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Unequal lives: a sociodemographic analysis of COVID-19 transmission and mortality in India

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ABSTRACT

Objectives: Existing socio-economic inequalities shape, in very particular and measurable ways, the differential impact that a disease has on different sections of the same society. This is particularly true of COVID-19, which has rapidly exhausted the public health system in India, and magnified the gradient of vulnerability in an underserved populace. Using publicly available data, we have aimed to deconstruct this gradient into individual variables of inequality and quantify their impact on the transmission and mortality outcomes of COVID-19 in India.

Study design: Sociodemographic analysis.

Methods: We quantify doubling times and case fatality ratios for all districts in India, then correlate them to 20 variables of socio-economic vulnerability and demographic structure. Variables that exhibit persistent correlation are then analysed using multivariate beta regression models to validate their impact on COVID-19 outcomes in India.

Results: The transmission of COVID-19 in India is enhanced by the lack of access to indoor latrines, drainage facilities, electricity, and proximate sources of drinking water. Transmission is slowed by the presence of an elderly population. Fatality rates relate negatively to an area’s medical infrastructure and the presence of a college-educated populace.

Conclusions: An interactive matrix of social inequalities, cultural practices, and behavioural patterns determines the path of COVID-19 through a community. Specific variables exhibit patterns of persistent vulnerability; others indicate a resistance to infection and mortality. This body of evidence, when incorporated into policy design, may lead to localised, need-sensitive models of intervention, both for preventive measures and medical care.

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Introduction

In the spread of an infectious disease, the human population is as much the victim as it is the vector. But not all vectors are created equal. When mapped on a bounded geographical space, particularly a diverse one, the path of an infectious disease manifests as a barium test for the anatomy of its inequalities.1–3 Indeed, while the World Health Organisation Commission on the Social Determinants of Health had been founded in 2005, the pathogenic behaviour of social inequalities has been seminally established in the literature for nearly two centuries.4,5 Contemporary studies have demonstrated conclusively that the gradient of localised inequalities – indexed by social marginality,2,6 employment status,7,8 educational attainment,9 wealth/asset gap,10 access to social or public support systems,11 and mortality patterns10,13 – affects the differential impact of both non-communicable12 and infectious12 diseases and can only be addressed by evidence-based, ethical policies focused on public good.12–14

If one goal of disease modelling is to aid the efficacy of public health responses and to eventually contribute towards more equal
outcomes in health, then it is crucial to locate the socio-economic variables that map onto patterns of persistent transmission and mortality. In the contemporary instance of COVID-19, the centrality of age structure and its clinical implications in assessing spread and mortality outcomes has already been established. Age structure, however, is only one of several demographic factors that is shaping the path of COVID-19 through a community. To more fully understand the impact of inequality on COVID-19 outcomes – particularly in India, where even small spatial units present considerable diversity in age structure, income, housing, caste, ethnicity, religion, educational attainment, migration status, and availability of health services – a more comprehensively ecological approach is necessary. Similar analysis has yielded information as to how socio-economic disparities may have played a role in past epidemics. The evidence from such an analysis can help shape ‘smart’ interventions responsive to specific lacunae at each unit rather than a monolithic national model.

Although multiple modelling studies have attempted to analyse and predict the spread of COVID-19 in India from the perspective of epidemiological models, the correlation of impact and ecology has not been explored so far. In this study, we have thus attempted to correlate the trajectory of spread and mortality of COVID-19 in India with variables of social and economic vulnerability persistent within its populace. We hope that our findings shall contribute towards a more inclusive epistemology of the virus, as well as serve as the beginnings of a repository that shall inform an evidence-based model of public health policy that is sensitive to socio-economic gradients and adaptive to local variations of need.

Methods

The analysis in this article was done with data accumulated up to 2 July 2020, the beginning of Unlock 2.0 phase in India’s COVID-19 containment protocol. Data were obtained from the crowd-sourced database http://covid19india.org/. This database aggregated data from various official state bulletins and other sources, validated the data through a team of volunteers, and finally made the data publicly available for all districts in a standardised machine-readable format.

To detect localised patterns, we chose districts as our unit of spatial analysis, for it is the smallest administrative unit for which we have consistently available data. We use doubling time ($T_D$) as the measure of transmission dynamics, calculated from the date of the first case report in each district for 707 districts in India (which was the total number of districts with more than a single case at the time of the analysis). For mortality, we use case fatality ratio (CFR), estimated for 433 districts in India (there were as yet no recorded deaths in the remaining districts). The CFR data were averaged over a period of 15 days preceding the last date of measurement to minimise fluctuations due to initial transients. Based on the available data, the CFR was estimated for 433 districts in India (there were as yet no recorded deaths in the remaining districts). Sample time series plots, for both the doubling time and the CFR, are shown for two districts in Suppl. Fig. S1.

