Population:** The total population size of a region is also a potential driver for increasing propagation rate of an infectious disease as has been previously cited (Garnett & Lewis, 2007). This study attempts to capture the effect of variable population sizes, on account of differing population growth, within each state/UT on the transmission of novel coronavirus.
3. **Literate population:** A lower level of education can be associated with low expenditure on health and on nutritious items. This could weaken immunity and increase the occurrence of comorbidites for Covid-19, such as diabetes, kidney disorders, etc., in such socially deprived group (Khalatbari-Soltani, Cumming, Delpierre, & Kelly-Irving, 2020).The ***literacy rate*** of the habitants of a region is considered to evaluate its impact on the trend of rising infected cases in that particular region.
4. **Median age:** This parameter analyses the demographic structure of a region. The fact that few age groups have weaker immune response to infectious diseases and are at an increased risk of getting severe form of infection than others, makes the inclusion of this independent variable appropriate.
5. **Poverty level:** The economic position of the people belonging to an area is also of importance as it determines the percentage of population having limited access to health care resources. There exists a close association among poverty and poor health status, signaling that health status is depends on the economic status of an individual (Hati & Majumder, 2013). A poverty-stricken population is also highly vulnerable to outbreak of infectious diseases owing to subpar living conditions. This factor has been incorporated in the study using ***headcount ratio*** (the proportion of population existing below the Tendulkar Poverty Threshold Line).

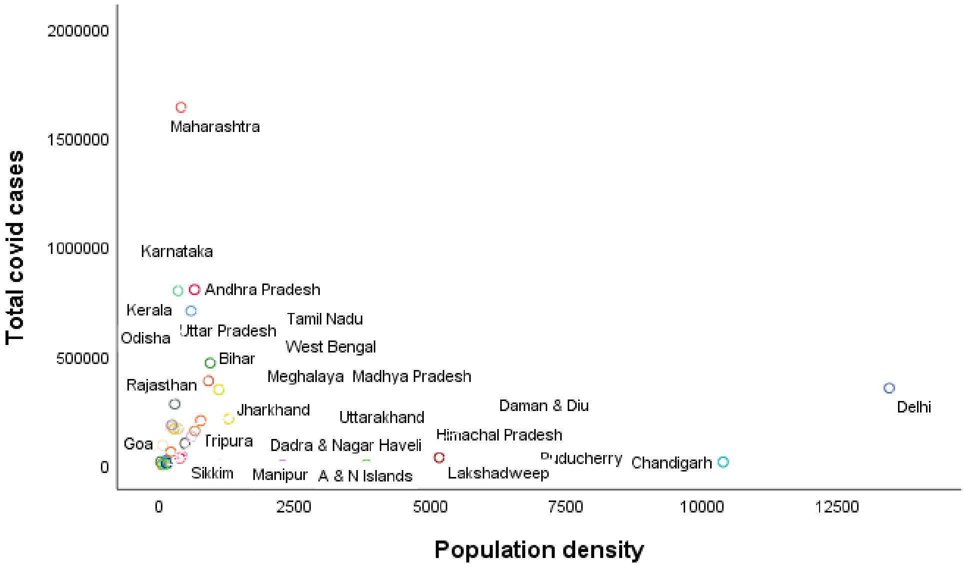
The variables discussed above have been analysed and their descriptive statistics are shown in Tab. 2 below:

Table 2: Descriptive statistics of different variables considered for analysis

	N	Minimum	Maximum	Mean	Std. Deviation
Total covid cases	35.00	.00	1,638,961.00	217,916.11	333,060.78
Headcount ratio	35.00	1.00	39.90	18.49	11.58
Literacy rate	35.00	61.80	94.00	77.85	8.58
Population density	35.00	18.00	13,446.00	1,372.09	2,860.64
Median age	35.00	23.10	33.20	28.02	2.35
Population	35.00	68,000.00	225,967,000.00	37,151,828.57	48,833,903.14
Valid N (listwise)	35.00				

The variation of Covid-19 cases with some select variables has been studied and the same is illustrated in various figures subsequently.

