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ABSTRACT

Objectives This research studies the role of slums in the spread and control of infectious diseases in the National Capital Territory of India, Delhi, using a detailed social contact network of its residents.
Methods We use an agent-based model to study the spread of Influenza in Delhi through person-to-person contact. Two different networks are used; one in which slum and non-slum regions are treated the same and the other in which 298 slum zones are identified. In the second network slum-specific demographics and activities are assigned to the individuals whose homes reside inside these zones. The main effect of integrating slums is that the network has more home-related contacts due to larger family size and more outside contacts due to more daily activities outside home. Various vaccination and social distancing interventions are applied to control the spread of Influenza.
Results Simulation based results show that when slum attributes are ignored, the effectiveness of vaccination can be overestimated by 30%-55%, in terms of reducing the peak number of infections and the size of the epidemic, and in delaying the time to peak infection. The slum population sustains greater infection rates under all intervention scenarios in the network that treats slums differently. Vaccination strategy performs better than social distancing strategies in slums.
Conclusions Unique characteristics of slums play a significant role in the spread of infectious diseases. Modeling slums and estimating their impact on epidemics will help policy makers and regulators more accurately prioritize allocation of scarce medical resources and implement public health policies.
Policy Implications Currently, over a billion people reside in slums across the world and this population is expected to double by 2030. This study uses Influenza as an example to demonstrate the need to understand the role of slum populations in the spread and containment of infectious diseases.

Strengths and limitations of this study

- We show that the unique attributes of slums must be accounted for in understanding the spread and control of infectious diseases.
- Policymakers should give special consideration to slums when allocating limited resources.
- Intervention strategies have been applied one at a time but a combination of them could be used simultaneously to more aggressively control the epidemic.
- This study does not consider age-specific susceptibility or immunity from past infections; all agents are assumed to be equally susceptible.
- Co-location based contact time is used as a proxy for physical proximity and short-distance airborne transmission.

INTRODUCTION

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Infectious disease is one of the leading causes of human morbidity and mortality worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000 people in the United States (US) are hospitalized with Influenza-like illnesses (ILI) symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the National Institute of Virology has shown that ILI cases are present throughout the year, although they peak in rainy and winter seasons.[3] It carries a significant economic burden through reduced productivity and high costs of health care.[4-7] A CDC study finds that for outpatient and non-medically attended individuals, acute respiratory infections cost 1%-5% of monthly per capita income in India. In contrast, cost of inpatient care can be as high as 6%-34% of annual per capita income.[8] For developed countries, the annual cost of Influenza is estimated to be between $1-$6 million per 100,000 people, according to the World Health Organization.[9]

In 2007, India established an Integrated Disease Surveillance Program (IDSP), which included a network of 12 regional laboratories, to minimize the threat of avian influenza and other highly infectious zoonotic diseases.[10] India faces some unique challenges in surveillance, prevention and control because of the seasonality of Influenza at sub-regional levels. This seasonal variation depends upon latitude, monsoon season, humidity and climatic factors of the regions. Acute respiratory infections are estimated to be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13] estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in year 2011, and children under age 5 had the highest incidence of them.

Given that Influenza is airborne and spreads through close proximity, population density is an important factor in its spread. In India, the average population density is about 1000 people per square mile; in the slums, it can be 10 to 100 times higher.[14] Larger household size and crowding make it easier to transmit airborne infections).[15-18] For example, Baker et al.[16] find that meningococcal disease risk among children doubles with the addition of 2 adolescents or adults (10 years or older) to a 6-room house. Other than overcrowding, slums are characterized by their lack of medical services,[19-20] which makes slum residents highly vulnerable to infectious diseases. Diseases like cholera, malaria, dengue and HIV are common in slums across the world.[21-23]

This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8 million people live in slum areas, as an example city to study the spread and control of Influenza. Delhi is an interesting case study. It ranks fourth in the world in urban population, and, among the top 25 largest urban areas, it ranks tenth in population density. Moreover, the results are likely to be generalizable to other slum areas within and outside of India.

This paper is an extension of the work done in Chen et al.[4], which shows that slum populations have a significant effect on Influenza transmission in urban areas. Ignoring the influence of slum characteristics underestimates the speed of an outbreak and its extent. However, Chen et al.[4] do not consider any interventions on the epidemic spread. *The focus of this research is to study the effect of different intervention strategies on several subpopulations (slum, age and gender) in two different Delhi networks, i.e., original (referred to as Network 1) and refined (Network 2).*

The original network used in Xia et al.[24] studied the spread and control of Influenza in Delhi using Network 1, which did not take into account the special attributes of the slum population, such as larger family sizes and different types of daily activity schedules. Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for slum demographics and slum activities, but did not study intervention strategies. In Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.

The goals of this work focus on understanding the effects of pharmaceutical and non-pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI) include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing measures such as school closure, quarantine and staying home. These effects are studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a scenario where interventions can be applied to a limited number of individuals, we explore how resources should be split between slum and non-slum subpopulations in order to achieve the best outcomes with respect to total infection rate (i.e., the cumulative fraction of a population infected), peak infection rate (i.e., the maximum fraction of a population infected on any day), and time-to-peak infection.

METHODS

We use an agent-based modeling (ABM) approach to simulate the spread and containment of Influenza in social contact networks of Delhi, India. We compare two networks, one considers slum-specific attributes, and the other does not. In this section, we describe the networks, the disease model for each agent, the interventions, and the heterogeneities of the problem that make ABM uniquely suited to study epidemics.

Social Contact Networks: This study uses two synthetic social networks of Delhi, created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found in Xia et al.[24], Chen et al.[4], Barrett et al[25], Bisset et al.[26] and references therein. The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined network developed in Chen et al.[4], *Network 2*.

Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set of activities of individuals, and the locations of those activities including geo-locations of residential areas, shopping centers, and schools, collected through surveys by MapMyIndia.com. By assigning activity locations to individuals' activities, people are located at particular times at particular geographic coordinates (including office buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between individuals are estimated when each person is deemed to have made contact with a subset of other people simultaneously present at the same location. This gives rise to a synthetic social contact network where network edges represent these contacts.

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Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the individuals whose homes reside in the slum polygons. Slum residents' attributes and their daily sets of activities are collected through a ground survey in Delhi slums, by a vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from *MapMechanic.com*. Individuals living in the slum regions are a part of the slum population. All other individuals are part of the non-slum population. Network 2 is a geo-located, and contextualized social contact network of Delhi with slums integrated in it.

Following are the main differences between the original network (Network 1) and the refined network (Network 2). The original social contact network treats the slum regions like any other region in Delhi in terms of assignment of demographics and individual activities, i.e. no special consideration is given to slum residents. The refined Network 2 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific demographics and activities to the individuals whose homes reside inside these polygons. Thus, the number of individuals is the same in both populations. The slum population constitutes about 13% (1.8 million) of the entire Delhi population of 13.8 million people. The main effect of integrating slums is that Network 2 has more home-related contacts due to larger family size and more outside contacts due to more daily activities outside home. Also, those individuals who reside outside of slum zones have the same activities in both networks. Overall, there are over 231 million daily interactions between pairs of individuals. Table S1 compares those two networks as well as data sources for slum and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are in the supplementary information (SI)). We refer to Chen et al.[4] for more detailed information about the two networks. Several plots of properties and structural characteristics of Networks 1 and 2 are given in Chen et al.[27].

Disease Model: An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. Each node in the network represents an individual, and each edge represents a contact on which the disease can spread. A contact represents possible transmission between two people that are co-located for some duration (based on their activity schedules). This is an approximation to model direct contact and short-distance airborne transmission.

We start each epidemic simulation with 20 index cases, randomly chosen. (We find that results are not sensitive to the number of initial infections.) The detailed description of the SEIR model as well as the choices of transmissibility value, $R_{0,}$ the explicit incubation and exposed periods can be found in the supplementary information. This disease model has been used in other works such as Liao et al.[28], Marathe et al.[29].

The transmissibility value for disease transmission is that for the strong influenza model in Chen et al.[4]. That work used mild, strong, and catastrophic influenza models, so we chose the intermediate transmissibility. This corresponds to base attack rates (i.e., cumulative infection fractions) of 0.42 and 0.48, respectively, in Networks 1 and 2. These rates are generally higher than those in some other studies that either compute experimental attack rates from cases or compute them in modeling studies such as this one. Attack rates used by past researchers for different strains of influenza include Asia [0.22 to 0.50],[30] Southeast Asia [0.11 to 0.31 in children [31]; 0.05 to 0.65 [32]], and India [0.111 to 0.235 [33]; 0.074 to 0.424 [34]; 0.045 to 0.294 [35]; 0.008 to 0.100 [36]; 0.209 for various strains [13]]. The results of Chen et al.[4] indicate that the results here, for this particular transmissibility, will be qualitatively the same for other transmissibility, but will scale down or up as transmissibility changes in the same direction.