For an analysis of the correlation between social vulnerability with disease transmission and mortality, we chose 20 indices from a range of sociodemographic variables from the Census of India 2011 (Census of India, 2011). The variables were chosen to represent a cross-section that mapped most closely with the Social Determinants of Health, which are demographic and infrastructural variables, which have been shown to correlate with health outcomes. These are, broadly, economic stability, education access and quality, health care access and quality, neighbourhood and built environment, and social and community context. A detailed list of the 20 sociodemographic variables, along with their definition, and their categorisation within the Social Determinants of Health framework is given in Table 1.

To validate that the observed trends were robust, we created five categories of districts for both the doubling time ($T_D$) and CFR. Note that the number of districts at the time of Census of India 2011 was 591, and hence the analysis could only be performed for these districts. For the $T_D$ analysis, the five subsets were (1) all districts with greater than one confirmed case ($N_{all} = 578$), (2) districts with more than 50 confirmed cases ($N_{50} = 488$), (3) districts with more than 70 confirmed cases ($N_{70} = 452$), (4) districts with more than 100 confirmed cases ($N_{100} = 403$), and (5) districts with more than 150 confirmed cases ($N_{150} = 323$). For CFR analysis, the five subsets were as follows: (1) all districts with at least one confirmed death ($N_{all}^D = 383$), (2) districts with at least five deaths ($N_{5}^D = 176$), (3) districts with at least 10 deaths ($N_{10}^D = 105$), (4) districts with at least 20 deaths ($N_{20}^D = 61$) and (5) districts with at least 30 deaths ($N_{30}^D = 38$). These thresholds were chosen from the distribution of cases and mortality statistics for all districts (Fig. 1). A time evolution of the cumulative frequency distribution of reported cases and fatalities at landmark points in India’s national containment strategy is shown in Suppl. Fig. S2.

We used Spearman’s rank correlation to study the correlation of doubling time and CFR with these indicators. Those that showed consistent trends across all five subsets were then selected for a multivariate regression analysis to analyse the differential impact of each of these factors on COVID-19 outcomes in India.

Our analysis showed persistent patterns of socio-economic vulnerability affecting disease progression – patterns that can provide invaluable support to the designing of evidence-based, locally responsive intervention and policy.

Results

Given India’s immense diversity, there is little actionable meaning to ‘national doubling time’ or ‘national CFR’. For the data to successfully translate into effective intervention, analysis must unearth the localised patterns submerged under national-level, and even state-level, averaged values. To illustrate this ‘hidden’ variability, we have shown the results for the state of Maharashtra in Fig. 2. The red vertical line represents the state average for Maharashtra, whereas each bar represents the districts. Note the diversity of distribution both within the state and within each district. Similarly, the spectrum of district-level distribution for the entire nation is shown in Fig. 3: doubling time ranges from 2 to 60 days and CFR from 1% to 28%. The histograms for distributions of average doubling times and average CFR for all districts in India are shown in Suppl. Fig. S3. It is therefore vital to perform fine-grained spatial analysis to identify true spread patterns and areas that need urgent intervention.

We begin with the results of the correlation analysis. For doubling time, we discuss only those 11 correlations where significance $P \leq 0.05$ and is consistent across all five subsets. Five sociodemographic indicators are positively correlated with the doubling time, and hence with a slower spread of the disease: (1) literacy rate, (2) proportion of elderly population, (3) population of main workers, (4) proportion of houses in a ‘good’ condition and (5) the availability of medical facilities in the district. Conversely, six indicators are negatively correlated with doubling time and hence with a faster spread of the disease: (1) proportion of children in the district, (2) proportion of marginal workers, (3) proportion of houses with no drainage, (4) proportion of houses with no latrine, (5) proportion of houses with no electricity, and (6) proportion of houses where the source of drinking water was ‘away’.

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For CFR, to account for smaller sample sizes, we discuss only those six correlations with a significance $P < 0.10$ in at least one subset and consistent trends across all five subsets. Of these, three sociodemographic indicators are correlated with low mortality: (1) the availability of medical facilities in the district, (2) the proportion of college graduates and (3) the population of marginal workers. Conversely, these three are correlated with higher CFR: (1) proportion of houses with no latrine, (2) proportion of houses with no electricity and (3) the population of main workers in the district.

A summary of the correlation coefficients of these significant variables, both for doubling time and CFR, is shown in Fig. 4. The full list of correlation coefficients and significance values is in the Suppl. Table S1 (doubling time) and Suppl. Table S2 (CFR).