Figure 3: Variation of Covid-19 cases with population density across different states in India

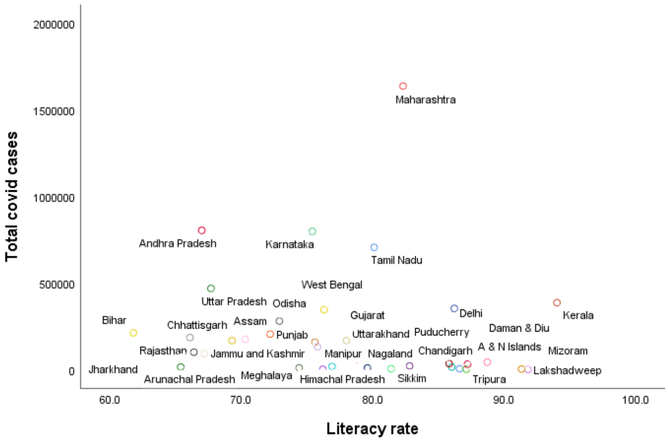


Source: Covid19-India.org; data.gov.in

It can be observed in Fig. 3 that states with high population density such as Uttar Pradesh, Kerala, and West Bengal are among the highly affected states in India. The exception on behalf of Delhi is due to the fact that despite having a high population density of 13,446 persons per sq. km., the number of Covid-19 cases is not proportionally high because of the total population being less than 2 Crore.

Another anomalous observation in the state of Maharashtra is all the more so because of scattered distribution of population within the state, where cities such as Wardha, Satara being sparsely populated as compared to Mumbai, Pune.

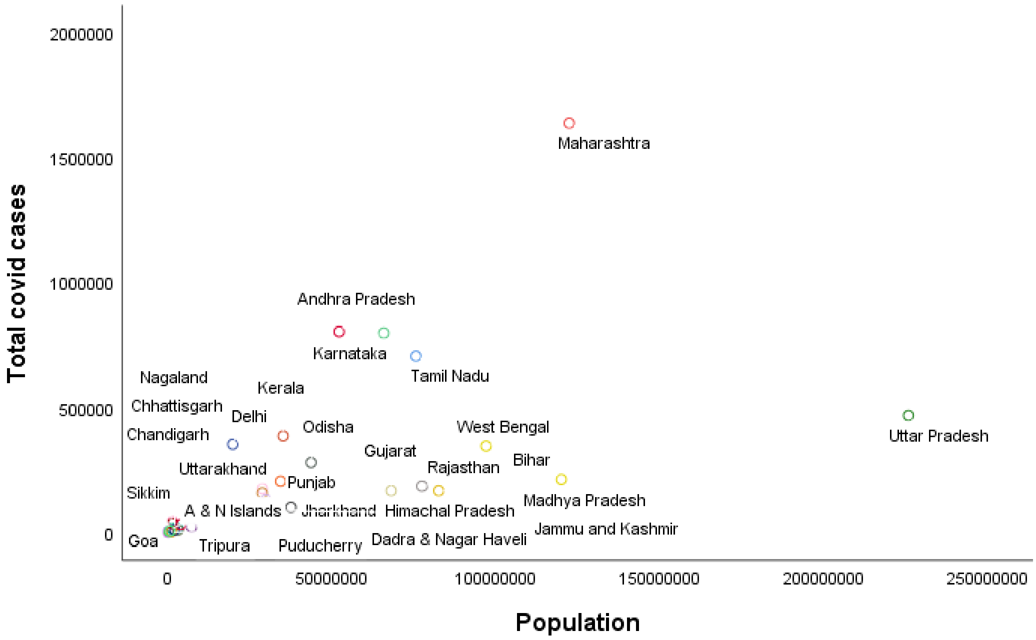
Figure 4: Variation of Covid-19 cases with literacy rate across different states in India



Source: Covid19-India.org; Census 2011

The variation of registered Covid-19 cases is scattered with respect to literacy rate among different states (as shown in Fig. 4) and no clear pattern emerges out as the regions with relatively high literacy rate have low quantum of novel coronavirus infections but so do some regions where literacy rate is poor.