Interventions: This work considers three vaccination scenarios, i.e., vaccinate when cumulative infection rate is 0% (VAX0, i.e. vaccinate on day 1), 1% (VAX1), and 5% (VAX5). Three classes of social distancing strategies are considered: (i) stay-home (SHO) if infected i.e. eliminate all non-home related contacts but continue to maintain contacts within the household; (ii) close-schools when cumulative infection rate has reached 1% (CS1) and when it has reached 5% (CS5) i.e. eliminate school related contacts; and (iii) (ISO), in which all contacts, including home contacts, of a person are eliminated when a person becomes infectious. For vaccination, five different compliance rates (10%, 30%, 50%, 70%, 90%) and two different vaccine efficacies (30% and 70%) are considered. Interventions are applied to slum residents, non-slum residents, and the entire region of Delhi. For each experiment, 25 replicates are simulated for 400 days, and their mean results are reported. Table S2 summarizes all the interventions considered, and Table S3 contains all variables in simulations, including intervention parameters.

Heterogeneities captured: There are several heterogeneous aspects to this problem that motivate the use of an ABM approach: (i) the 298 slum zones have populations that vary by more than four orders of magnitude in size; (ii) the geographic extent of slum zones differ; (iii) the slum zones are located at irregular spatial intervals throughout Delhi; (iv) the activity patterns of people living in slums are different from those in the non-slum region; and (v) each individual interacts with specific others based on co-location.

The implications of these heterogeneities include the following. First, the particular synthetic households that live within slums are predicated on the number of slum zones, their locations, and their spatial geometries. These homes have larger family size and hence more home contacts. Second, slum individuals have different activity patterns which change the co-located contacts of each slum person: that is, with whom they interact and for how long. For example, see the supplemental Figure S6 of Chen et al.[27]. The average total contact durations by activity type and by slum/non-slum residents are provided, which show that non-slum people have greater contact durations for work, school, and college activities, but less for home and other types. Overall, a slum person has about 50% greater total contact duration per day compared to a non-slum person. Figure S7 of the same supplemental shows that in the age range 20 to 60 years (by year), females that live in slums have more contacts per day than their male counterparts. However, females whose homes are outside of slum regions have average number of daily contacts that are below their male counterparts.

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RESULTS AND ANALYSIS

Our results are grouped as follows. (1) Comparisons of Network 1 and Network 2 for base case and intervention cases. (2) Results for both networks based on demographic classes, such as slum/non-slum, gender, and age groups, for a wider range of intervention strategies. (3) Effects of pharmaceutical and non-pharmaceutical interventions for a wide range of parameter values. (4) Effects of different resource allocation strategies.

All differences are tested with the two-sample t-test and they are all statistically significant with p-values smaller than 2.2e-16. The 95% confidence intervals are given for each comparison. Here is a brief summary of selected results with examples of mechanisms, to provide a high-level overview. Details of results follow this summary and these details matter because there are many factors (inputs) in a simulation whose interactions change results.

(1) Ignoring the unique attributes of slums in a population overestimates the benefits of the interventions. For example, in the case of vaccination intervention (efficacy 30% and compliance 30%), the values for the epidemic size (i.e., cumulative percentage of infected), peak infection rate, and time to peak are 33.1%, 3.0%, and 184 days, respectively, in Network 2, whereas they are 23.3%, 1.34%, and 286 days in Network 1. In relative terms, the epidemic size and peak infection rate are underestimated by 42.2% and 123.2% respectively, while the time to peak is overestimated by 35.7% in Network 1 (see Figure 1 and Table S5). The larger family sizes for slum families in Network 2 and the increased number of edges result in larger outbreaks and faster time to peak infections.

(2) Interventions are more effective in Network 1 than Network 2 for all types of interventions: vaccination, closing schools, staying home, and isolation. These trends also hold over wide ranges of efficacy and compliance (see Figures 3, 4, S1, S2 and S7). Hence, not accounting for slums gives overly optimistic results for the effectiveness of the interventions. The reduced average family size in Network 1 means fewer within-home edges, which slows infection and reduces spreading. Closing schools and staying home interventions do not affect home edges. However, the magnitude of this effect varies with intervention conditions (e.g., compliance rate, time at which intervention is applied).

(3) Cumulative infection rates by subpopulation in Network 2 show that slums sustain greater infection rates than non-slums under all intervention scenarios, sometimes by as much as 44.0%. See Figure 4 and Table S9 for more details. This is due to the greater household sizes in slums.

(4) For Network 2, under a wide range of intervention compliance rates (10% to 90%), the isolation strategy is up to 32% more effective in containing an outbreak than vaccination (for 30% efficacy). Staying home is up to 18% more effective than vaccination at 50% compliance. See Figure 3 and Table S10 for more details. Isolation, although hard to implement from practical considerations, is most effective because

edges to susceptible individuals are removed (isolation also provides a good comparative case). Differences between staying home and vaccination depend on compliance rates.

(5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse effect in slums than in non-slum regions across compliance rates from 10% to 90%. See Figure 4 and Table S7 for more details. Early interventions mean actions are taken when outbreaks are smaller and are therefore more readily contained.

(6) A full-factorial design that splits resources between slum and non-slum regions indicates that the most effective intervention is to give vaccines to slums and apply social distancing to non-slums. Applying vaccine and social distancing to slum regions is the next most effective intervention. See Figure 5. By applying social distancing to non-slums, these individuals are kept isolated from slum individuals that are infected.

Comparison between Networks 1 and 2: Base case versus interventions

We start with a comparative analysis of the Influenza epidemic, with and without interventions, on Network 1 and Network 2 to measure the impact of integrating slums in the population on epidemic measures. Figure 1 shows the simulation time histories (averaged across 25 simulations) for the base case, and when vaccination is applied randomly to 30% of the population in each network with vaccine efficacy set at 30%. Mean infection rate is the daily fraction of infected individuals. Simulations for other vaccine efficacies and compliance rates give qualitatively similar results. Two sets of those results are shown in the supplemental information, see Figures S1 and S2. Note that Network 1 does not distinguish between slum and non-slum individuals, so the epidemic curve is not split by subpopulation.

Results in Network 2 differ significantly from results in Network 1 for both the base case and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a larger epidemic size and has higher peaks compared to the corresponding epidemic quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to plan, there will be a false sense of security and lack of urgency to implement interventions. For both the base case and the intervention case, ignoring unique characteristics of the slums will result in an underestimation of the infections and the speed of spread.

Figure 1 goes here

For the intervention cases, the time to peak infection decreases by 35.7%, i.e. from 286 days for Network 1 to 184 days for Network 2, meaning an influenza epidemic would peak roughly 100 days earlier than one would expect based on the results from Network 1. For the base case, time to peak infection drops by 20.8%, i.e. 34 days reduction for Network 2 as compared to Network 1.

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Percentage changes and differences must be viewed cautiously, and to illustrate this point, we present data for the key parameters in Tables S4 and S5. The difference in the peak infection rate (i.e., the maximum fraction of daily infected individuals during the simulation) between Networks 1 and 2 for the base case is 2.2%, or 47.6% in percentage change (see Table S4). For the intervention case shown in Table S5, the difference between the two networks is less (1.7%), but the percentage change is more (123.2%) because the magnitudes of the peak infection rates are reduced when effective interventions are used. We make note of this here and mainly use the percentage change values in discussing results. For more detailed comparison between vaccination intervention and the base case in Network1 and Network 2, we refer to Tables S6 and S7, Figures S3 and S4.

Comparison between Networks 1 and 2 based on individual demographic information

We divide the Delhi population into strata by age, gender, and geographic home location (i.e., slum and non-slum), and analyze mean cumulative infection rates by subpopulation for the two networks. In simulations, individuals are chosen at random in the entire network for vaccination. Various vaccination scenarios are investigated.

Figure 2 displays the cumulative infection rate results. On the x-axis, 'Total' refers to the entire population of Delhi. There are three breakdowns of the entire population. 'Slum' and 'Non-slum' refer to slum and non-slum regions, respectively. 'Male' and 'Female' denote the total number of males and females in Delhi, respectively. Four age groups are considered: 'Preschool' (0-4), 'School' (5-18), 'Adult' (19-64), and 'Senior' (65+). The black lines correspond to the mean cumulative infection rates for the base case. Other curves indicate vaccination strategies under different levels of vaccination rate (v) and vaccine efficacy (α). Two vaccination rates (30%, 50%) and two vaccine efficacy rates (30%, 70%) are shown in the figure.

For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all categories of individuals.

In Network 1, slum and non-slums are treated the same so the infection rates are identical in Figure 2. However, all scenarios in Network 2 show a higher burden of disease on the slum population. This is due to the fact that slum households have larger family size and more contacts on average than households in non-slum areas, see Chen et al.[27]. As shown later, we find similar patterns of infection in slum and non-slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.