We now turn to the results of the multivariate regression analysis. A cross-correlation analysis of the four household...
indicators indicates that these variables are interdependent and have a high degree of mutual correlation (see Suppl. Fig. S4). To carry out a regression analysis of the doubling time, we choose to retain two of them: (1) ‘away’ source of drinking water and (2) no electricity. As $t_D$ is a discrete data set, we use the logarithm of $t_D$ to perform an ordinary linear regression. We also calculated the doubling rate (inverse of the doubling time) and performed a multivariate beta regression (Ferrari and Cribari-Neto, 2004) with these nine variables as the rate lies in the (0,1) range. Both analyses yielded identical results. The average doubling time is positively related to the proportion of elder population (significant at $P < 0.05$) and negatively with number of houses with no electricity (significant at $P < 0.01$) and a distant source of drinking water (significant at $P < 0.05$). These trends were consistent across the different subsets analysed. The results of the beta regression model are summarised in Table 2.

As CFR lies in the (0,1) range, we have constructed a beta regression model with six predictor variables that emerged from Fig. 2. Box plots of variability in case fatality ratio and doubling times for all districts of the state of Maharashtra.

Fig. 3. Variability in average doubling times and average CFR at a district level for the entire country. The data are till the 2nd of July 2020.
Only those predictors with consistent correlations have been shown.

Some text in Table 3 has been omitted for brevity. The full table can be found in the paper.

**Table 2**

Coefficients from the beta regression model for the inverse doubling time.

|                      | Districts with | Districts with | Districts with | Districts with |
|----------------------|----------------|---------------|---------------|---------------|
|                      | >1 case        | >50 cases     | >100 cases    | >150 cases    |
| Elder population     | -0.14***       | -0.11***      | -0.12**       | -0.06**       |
| Distant drinking water| +0.05**        | +0.07**       | +0.07**       |               |
| No electricity       | +0.11***       | +0.13***      | +0.13***      | +0.11***      |

Only those predictors with consistent correlations have been shown.

*Significance at P ≤ 0.10; **significance at P ≤ 0.05; and ***significance at P ≤ 0.01.

**Table 3**

Coefficients from the beta regression model for the average CFR.

|                      | Districts with | Districts with | Districts with | Districts with |
|----------------------|----------------|---------------|---------------|---------------|
|                      | ≥ 1 fatality   | ≥ 5 fatalities | ≥ 10 fatalities | ≥ 20 fatalities |
| Medical facilities   | -0.24***       | -0.29**       | -0.22*        |               |
| College graduates    | -0.23***       | -0.24***      | -0.24***      | -0.22**       |

Only those predictors with consistent correlations have been shown.

*Significance at P ≤ 0.10; **significance at P ≤ 0.05; and ***significance at P ≤ 0.01.

The nature of social inequalities, however, is multidimensional. We have therefore chosen to correlate the outcome of COVID-19 in India individually to each variable of vulnerability, instead of a composite indicator such as ‘poverty’.

Five such variables exhibit a persistent pattern of influence on COVID-19 outcomes: houses without electricity and/or a proximate source of drinking water correlate with faster spread; a larger elder population correlates with slower spread; and a large college-educated population and the presence of medical facilities both correlate with lower mortality.

Cross-correlation analysis of the household variables indicates that absence of electricity and a proximate source of drinking water also relate positively with two other variables: the lack of drainage and of in-house latrines. Collectively, these household- based inequality indicators point to a pattern of multiple daily commutes to, and queuing for, the use of common facilities that are severely cramped and provide no opportunity for social distancing or COVID-19 a significant public health challenge. Indeed, prevention seems to rest almost exclusively on maintaining strict physical self-isolation, per UNDP, 2019.23

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disinfection between uses. These four also vary directly with the proportion of marginal workers, further indicating their positive relationship with poverty and the low probability that such households can survive lockdown-unemployment on savings. It should be mentioned here that a significant share of households in India is either one room (37.1%) or without any exclusive rooms (3.9%). Between March and June, when COVID-19 began its first wave in India in urban centres, social distancing meant that the cross-section of people living in non-electrified houses with a single room or no exclusive room had to stay indoors in darkness and heat—an impossible and inhumane expectation.

Although indicators of poverty correlate directly with marginal workers, we should not conflate main workers with stable working or living conditions. A significant body of recent biosocial research has demonstrated that immersion in unstable environments of scarcity causes a high allostatic load, resulting in greater vulnerability to poorer health outcomes.

The positive correlation of an elderly population to slower spread is an interesting outcome. Although multiple studies have shown that at an individual-level, elderly population are at a higher risk of adverse COVID-19 outcomes, our analysis suggests that at a population level, a higher elderly population correlates to slower doubling time. It is worth noting that while culturally a sizable percentage of India’s elderly population still live in large multi-generational families, the explosion of internal migration has created a pattern of households in which the elderly are ‘left behind’ either seasonally or permanently and are supported via remittance, savings, or local social networks. This keeps them from needing to participate in the mainstream labour force and may have contributed to their lower relative vulnerability vis-a-vis a younger, working population.