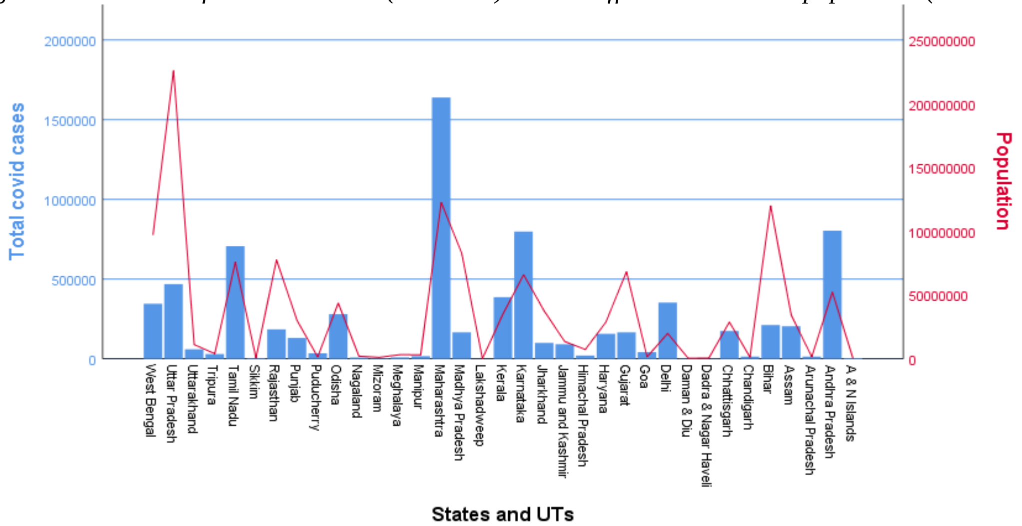
Figure 5: Variation of Covid-19 cases with population across different states in India



Source: Covid19-India.org; data.gov.in

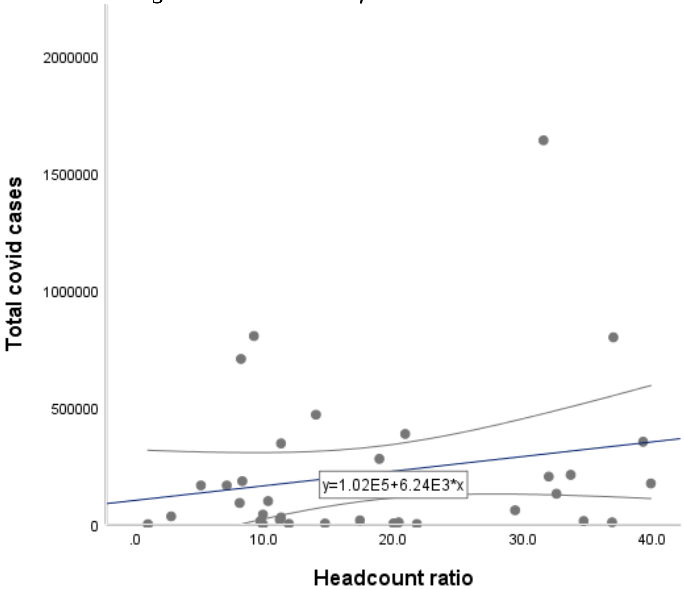
A general pattern of higher cases of infections with regions of high population is suggested in the above figure, with very few exceptions, such as of the state of Uttar Pradesh and Bihar. This pattern is clearly visible in the subsequent Fig. 6.

Figure 6: Variation of Covid-19 cases (bar chart) across different states with population (line chart)



Source: Covid19-India.org; data.gov.in

Figure 7: Variation of Covid-19 cases with headcount ratio



Source: Covid19-India.org; niti.gov.in

As evident from the above Fig. 7, the higher headcount ratio is associated with high confirmed cases with the exceptions of few northeastern states like Meghalaya, Arunachal Pradesh and some UTs such as Daman & Diu, where even after having high proportion of population below poverty line, the number of cases have been exceptionally low. On the other hand, states like Andhra Pradesh and Tamil Nadu are one of the worst affected states in the country despite of having relatively low headcount ratio.