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The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums results in overestimation of the benefits of interventions in terms of reduction in the mean infection rate and peak infection rate, as well as the time to peak. This optimism holds for slum, non-slum and total population under various levels of vaccination rates and efficacy rates in Network 2. See Table S8 for more detailed comparison of results between slum and non-slum in Network 2.

Figure 2 goes here

Comparison between Networks 1 and 2 across a wide range of intervention strategies

Next, we consider a variety of intervention strategies for comparative analysis. We consider vaccination, school closure, stay home, and isolation strategies. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at home (SHO) strategy, all non-home activities and interactions are eliminated but all contacts within the household are maintained. Under isolation (ISO) an individual has no contact with other individuals (even home interactions are eliminated). The stay-at-home and isolation interventions are implemented for compliant infectious individuals, after they become infectious, for the entire infectious duration.

Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a wide range of intervention strategies. For each strategy, five different compliance rates are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers are the actual number of infected individuals. Darker colors correspond to higher infection rates. Note that compliance rate is simply the vaccination rate for strategies VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire population. The 'Base' values do not vary with compliance because the base case has no intervention. Note that all heat maps in this paper use the same color scheme so that colors can be compared across figures.

Since Network 1 does not distinguish between slum and non-slum populations, we only compare the two networks for the whole of Delhi. The general pattern is similar for both networks. However, all interventions have a larger effect on Network 1 under the same compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0, stay-home, and isolation strategies in Network 1 as compared to those for Network 2.

Figure 3 goes here

Effect of vaccination versus social distancing on slum and non-slum subpopulations

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We now compare the impact of vaccination and social distancing on slum and non-slum subpopulations from Network 2. Social distancing interventions are close-schools, stay-home, and isolation.

The mean cumulative infection rates (and actual numbers of infections underneath) for each compliance level are shown in the heat maps in Figure 4 for slum and non-slum populations in Network 2. The axis labels are identical to those in Figure 3, as is the color scheme of the cells. The base case values are constant since there is no intervention and hence no compliance. Darker colors correspond to higher infection rates.

Compared to the base case, all interventions reduce infection rates to some extent. As the compliance rate increases, infection rates drop for all interventions. Infection rates drop to zero in slum and non-slum regions at a compliance level of 70% or higher, under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce the infection rates significantly, and this effect increases with compliance rate.

The following observations can be made from Figure 4. Social distancing i.e. SHO at low and intermediate compliance and CS at all compliance levels, are less effective in slum regions as compared to non-slum regions. This is because CS only eliminates school interactions for those attending school, and there are fewer school edges in slums compared to non-slum areas, as shown in Figure S5. The effectiveness of CS in slums is mitigated by the greater average number and duration of interactions at home in slums as compared to non-slums (see Figure S5 and Chen et al.[27]). Thus, if a person is sick, there is a greater chance of transmitting contagion to family members, who then may have activities outside of school, thus circumventing the CS intervention. At high compliance, SHO is effective because all interactions outside home (including school) are eliminated.[27]

These observations are also supported by Figure S6, which contains numbers of edges used to transmit contagion for a base-case run of Figure 1. There are several effects that bear on the above observations. First, in the cases of activities “work”, “other”, and “school”, the number of edges transmitting contagion from slums to non-slums is greater than the reverse: from non-slum to slum. Second, in two of these three activity categories, there is more slum to non-slum transmissions than slum to slum transmissions. Edges of transmission for slum dwellers is dominated by home interactions. The infected homes in slums serve as launching points to drive disease to non-slums through slum to non-slum interactions. (There are no ``mixed’’ edges at homes, and shopping and college activities have low levels of slum activity because of socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but we now return to Figure 4.

Isolation works well at 30% or higher compliance rates, but it is a much harder strategy to implement, especially in slums. However, it is considered here for comparative analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as compliance increases. However, close-school is generally less effective because this intervention removes only a fraction of interactions for a fraction of the population, i.e. school aged children. Simulations were also run for 70% vaccine efficacy. Since results are qualitatively similar for those parameters, these plots are provided in Figure S7.

Figure 4 goes here

Constrained resource allocation among slum and non-slum areas

We consider a specific scenario under Network 2. If only a limited number of vaccines are available, and only a certain fraction of individuals can be kept home during an epidemic, how should these interventions be applied to the slum and non-slum regions so that the epidemic can be controlled effectively? Given that slum residents' attributes differ from those of non-slum residents, is there a strategy that works better in slums than in non-slum areas? The total population in Delhi is about 13.8 million, which includes about 1.8 million slum residents. We assume that only 10% of the total population can be covered by interventions, half through vaccination and the other half through stay home. Enough vaccines are available to cover 5% of the total population (i.e. 692,183 vaccinated, corresponding to about 38.25% of slum or 5.75% of non-slum population), and 5% of the individuals can stay home (692,183 individuals; this is applied to only the infected individuals). Note that an individual may receive a vaccine and also stay at home if this individual, in spite of being vaccinated, gets infected.

We consider 4 different ways of applying interventions to 10% of the total population: (i) apply both interventions to slums, i.e. give all vaccines to slums and apply SHO only in the slums (VsSs); (ii) apply all interventions to non-slum areas (VnSn); (iii) give vaccines to slums and SHO to non-slums (VsSn) and (iv) give vaccines to non-slums and apply SHO to slums (VnSs).

For both types of intervention, the same number of individuals is chosen randomly from slum or non-slum areas. 10% of the total Delhi population amounts to 76.5% of slum population, 11.5% of the non-slum population, or a combination of 38.25% of the slum and 5.75% of the non-slum population (i.e. half from slums and half from non-slums). Figure 5 shows the mean cumulative infection rates, as well as the number of infected from the entire population of Delhi, the slums, and non-slum areas under each of the four scenarios.

The results in Figure 5 indicate that the mean infection rates are the lowest when vaccines are given to slums and social distancing is applied to non-slums, or both vaccines and social distancing are applied to slums. The benefits primarily accrue to the slum population because it drives down the fraction of infected slum residents from 0.74 to 0.55 or 0.58. Also, as described in the context of Figures 4 and S6 above, social distancing of the non-slum residents helps to isolate them from the infected slum residents. This effect also bears on the following.

Note that vaccination is more effective in slums (top 2 rows) than in non-slums (3^{rd} and 4^{th} rows from top) in reducing infections among slums and in the overall population. Although non-slums are marginally better off (compared to the base case), the overall infection rate drops and the slum population is significantly better off, leading to a Pareto-optimal situation. This is a counterintuitive result, since the density of population is much higher in the slums, which may lead to the belief that social distancing in slums will break up the dense clusters. However, a careful examination shows that keeping slum residents home is not an effective social distancing strategy because their family size is, on average, almost 3 times larger than the family size of non-slum households.[27] The high level of mixing at home makes social distancing ineffective in slums unless the infected individual is completely isolated. However, complete isolation is not viable in slum areas where the entire household may live in a single room.

Figure 5 goes here

DISCUSSION

With slum populations expected to grow to 2 billion by 2030,[37] it is becoming increasingly urgent to understand how to control the spread of infectious diseases in slum areas and measure its effect on urban populations. To our knowledge, a detailed study of interventions to control Influenza epidemics in slums, using an agent-based simulation model, has never been done before. Slum conditions are important for a city beyond the direct effects of disease transmission. For example, civil wars may be precipitated or exacerbated by disease outbreaks because they decrease social health and welfare. [38]

Even though slum regions contain only 13% of the total population of Delhi, Chen et al.[4] show that omitting their attributes leads to underestimation of the overall infection rate and the peak infection rate of the epidemic. This paper extends that work by evaluating the differential impact of interventions on slum and non-slum regions. Various vaccination and social distancing strategies are analyzed under different scenarios that show that the slum population is more prone to infections under the same control measures. Furthermore, taking account of slum populations significantly alters the disease dynamics in the *entire* population. Differences in key measures are demonstrated between the cases of accounting for slum populations and not: e.g., a 100% increase in the peak attack rate in some cases when slum regions' characteristics are taken into account, compared to the case when they are ignored.

Figure 4, which compares infections in slum with non-slum areas, shows that at very high compliance rates, some interventions can be equally effective in both slums and non-slums. However, such high compliance rates are typically not feasible due to practical realities on the ground, and also because they require timely diagnosis of infected cases. For SHO to be effective, the coverage rate needs to be 70% or more in both slums and non-slums, and the diagnosis of the infected individuals needs to be correct and immediate. In other words, effective control of a contagious epidemic in a

high density place like Delhi, would require either early and drastic action (e.g. ISO) or a highly compliant set of individuals, or a combination of these features.

This work overall demonstrates the power of agent-based and population modeling to evaluate complicated interaction-based epidemiological phenomena. Clearly, there are limitations to this work (noted above). But these agent and population approaches provide a platform for adding additional complexity. All of the figures demonstrate that quantitative results depend on complicated interplay among inputs. These results are important because they inform policy decisions. An equally important benefit of this type of work, but not often stated, is developing intuition about epidemic dynamics (in this case, with the effects of slums), to enable decision makers to reason about nuanced interactions among effects to a degree that is hard to obtain with other approaches that lack this level of detail.