The correlation between the availability of medical facilities and lower CFR is self-evident, and given the results of our analysis, it may perhaps be of interest to further investigate how these correlations might be influenced by more detailed and disaggregated metrics of health infrastructure, such as the numbers of operational primary health centres, community health centres and district hospitals in a given district, the comparative availability and access between public and private health facilities, availability of an attending physician, hospital beds, oxygen and other medical facilities. Furthermore, the negative correlation between a college-educated population and CFR merits some attention. Our correlation analysis indicates that college education is the inverse of every indicator of inequality and social marginality we have assessed: lack of electricity, proximate water source, latrines and drainage; marginal employment; and larger SC/ST population. In other words, a college education is indexical of relatively privileged socio-economic position: better access to housing and amenities, stabler income and higher probability of paid leave/work from home, capability to locate public health information and greater likelihood of affording medical care. Thus, the greater the proportion of the socially vulnerable in a district, the lower its probability of a large college-educated populace and the greater its vulnerability to COVID-19 mortality.

Our work presents a simple statistical association analysis between transmission patterns and outcomes of COVID-19 in India and variables of social vulnerability. We note that our analysis is necessarily ecological and not indicative of individual-level risk. There may potentially be other sociodemographic predictors of disease progression and mortality, and our results are open to potential confounding by these factors. Individual risk factors for COVID-19—as such as age, gender and other comorbidities—have been studied extensively in recent literature. Our aim was to shift the focus on collective social vulnerabilities and the causes that cause them at the most fine-grained level that the current data would permit us to do, which was at the level of the district. We note that districts in India are themselves large administrative units—and more fine-grained analysis can lead to higher correlations with the socioeconomic variables. Our analysis is also hindered by the non-categorisation of COVID-19 patient data into existing groups of vulnerability—such as income, caste, gender, rural-urban location, employment status and so on. With more extensive and complete data sets, it would be interesting to repeat this analysis, perhaps at a ward-level or block-level, and see if the qualitative conclusions from the current analysis still hold.

On the subject of data, we have selected our social indicators from the Census of India 2011, which are now a decade old. The profiles of the districts may have undergone changes in the intervening period, potentially affecting results. The disease data have considerable heterogeneity in metrics. Indian states have had differential testing policies, different capabilities for contact tracing and tracking, different definitions for a ‘COVID-19 death’ and different data disclosure policies. Indeed, recent large-scale seroprevalence studies in Indian cities indicate that COVID-19 cases may have been severely underreported, and questions have been raised about the restrictions on enumerating mortality.

Our analysis is not without caveats. The analysis in this article was carried out for data ending on 2 July 2020. This was the beginning of the Unlock 2.0 phase, as has been discussed in the Methods section. The pandemic continued to permeate through India, with a second wave between April 2021 and May 2021 and a third wave between January 2022 and March 2022. However, post-July 2020, certain states and districts stopped sharing data in the public domain, which would make a comprehensive assessment difficult. However, if this complete and validated data set becomes available, it would be interesting to see if the conclusions of our analysis hold true for the wider pandemic. For assessing transmission, we have used an average of the doubling time of the district. Although this provides a model-independent characterisation of the transmission dynamics, it must be used with caution. When the pandemic has run its course in a district, the doubling time will grow continuously, and hence including this period in the averaging timespan can inflate the characteristic doubling time. Our data, capped at 2 July 2020, have the advantage of not having seen this period in any district. On the other hand, in the case of CFR, for some districts—especially those with low mortality counts, the average CFR may not be yet reflective of the final value because the disease is still in its early stages in these districts. We also note that estimation of the CFR depends crucially on the detection and testing of mild and asymptomatic cases and is thus subject to variation depending on the high non-uniformity amongst Indian districts in terms of public awareness about symptoms and testing, health facilities available to conduct the tests, and the public health system’s capability to record and transmit that data reliably.

Our study validates the hypothesis that inequalities embedded in the social structure of the nation affect the dynamics of disease transmission and mortality outcomes. This is particularly relevant in the case of COVID-19 because many of India’s early quarantine facilities had unwittingly replicated the very conditions that have been positively correlated with a faster spread (overcrowding, single common source of drinking water, inadequate number of common latrines, common pool of untested and symptomatic populations). Our hope is that this study shall provide policymakers with an evidence-based tool to identify risk factors specific to a locality and design targeted interventions for them while also ensuring they cause minimal unintended harm.
Author statements

Ethical approval
No ethical approval was required for this study.

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Competing interests
All authors declare no support from any organisation for the submitted work; no financial relationships with any organisations that might have an interest in the submitted work in the previous three years; and no other relationships or activities that could appear to have influenced the submitted work.

Data availability
The analysis in this manuscript uses data available in the public domain.

Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.puhe.2022.11.009.

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