1.2 Model Development

An Ordinary Least Squares (OLS) multiple linear regression model has been employed in E-views in our study to estimate the dependence of reported cases until October 24, 2020on aforementioned parameters. A basic linear regression equation was first formed and then different versions of the model were built to incorporate the effect of five variables on the Covid-19 cases. Finally, a semi-log model was determined the best fit model.

The so obtained regression model is shown below with following form:

$\text{Log}(y) = a_0 + \sum \alpha_i x_i + \sum \log (p_i) + \varepsilon$

where, y is the cumulative covid cases till Oct. 24, 2020, α_i is the slope parameter/coefficient of i^{th} independent variable, x_i is the i^{th} independent variable, p_i is i^{th} independent variable whose log transformation is considered, a_0 is the intercept parameter that indicates the value of dependant variable/ regressand when the values of all regressors are set to zero, and ε is a stochastic disturbance term which takes care of other factors unaccounted for in the model.

3. RESULTS

Table 3: Result of OLS multiple regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.317891	1.517629	-5.480847	0.0000
LOG(POPULATION)	0.804511	0.061831	13.01148	0.0000
POPULATION_DENSITY/1000	0.084548	0.030945	2.732204	0.0108
LITERACY_RATE	-0.041079	0.017435	-2.356155	0.0257
MEDIAN_AGE	0.320758	0.052742	6.081618	0.0000
HEADCOUNT_RATIO	0.021569	0.007500	2.875982	0.0076
R-squared	0.949645			
Adjusted R-squared	0.940653			
F-statistic	105.6102			
Prob(F-statistic)	0.000000			

The above regression results (in Tab. 3) suggest that the variables – population, median age and headcount ratio are statistically significant at 1% level of significance, while population density and literacy rate are statistically significant at 5% level. Moreover, it is found that all the regressors, except for literacy rate, are positively correlated with the regressand, suggesting an increase in any one of them would consequently lead to a higher degree of transmission of the disease.

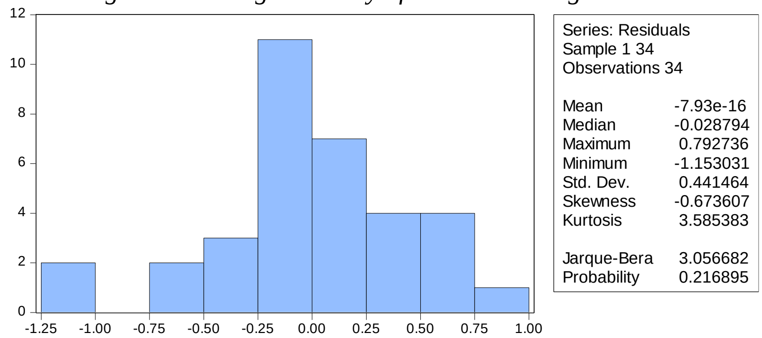
As per the model, a percentage increase in population size would increase the number of Covid-19 cases by approximately 0.80%. Furthermore, a unit increase in literacy rate shall decrease the count of Covid-19 cases by 4.11%, while a unit increase in headcount ratio would increase novel coronavirus cases tally by 2.16%.

Similarly, it can be deducted that an increase in median age by 1 year would result in increase of cases by a staggering proportion of 32.08%. In a similar manner, increasing number of persons per sq. km. by a thousand units would result in escalation in the aggregate cases by a remarkable 8.45%.

Further, analyses were conducted on the residuals to ensure the model meets the basic OLS assumptions.

1.3 Test of Normality

Figure 8: Testing normality of the model using residuals



The assumption for normality is one of the crucial ones as the t-test; F-test and analysis of variance (ANOVA) technique require that the disturbance term follows a normal distribution. For the purpose of checking normality, Jarque-Bera (JB) test has been applied and the results are shown in Fig. 8. The computed p-value of the estimated JB statistic is reasonably high which cannot reject the null hypothesis of normal distribution of the error term.