Despite this being the first work of its kind—to model the outbreak of influenza in a city-level population, along with a host of intervention strategies and parameter values, that includes the effects of slum populations—there are limitations of this work and areas for improvement and for future work. For example: (1) Examination of different population level base attack rates. (2) Different susceptibilities and infectivity for individual agents; e.g., based on age. (3) Effects of asymptomatic infections (although we have addressed this to some extent with compliance and efficacy of interventions). (4) Seasonal effects.[39-40] (5) Effects of immunity for an individual from previous infections (in previous seasons). (6) Evaluation of interaction of different strains from season to season. (7) Comparison of tropical versus subtropical factors. (8) Evaluation of a specific outbreak scenario. (9) Impact of sickness on absenteeism from work and its economic ramifications. (10) Effects on rural versus urban populations. (11) Using combinations of interventions rather than one at a time; this was only done here in Figure 5. However, to disambiguate results, it is prudent to first examine individual interventions. (12) To capture close-proximity airborne transmission, one could use actual physical proximity. Here, we use colocation.

Returning to the practical implications and recognizing this work's limitations, this research demonstrates that modeling slum populations is important, not only for understanding disease dynamics, but also for designing effective control measures. Ignoring the influence of slum characteristics on their urban environment will significantly underestimate the speed of an outbreak and its extent, and hence will lead to misguided interventions by public health officials and policy planners. This research also analyzes the effect of different intervention strategies on slum and non-slum subpopulations. Under limited resources, policymakers should give special consideration to slums in order to control the spread in not only the slum areas, but also the city as a whole. Given the large family size and high population density in the slum regions, it is harder to break up the social network through social distancing strategies. This research provides simulation-based evidence that it may be more effective to concentrate pharmaceutical resources in the slum regions to control the epidemic. The social distancing strategies are ineffective in slums because of a large number of contacts at home. Unless one applies complete isolation, which is not feasible in slums, unless isolation is orchestrated by health professional, just staying at home still keeps a large number of contacts and pathways of spread intact.

Contributorship statement

AA, SE, CK, AM, MM, SS, AV designed and conceived the study. SC carried out the experiments and simulations. SC, CK, AM performed data analysis. SG, CK, BL, AM, MM, EKN, MLW helped with reviewing the results and writing the paper.

Competing Interests

There are no competing interests.

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Data Sharing Statement

Data pertaining to figures and statistical analysis are partially provided in the supplementary file, and also can be obtained by contacting the corresponding author through email.

Main manuscript

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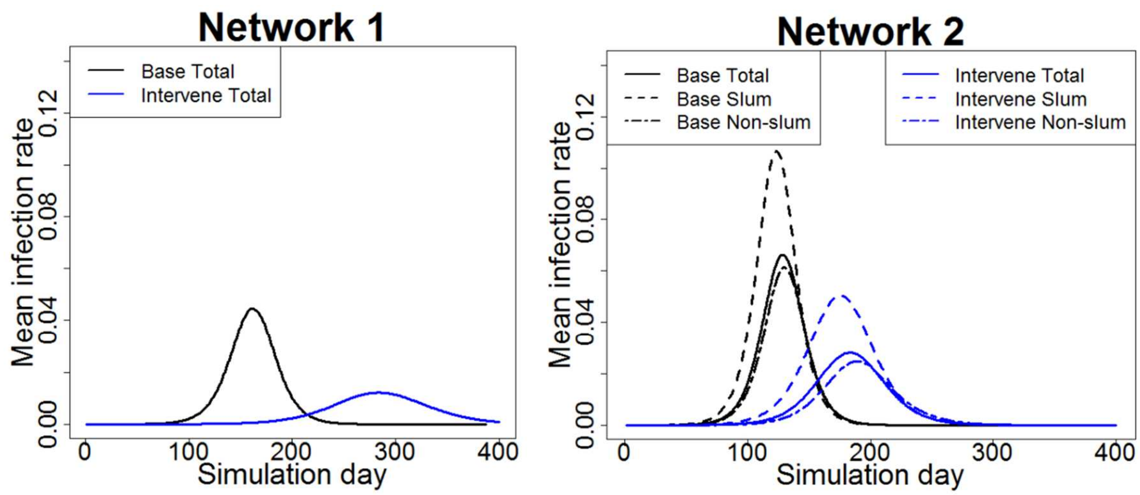


FIGURE 1: Epidemic curves for base case and vaccination case. The vaccines are given randomly to 30% of the entire population and the vaccine efficacy is 30%. For Network 2, epidemic curves are shown for total population and slum and non-slum subpopulations. 'Intervene Total' refers to the epidemic curve of the entire Delhi population when the vaccine intervention is applied. 'Intervene Slum' refers to the epidemic curve for just the slum population, and 'Intervene Non-slum' refers to the epidemic curve for just the non-slum population for the intervention case. Epidemic curves for a variety of compliances and efficacies are reported in Figures S1 and S2.

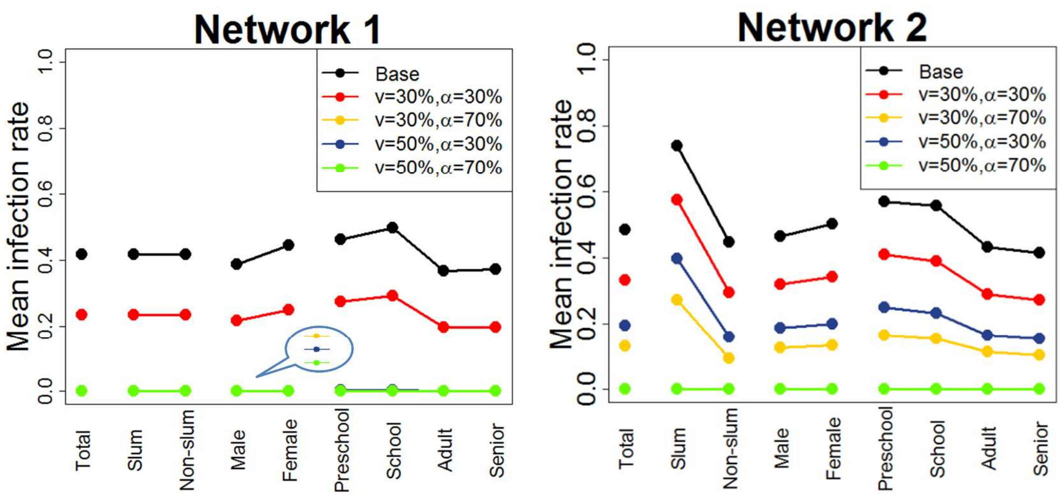
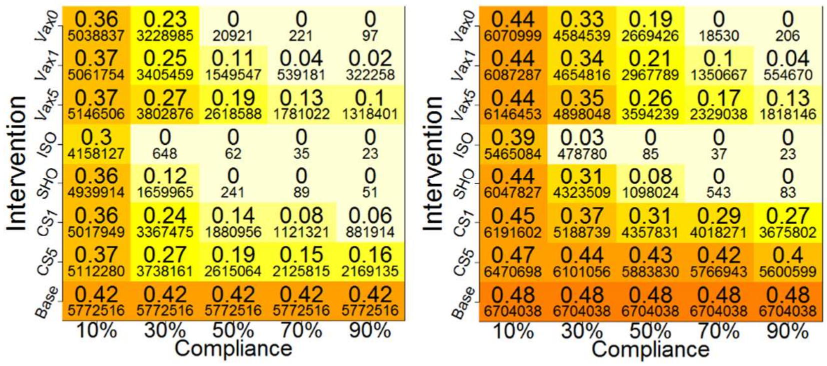
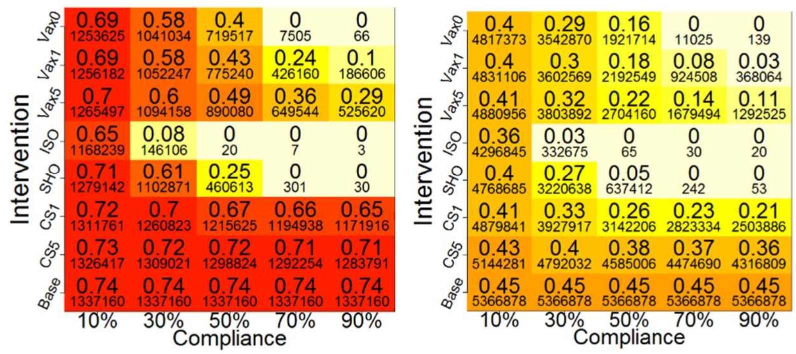


FIGURE 2: Mean cumulative infection rates for different subgroups in the two networks. Two vaccination rates (v = 30%, 50%) and two vaccine efficacy rates (α = 30%, 70%) are considered. Individuals are chosen at random in the entire network for vaccination on day 0. Mean infection rates are calculated within each group. The last several lines in the plot for Network 1 are overlapping at the bottom because the mean infection rates are almost zero under those scenarios. ‘Total’ refers to the entire population of Delhi. ‘Slum’ and ‘Non-slum’ refer to slum and non-slum regions, respectively. ‘Male’ and ‘Female’ denote the total number of males and females in Delhi, respectively. Age groups are denoted by ‘Preschool’, ‘School’, ‘Adult’, and ‘Senior’.