1.4 Test of Non-autocorrelation

Table 4: Testing autocorrelation

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. | . |</td><td>. | . |</td><td>1</td><td>0.056</td><td>0.056</td><td>0.1178</td><td>0.731</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>2</td><td>-0.061</td><td>-0.064</td><td>0.2595</td><td>0.878</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>3</td><td>0.095</td><td>0.103</td><td>0.6125</td><td>0.894</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>4</td><td>-0.045</td><td>-0.063</td><td>0.6957</td><td>0.952</td></tr>
<tr><td>**| . |</td><td>**| . |</td><td>5</td><td>-0.235</td><td>-0.219</td><td>3.0199</td><td>0.697</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>6</td><td>-0.180</td><td>-0.180</td><td>4.4356</td><td>0.618</td></tr>
<tr><td>. |** |</td><td>. |** |</td><td>7</td><td>0.303</td><td>0.333</td><td>8.6010</td><td>0.283</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>8</td><td>-0.113</td><td>-0.152</td><td>9.1987</td><td>0.326</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>9</td><td>-0.042</td><td>0.014</td><td>9.2837</td><td>0.412</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>10</td><td>0.169</td><td>0.042</td><td>10.739</td><td>0.378</td></tr>
<tr><td>.*| . |</td><td>**| . |</td><td>11</td><td>-0.172</td><td>-0.256</td><td>12.314</td><td>0.340</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>12</td><td>-0.214</td><td>-0.104</td><td>14.860</td><td>0.249</td></tr>
<tr><td>**| . |</td><td>**| . |</td><td>13</td><td>-0.268</td><td>-0.265</td><td>19.055</td><td>0.121</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>14</td><td>0.021</td><td>-0.071</td><td>19.081</td><td>0.162</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>15</td><td>-0.110</td><td>-0.011</td><td>19.857</td><td>0.177</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>16</td><td>-0.032</td><td>-0.074</td><td>19.927</td><td>0.224</td></tr>
</table>

In autocorrelation/serial correlation, the error term is correlated with lagged error term of n^{th} order. To test for the same, correlograms-Q-statistics test is performed. The insignificant Q-statistics shown in Tab. 4 that there is no serial correlation among the error terms.

1.5 Test of Multicollinearity

The classical linear regression model assumes that there is no exact linear relationship among the explanatory variables, i.e. there exists no multicollinearity. To test the presence of the same, Variance Inflation Factor (VIF) is used. It primarily indicates inflation in the variance of an estimator if multicollinearity exists in the model. For perfect collinearity, VIF is infinite and for absolutely no collinearity among the independent variables, VIF is 1.

Table 5: Testing multicollinearity

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	2.303197	340.9290	NA
LOG(POPULATION)	0.003823	151.5792	2.034567
POPULATION_DENSITY/1000	0.000958	1.413239	1.156521
LITERACY_RATE	0.000304	272.8553	3.049295
MEDIAN_AGE	0.002782	323.9674	2.220621
HEADCOUNT_RATIO	5.62E-05	4.021919	1.097702

Results from the Tab. 5 are suggestive of no collinearity in the sample data used as there is no aberration observed in the outcome obtained.

1.6 Test of Heteroskedasticity

Table 6: Testing heteroskedasticity – Breusch-Pagan-Godfrey Test

F-statistic	0.723532	Prob. F(5,28)	0.6114
Obs*R-squared	3.890245	Prob. Chi-Square(5)	0.5653
Scaled explained SS	3.410595	Prob. Chi-Square(5)	0.6370

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.088940	0.998745	-0.089052	0.9297
LOG(POPULATION)	-0.033260	0.040691	-0.817389	0.4206
POPULATION_DENSITY/1000	-0.012644	0.020365	-0.620894	0.5397
LITERACY_RATE	-0.011058	0.011474	-0.963785	0.3434
MEDIAN_AGE	0.058091	0.034709	1.673625	0.1053
HEADCOUNT_RATIO	0.003643	0.004935	0.738146	0.4666