(a) Total Delhi Network 1 (b) Total Delhi Network 2

Figure 3. Mean cumulative infection rates under different interventions for Network 1 and Network 2. The larger font numbers are fractions of populations that are infected and the smaller font numbers are counts of infected individuals. Colors of the boxes correspond to the values of the large numbers (i.e., fractions of infected), and the same scheme is used for both plots for comparisons—and for all plots in this paper. Five different compliance rates are examined (10%, 30%, 50%, 70% and 90%), and 4 types of intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when the cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5) of the total population. The vaccine efficacy is set at 30%. For close-schools, two trigger points are used: when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected at random from the entire Delhi population, and the cumulative infection rates are calculated for each network.



(a) Slum (b) Non-slum

Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond to higher infection rates. The smaller font numbers are counts of infected individuals. The vaccination efficacy is fixed at 30%. Five different compliance rates (10%, 30%, 50%, 70% and 90%) and 4 types of intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population, and the mean infection rates are calculated separately for the slum and non-slum subpopulations. Although not reported here, qualitatively similar results are found for other transmission rates, as well as for higher vaccine efficacy (70%). Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals.

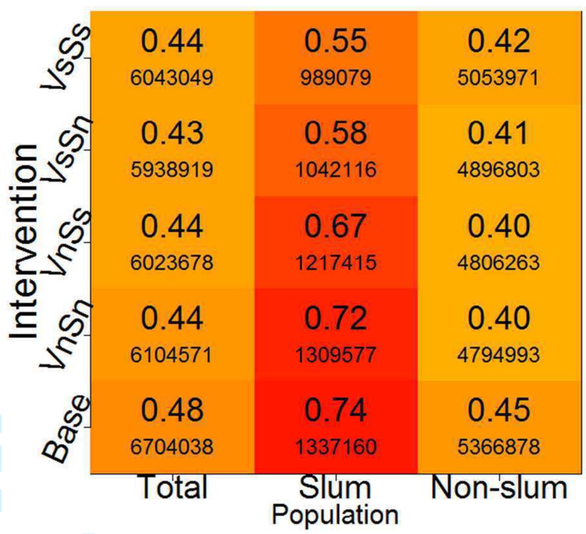


FIGURE 5: Mean cumulative infection rates for each category listed on the x-axis, for Network 2, under four different intervention scenarios. The color scheme of the boxes are based on the large values in the boxes—the cumulative infection rates. Darker colors correspond to higher infection rates. Smaller font values are the number of infected individuals. The vaccine efficacy is set at 30%. VsSs refers to the case when vaccines and social distancing are both applied to slum residents; VnSn refers to the case when vaccines and social distancing are applied to non-slum residents. Similarly, VsSn means vaccines are given to slums and stay home is applied to non-slums; and VnSs means vaccines are given to non-slums and stay home is applied to slums. Base refers to the case where no intervention is applied. The smaller-font numbers under the infection rates show the actual number of infected individuals in each category listed on the x-axis.

Supplemental Information

Disparities in Spread and Control of Influenza in Slums of Delhi

A. Adiga, S. Chu, S. Eubank, S. Gupta, C. J. Kuhlman, B. Lewis, A. Marathe, M. Marathe, E. K. Nordberg, S. Swarup, A. Vullikanti and M. L. Wilson

Supplemental Information

Presentation of Results.

For each set of input parameters, 25 replicates were run using agent-based simulation and the results presented are the average values over the 25 replicates. Also, 95% confidence intervals (CIs) are given when appropriate.

Comparisons Between Network 1 and Network 2.

Table S1 shows some differences between network1 and network 2 due to their different ways of modeling slum population. Note that these two networks are the same ones as those used in Chen et al.[1]. Further comparisons between the two networks are found in Chen et al.[2].

Table S1. Comparison of two networks as well as data sources for slum and non-slum Delhi, India.

	Network 1		Network 2	
	Slum	Non-slum	Slum	Non-slum
Population Size	0	13.8 million	1.8 million	12 million
Average Household Size of Slum Region	5.2		15.5	
Daily Activities	33,890,156		39,077,861	
Number of Edges	210,428,521		231,258,772	
Data Sources	MapMyIndia.com		MapMyIndia.com Indiamart.com MapMechanic.com	

Network 2 contains 298 slum zones, while network 1 models the whole population as non-slum. For network 1, the non-slum demographics and activities data is collected by survey through MapMyIndia.com. While for slum population, we collected additional data by Indiamart.com and MapMechanic.com for slum demographics and activities as well as slum polygons. More detailed demographic and activity differences can be found in the Chen et al.[1]

Terminology and Abbreviations for Interventions.

Table S2 contains abbreviations for different interventions and their meanings. Stay-at-home (SHO) and social isolation (ISO) interventions are applied to a person immediately after they become infected, while close-schools (CS) and vaccinations (VAX) may be applied after a specified fraction of the total population has been infected.

Table S2: Summary of abbreviations for interventions and their meanings.

Abbreviation	Definition
CS	Close-schools: School-related interactions are eliminated.
CSx	Close-schools is implemented after the total fraction of the population

	that has been infected reaches x.
ISO	Social isolation: a person who is socially isolated does not interact with any other person, even people in their home. Isolation is triggered only after a person becomes infectious.
SHO	Stay at home: All out-of-the-home activities for this person are eliminated, and this person only interacts with others at home. Stay at home is triggered only after a person becomes infectious.
VAX	Vaccination: a person who is vaccinated has a reduced probability of contracting the virus.
VAXx	Vaccination of an individual occurs after the total fraction of the population that has been infected reaches x.

Table S3 contains the variables used in simulations. The transmissibility corresponds to strong flu in Chen et al.[1] For vaccination, efficacy is either 30% or 70%. That is, for 30% efficacy, a person who gets vaccinated has reduced their susceptibility to infection by 30%.

Table S3: Summary of parameters and values used in simulations.

Category	Values
Networks of Delhi	Network 1 (does not model slums); Network 2 (models slums).
Seeding	20 people selected randomly over the entire population at time 0 as index cases.
Transmissibility	0.000027.
Intervention approaches.	Base case (no intervention); close-schools (CS); stay-home (SHO); isolation (ISO); vaccination (VAX).
Intervention/compliance rates.	10%, 30%, 50%, 70%, 90%.
Efficacy of vaccination intervention.	30%, 70%.
Intervention trigger time	Cumulative infection rate reaches 0%, 1% and 5%.
Simulation replicates	25

The Agent Epidemic States and Disease Model.

An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. An infectious person spreads the disease to each susceptible neighbor independently with a probability referred to as the transmission probability, given by

$$p = \lambda \left(1 - (1 - \tau)^{\Delta t}\right),$$

where λ is a scaling factor to lower the probability (e.g., in the case of vaccination), τ is the transmissibility and Δt is the duration of interaction in minutes. Durations of contact are labels on the network edges. A susceptible person undergoes independent trials from all of its neighbors that are infectious. The transmission probability is a function of the number and duration of contacts.[3] This is selected to simulate an Influenza model resulting in a R_0=1.26 (cumulative attack rate 42%, corresponding to a transmissibility of 0.000027 per minute of contact time) for Network 1, and R_0=1.39 (cumulative attack rate 48%) for Network 2.[4] This transmissibility value is used uniformly throughout this study and corresponds to the probability at which an infectious node infects a susceptible node per minute of contact.

At each time (day), if an infectious person infects a susceptible person, the susceptible person transitions to the exposed (or incubating) state. The exposed person has contracted Influenza but cannot yet spread it to others. The incubation period is assigned per person, according to the following distribution: 1 day (30%); 2 days (50%); 3 days (20%). At the end of the exposed or incubation period, the person switches to an infected state. The duration of infectiousness is assigned per person, according to the distribution: 3 days (30%); 4 days (40%); 5 days (20%); 6 days (10%). After the infectious period, the person recovers and stays healthy for the simulation period. This sequence of state transitions is irreversible and is the only possible disease progression.

Epidemic Curves for Other Interventions, for Varying Efficacy and Compliances.

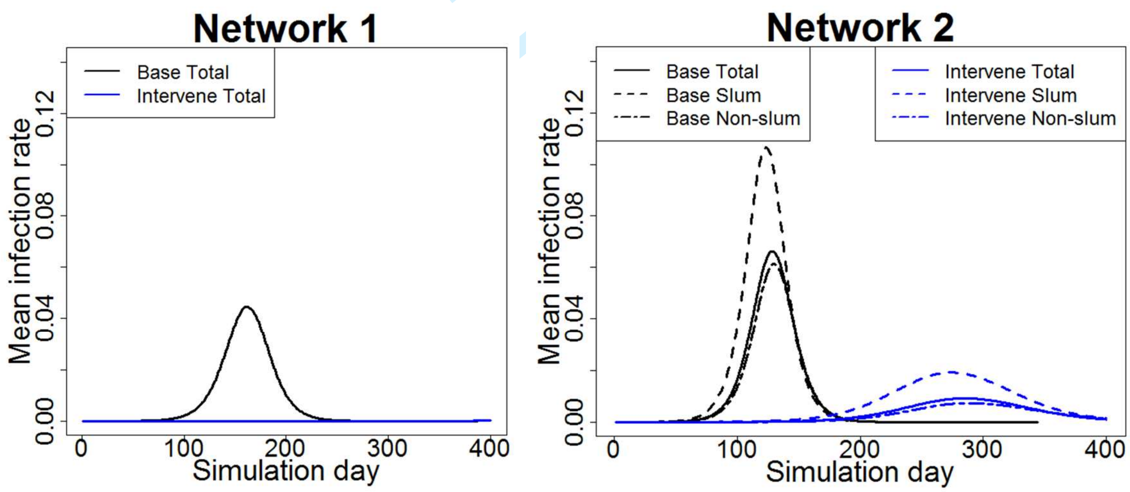


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

Supplemental Information

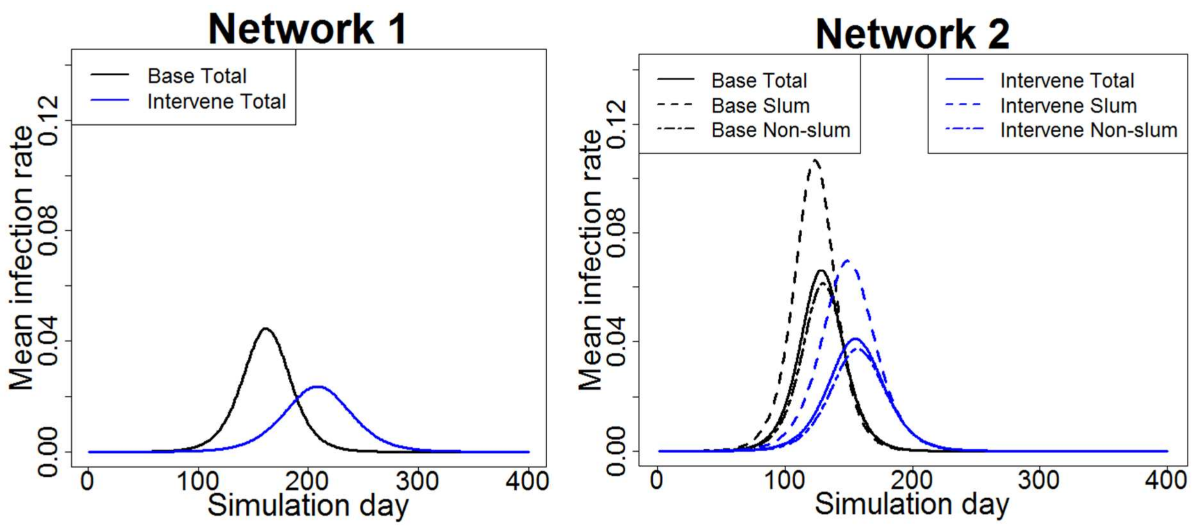


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.

Tabulations of Basic Results: Comparisons between Networks 1 and 2 for Compliance of 30% and Efficacy of 30%.

Table S4 summarizes differences in key epidemic parameters for Networks 1 and 2 for the base case with no interventions. The peak infection rate is the maximum fraction of individuals who are infected on any day, the time to peak is the day on which the peak infection rate occurs, and cumulative infection rate is the cumulative fraction of individuals who get infected in the epidemic. Under the base case, the peak infection rate in Network 2 is 47.6% (95% CI: 47.4%-47.8%) greater compared to that in Network 1 (47.6%=(6.87%-4.65%)/4.65%). The time to peak infection for Network 2 is decreased by 20.8% (95% CI: 19.2%-22.7%) compared to that in Network 1. The cumulative infection rate (or attack rate) is also underestimated under Network 1 by 16.1% (95% CI: 16.1%-16.2%) compared to Network 2. These results, presented in the main paper, are tabulated here in Table S4 for convenience and comparison.

Table S4: Comparisons of key epidemic parameters for Networks 1 and 2 for the base case.

Base	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	162	128	34 (95% CI: 31-37)	20.84% (95% CI: 19.19%-22.71%)
Peak Infection Rate	4.65%	6.87%	2.215% (95% CI: 2.206%-2.224%)	47.6% (95% CI: 47.4%-47.8%)
Cumulative Infection Rate	41.70%	48.43%	6.73% (95% CI: 6.71%-6.75%)	16.1% (95% CI: 16.1%-16.2%)

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Table S5 shows results when 30% of the population that is selected uniformly at random is vaccinated with a vaccine that is 30% effective. The contrast between the two populations is even greater when considering interventions. The peak infection rate of the entire population increases by 123.2% (95% CI: 122.7%-123.7%) in Network 2 compared to Network 1 for the intervention, versus 47.6% difference between the networks in Tables S4. The time to peak decreases by 35.7% (95% CI: 32.9%-38.8%) in Network 2 compared to that in Network 1, for the intervention case, compared to only 20.84% percentage change between the two Networks for the base case in Table S4. The cumulative infection rate (or attack rate) is also underestimated, which is 42.2% (95% CI: 41.5%-42.8%) greater on average in Network 2 compared to Network 1 for the intervention case. Hence, the differences between key epidemic results for Networks 1 and 2 that are generated for the intervention case are even more pronounced than they are for the base case. These values are all statistically significant.

Table S5: Comparisons of key epidemic parameters for Networks 1 and 2 for a vaccination intervention before the epidemic starts (VAX0), where the vaccine efficacy is 30% and the compliance rate is 30%.

Vaccination	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	286	184	102 (95% CI: 94-111)	35.7% (95% CI: 32.9%-38.8%)
Peak Infection Rate	1.34%	2.99%	1.65% (95% CI: 1.64%-1.66%)	123.19% (95% CI: 122.69%-123.65%)
Cumulative Infection Rate	23.3%	33.1%	9.82% (95% CI: 9.67%-9.96%)	42.17% (95% CI: 41.51%-42.77%)

Effect of intervention on Networks 1 and 2 individually.

Tables S6 and S7 show that, generally, Network 1 is more responsive to intervention than Network 2. In Network 1, the percentage changes in time-to-peak, peak infection rate, and cumulative infection rate, due to intervention, are 76.4%, -71.2%, and -44.1%, respectively. For Network 2, these values are 43.3%, -56.5%, and -31.6%, respectively. The reason for lower impact in Network 2 is the greater connectivity of households in slums, which helps drive the contagion.

Network 1, With and Without Interventions.

In Network 1, vaccination delays the time to peak infection by 76.41%, from 162 to 286 days on average, with 95% CI: 71.53%-81.28%. The peak infection rate is reduced by 3.3121 percentage points, from 1.34% to 4.65%, which is a relative percentage difference (RPD) of -71.20%, with 95% CI: -71.02% to -71.38%. These and cumulative infection rate data are given in Table S6.

Table S6: Comparisons of a vaccination intervention (30% vaccination rate, 30% efficacy of a vaccination) with the base case in Network 1 Delhi.

Network 1,Total	Base	Vaccination	Compare-absolute	Compare-relative
Time to Peak	162	286	124 (95% CI: 116-132)	76.41% (95% CI: 71.53%-

				81.28%)
Peak Infection Rate	4.65%	1.34%	3.31% (95% CI: 3.30%-3.32%)	71.20% (95% CI: 71.02%-71.38)
Cumulative Infection Rate	41.7%	23.3%	18.40% (95% CI: 18.25%-18.55%)	44.13% (95% CI: 43.77%-44.48%)

Network 2, With and Without Interventions.

The comparison between vaccination intervention and the base case in Network 2 is detailed in Table S7 below.

In Network 2, for the total population, vaccination delays the time to peak infection by 43.27% (95% CI: 40.14%-46.41%) relatively, from 128 to 184 days on average, while the peak infection rate is reduced by about 3.88% from 2.99% to 6.87% on average (56.47% relatively with 95% CI: 56.35%-56.56%). The total infection rate is reduced by 15.31% from 33.12% to 48.43% (31.62% relatively with 95% CI: 31.57%-31.67%).