R-squared	0.114419	Prob(F-statistic)	0.611449
F-statistic	0.723532	Durbin-Watson stat	2.049971

The assumption that the error term has constant variance (i.e. the disturbance tern is homoskedastic) is tested using the Breusch-Pagan-Godfrey Test. As per the above Tab. 6, the null hypothesis of no heteroskedasticity cannot be rejected as p-value is greater than 0.05 and therefore, the test suggests that the model is homoskedastic. Further, the more powerful ARCH LM test is also considered to validate the results of the above test.

Table 7: Testing heteroskedasticity –ARCH Test

F-statistic	0.165691	Prob. F(1,31)	0.6868
Obs*R-squared	0.175443	Prob. Chi-Square(1)	0.6753

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.188977	0.062492	3.023995	0.0050
RESID^2(-1)	-0.070729	0.173759	-0.407052	0.6868

R-squared	0.005316	Prob(F-statistic)	0.686767
F-statistic	0.165691	Durbin-Watson stat	2.036321

From above table, it can therefore be concluded that there is no heteroskedasticity in the model.

4. CONCLUSION

The results indicate the relevance of socio-economic and demographic determinants in the transmission of Covid-19 across states and UTs. The analysis reveals that the variables – age of population, population density and overall population size in a region along with income of its residents and their level of education strongly impact the transmission of the novel coronavirus infection in one's vicinity.

Further, the results throw light on the fact that of all the variables studied; increase in median age of the inhabitants may increase the cumulative cases to staggering levels, taking cognizance of the fact that given the age group of 50 years or above is highly prone to the disease. The finding elucidates the higher risk of hospitalization or mortality with increased age of population in a state. The observation is consistent with a previous study which also suggests that proper social and medical care shall be provided to high risk elderly population in order to restrict the community transmission of the contagious infection (Singh, Khullar, & Sharma, 2020).

The outcome from the present study indicates that in states having age of the population higher than the country average and high headcount ratio, it would become an arduous task to control the wide-spreading SARS-CoV-2 disease. One such state is Maharashtra, where the number of cases is currently the highest in the country. Moreover, in regions such as Delhi, where the population density is one of the highest in the country and so is the proportion of population below the Tendulkar poverty line, the case tally is one of the highest as compared to other cities. When compared with other cities, such as Chandigarh, having the same level of literacy rate and age of population but a remarkable difference in the population percentage existing below the poverty line and the population density, the total Covid-19 cases in the region are many times lower than that reported in Delhi.

The governments and other concerned authorities should, therefore, consider dividing regions based on the socio-economic and demographic parameters and scale up the medical facilities available in the regions having high potential of transforming into epicenters for the outbreak of theSARS-CoV-2 disease. A similar approach of identifying high risk regions could be followed in future in order to avoid outbreak of fatal diseases.

Apart from the variables studied in this paper, the role of other factors in the transmission of the contagious infection could be analysed. One such driver is the migrant population in a region. Given that there were a large number of interstate movements of migrant workers from urban region to their respective villages because of the country wide lockdown that was imposed. There might be an effect of this reverse migration on surge of Covid-19 cases. Subsequent to the deluge of repatriated migrants, variation in the spread of the novel coronavirus in rural, semi-rural or urban areas may also be studied.

The other driver which may be responsible for unequal spread of overall Covid-19 cases could be the availability of health infrastructure of each state or UT. Poor availability of health infrastructure in socially backward regions and insufficient existing health care facilities for densely populated regions (Hati & Majumder, 2013)are few of the primary reasons this pandemic has immensely scaled up in select regions of the country. The improvement of health infrastructure by boosting government health expenditure in relation to gross state domestic product (GSDP) may go a long way in the near future to constrain any impending outbreak.

The importance of localized response to a crisis while considering the regional demographics and socio-economic status has been emphasized in this study. Going forward, it is expected that local governing bodies might take cognizance of the dynamics in the vicinity while strategizing their comebacks.

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