In slum regions in Network 2, vaccination delays the time to peak infection by 43.09% (95% CI: 39.78%-46.4%) relatively, from 123 to 176 days on average, while the peak infection rate is reduced by about 5.70% from 5.42% to 11.12% on average (51.26% relatively with 95% CI: 50.88%-51.64%). The total infection rate in slums is reduced by 16.35% from 57.53% to 73.88% (22.13% relatively with 95% CI: 22.07% to 22.19%).

In non-slum regions in Network 2, the time to peak is delayed by 43.44% (95% CI: 40.32%-46.56%) relatively, from 130 to 186 days on average, while the peak infection rate is reduced by about 3.68% from 2.69% to 6.36% on average (57.79% relatively with 95% CI: 57.64%-57.94%). The total infection rate in non-slums is reduced by 15.16% from 44.60% to 29.45% (33.98% relatively with 95% CI: 33.93% -34.03%).

Table S7: Comparisons between the base and vaccination cases for Network 2. The three parameters (time to peak, peak infection rate and cumulative infection rate) are broken out, and for each, values for the total population, and slum and non-slum subpopulations are given. The vaccination rate is 30% and efficacy is 30% for those receiving the vaccine.

Network 2, Time to Peak	Base	Vaccination	Compare-absolute	Compare-Relative
Total	128	184	55 (95% CI: 51-59)	43.27% (95% CI: 40.14%-46.41%)
Slum	123	176	53 (95% CI: 49-57)	43.09% (95% CI: 39.78%-46.4%)
Non-Slum	130	186	56 (95% CI: 52-60)	43.44% (95% CI: 40.32% - 46.56%)

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Network 2, Peak Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	6.87%	2.99%	-3.88% (95% CI: -3.870% -3.884%)	-56.46% (95% CI: -56.35% -56.56%)
Slum	11.12%	5.42%	-5.70% (95% CI: -5.66% -5.74%)	-51.26% (95% CI: -50.88% -51.64%)
Non-Slum	6.36%	2.69%	-3.68% (95% CI: -3.67% -3.69%)	-57.79% (95% CI: -57.64% -57.94%)

Network 2, Cumulative Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	48.43%	33.12%	-15.31% (95% CI: -15.29% -15.34%)	-31.62% (95% CI: -31.57% -31.67%)
Slum	73.88%	57.53%	-16.35% (95% CI: -16.30% -16.39%)	-22.13% (95% CI: -22.07% -22.19%)
Non-Slum	44.60%	29.45%	-15.16% 95% CI: (-15.14% -15.18%)	-33.98% (95% CI: -33.93% -34.03%)

Effect of interventions on slum and non-slum subpopulations of Network 2, compared to the base case.

The data used in comparing key outbreak parameters in slum and non-slum regions are taken from Table S7, and the corresponding epidemic curves are in Figure 1. The percentage change in peak infection rate due to intervention in slum (-51.3%) and non-slum (-57.8%) regions in Network 2, are comparable, although the magnitudes of the peak infections in slums are about twice those in the non-slum regions. For the cumulative infection rates, the relative drop from the intervention is greater for the non-slum (-34.0% vs. -22.1%) population than it is for the slum population, but the absolute drop is about the same (-16.3% vs. -15.1%).

Table S8: Comparison of results between slum and non-slum in Network 2. The input data is the same as in Table S7.

Network 2, **Base**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	123	130	7(95% CI: 4-9)	5.26% (95% CI: 3.37%-7.16%)
Peak Infection Rate	1.12%	6.36%	4.76% (95% CI: 4.72%-4.80%)	42.79% (95% CI: 42.46%-43.14%)
Cumulative	73.88%	44.60%	29.25%	39.63%

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infection rate			(95% CI: 29.25% - 29.31%)	(95% CI: 39.59%-39.67%)

Network 2, **Vaccination**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	176	186	10(95% CI: 5-15)	5.23% (95% CI: 2.58%-8.46%)
Peak Infection Rate	5.42%	2.69%	2.74% (95% CI: 2.71% - 2.76%)	50.46% (95% CI: 50.06%-50.86%)
Cumulative infection rate	57.53%	29.45%	28.08% (95% CI: 28.04%-28.12%)	48.82% (95% CI: 48.74%-48.89%)

Figure S3 contains the percentage changes between the base case and intervention case for Networks 1 and 2 for the three parameters in the legend, and further breaks down Network 2 into slum and non-slum subpopulations. This plot provides a summary of differences between the base and intervention cases. For all four conditions considered, the intervention reduces the severity of an epidemic. It delays the time when the infection peaks, and reduces the peak infection and the cumulative infection rates. Note that the intervention has a larger effect on the epidemics when applied to Network 1, as consistent with Figure 1.

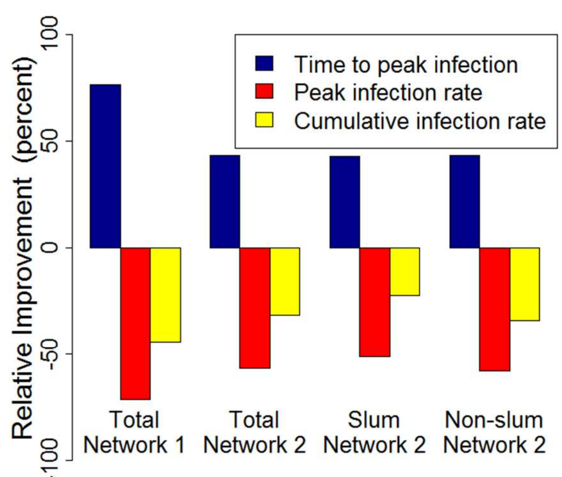

Figure S3: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 than Network 2, while, for Network 2, it is slightly more effective for the non-slum population than slum. Details of the data associated with this plot are provided in Tables S6 and S7.

Figure S4 provides the same data in as in Figure S6, but now the data are provided as absolute differences, rather than as percentage changes. (There are three separate plots owing to the different ranges in absolute differences. Qualitatively, the time to peak infection (blue bars) does not change between the two networks and the two

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subpopulations of Network 2 (Figure S3 versus Figure S4(a)). However, the red bars in Figure S3 are qualitatively different from those in Figure S4(b), when considering absolute changes. That is, the magnitude of the percentage change in peak infection rate between the base and intervention cases is greatest in Network 1 (Figure S3, red bars), while in Figure S4(b), it is least on an absolute change basis. Similarly, the slum population in Network 2 shows the least percentage change in Figure S3, but the greatest absolute change in Figure S4(b). Rankings of the subpopulations in Network 2 is also reversed for cumulative infection rate: the percentage change is greatest in the non-slum region, while it is greatest for the slum regions in absolute terms.

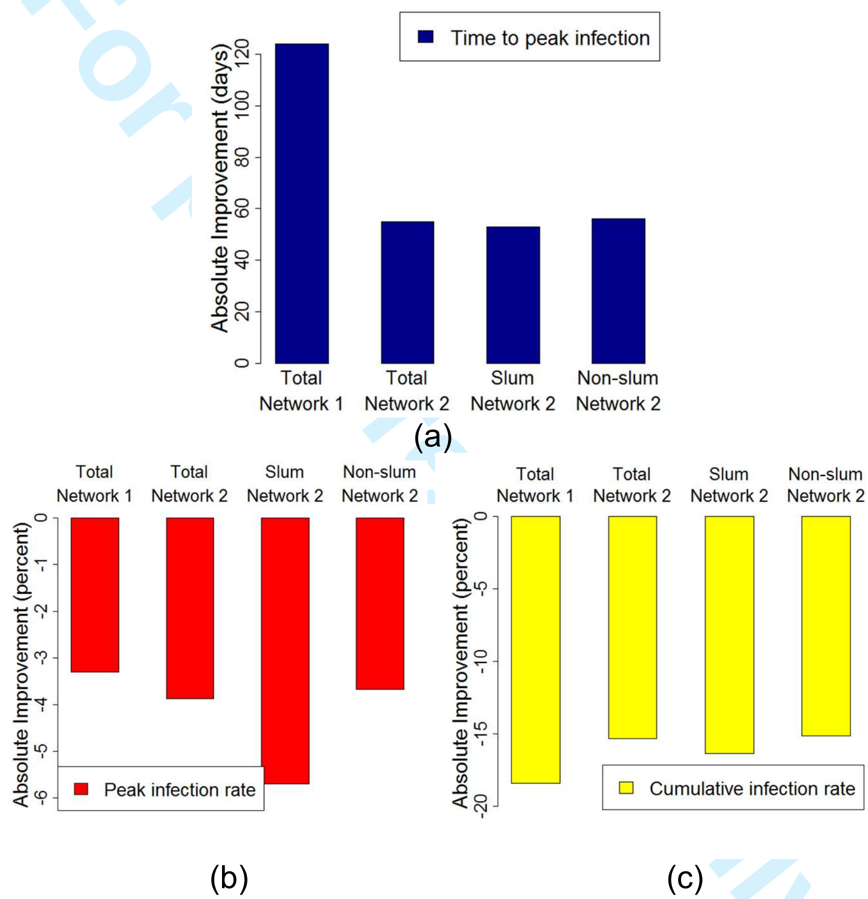

Figure S4: Comparison of absolute difference in improvement; the relative differences are shown in Figure S6. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S6 and S7.

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Evaluation of Network 2 Home and School Contacts.

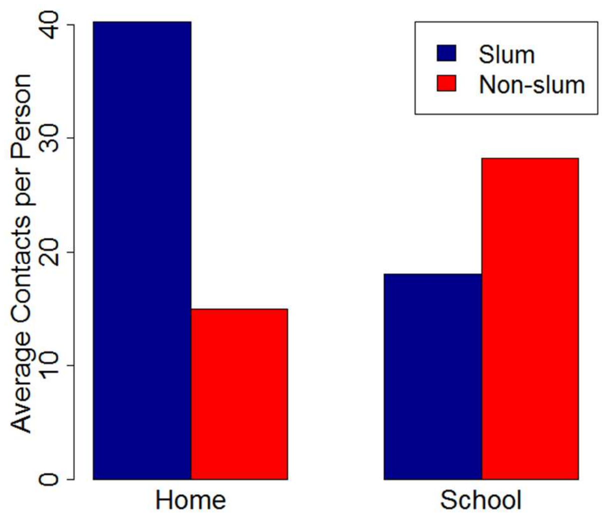

Figure S5: Comparison of average contacts per person in slum and non-slum regions for home and school activity types in Network 2.

Evaluation of Network 2 Edges Transmitting Infection.

Figure S6 provides counts of edges used to transmit infection for a base case simulation in Network 2 of Figure 1 of the main text. Edges are broken down by activity types of people who are interacting during transmission. Data are also broken down by the classifications of individuals interacting (e.g., slum and nonslum, see legend).

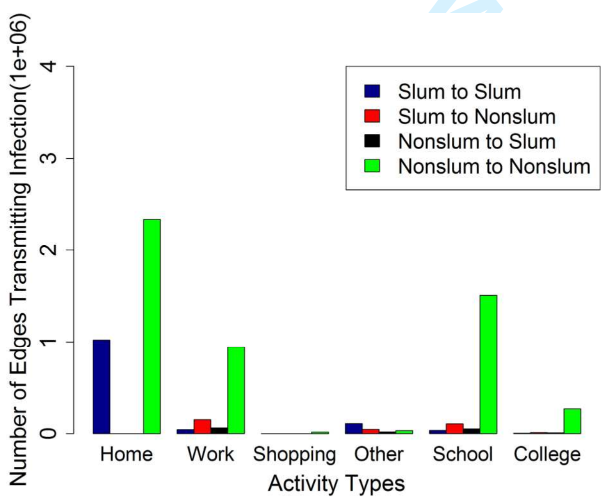

Figure S6. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater than nonslum-to-slum ones because once infection gets into a slum household, it may spread within the household more (because there are more people and connections). Thus, a slum household carries more infection to its interactions with nonslum people. The “Other” activity category, like home activity, shows more edges carrying infection for slum-to-slum interactions than slum-to-nonslum, which is consistent with Figures S4 and S6 of Chen et al.[2], where further network characteristics are given.

Table S9 shows the effect of delay in applying interventions. The numbers show the percentage difference in cumulative infection rate in slums and non-slums of Network 2 for the specified interventions and compliance rates at different trigger levels. For example, the value 30.55% at 0.1% compliance means that for intervention close-schools, where this intervention is implemented after 5% of the total population is infected, the fraction of people in slums that get infected is 30.55% greater than the fraction of non-slum residents who get infected.

Table S9. Differences of epidemic size between slum and non-slum regions for Network 2 for base case (no intervention); close-schools (CS) after 1% total outbreak fraction (CS1) and after 5% total outbreak fraction (CS5); stay at home (SHO); social isolation (ISO); vaccination (VAX) after 1% total outbreak fraction (VAX1) and after 5% total outbreak fraction (VAX5), under various compliance rates. The vaccination efficacy is 30%.

Compliance	Base	CS5	CS1	SHO	ISO	VAX5	VAX1
0.1	29.30%	30.55%	31.94%	31.06%	28.85%	29.37%	29.27%
0.3	29.30%	32.52%	37.03%	34.18%	5.31%	28.85%	28.21%
0.5	29.30%	33.67%	41.07%	20.16%	0.00%	26.72%	24.62%
0.7	29.30%	34.23%	42.57%	0.01%	0.00%	21.94%	15.87%
0.9	29.30%	35.07%	43.95%	0.00%	0.00%	18.31%	7.25%

Table S10 examines the difference in effects of interventions on the cumulative infection rate in Network 2. These data use both the stay home (SHO) and the isolation (ISO) interventions as base cases. Each entry represents the difference between the cumulative infection rates for the specified pharmaceutical interventions and SHO or ISO. For example, 18.03% means that the cumulative infection rate for vaccinating after 5% of the population is infected, is 18.03% greater than that for the intervention of SHO; 31.92% means that the cumulative infection rate for vaccinating after 5% of the population is infected is 31.92% greater than that for the intervention of ISO. Thus, the larger the magnitude of a positive number, the greater the effectiveness of SHO or ISO compared to the specified pharmaceutical intervention.

Table S10. Differences in epidemic size between stay at home (SHO) interventions, social isolation (ISO) interventions and pharmaceutical interventions (VAX0, VAX1, VAX5), under various compliance rates. The compliance rate and efficacy for vaccination is 30% and 30%, respectively.

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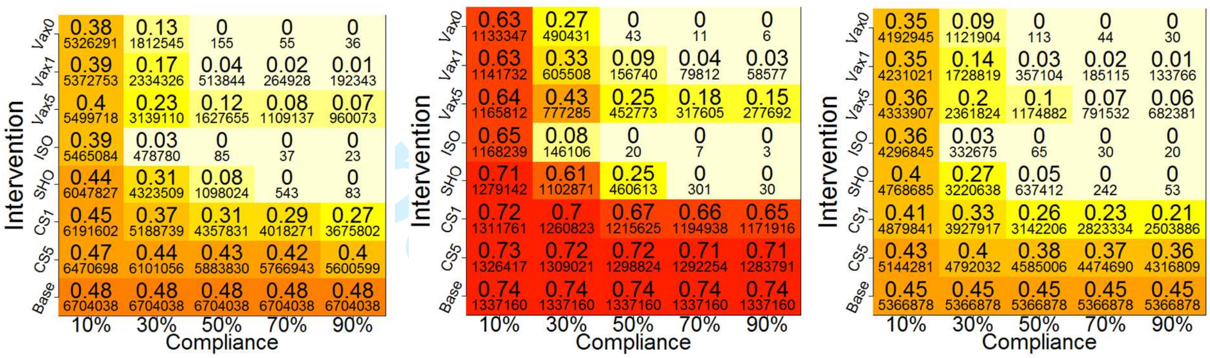
Compliance	Vax5-SHO	Vax1-SHO	Vax0-SHO	VAX5-ISO	VAX1-ISO	VAX0-ISO
0.1	0.71%	0.29%	0.17%	4.92%	4.49%	4.38%
0.3	4.15%	2.39%	1.89%	31.92%	30.17%	29.66%
0.5	18.03%	13.51%	11.35%	25.96%	21.44%	19.28%
0.7	16.82%	9.75%	0.13%	16.82%	9.76%	0.13%
0.9	13.13%	4.01%	0.00%	13.13%	4.01%	0.00%



(a) Total Delhi (b) Slum (c) Non-slum

Figure S7. Heat map of mean cumulative infection rates in Delhi, and slum and non-slum regions under different intervention strategies for Network 2. The vaccination efficacy is fixed at 70%. Five different compliance rates, i.e., 10%, 30%, 50%, 70% and 90% and 4 types of intervention strategies, i.e. vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO), are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used i.e. when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population and the mean cumulative infection rates are calculated separately for the total population, and slum and non-slum subpopulations. Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals. Darker colors correspond to higher infection rates.

Supplemental Information

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Disparities in Spread and Control of Influenza in Slums of Delhi

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Main manuscript

Disparities in Spread and Control of Influenza in Slums of Delhi

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ABSTRACT

Objectives This research studies the role of slums in the spread and control of infectious diseases in the National Capital Territory of India, Delhi, using a detailed social contact network of its residents.

Methods We use an agent-based model to study the spread of influenza in Delhi through person-to-person contact. Two different networks are used; one in which slum and non-slum regions are treated the same and the other in which 298 slum zones are identified. In the second network, slum-specific demographics and activities are assigned to the individuals whose homes reside inside these zones. The main effects of integrating slums is that the network has more home-related contacts due to larger family sizes and more outside contacts due to more daily activities outside home. Various vaccination and social distancing interventions are applied to control the spread of influenza.

Results Simulation based results show that when slum attributes are ignored, the effectiveness of vaccination can be overestimated by 30%-55%, in terms of reducing the peak number of infections and the size of the epidemic, and in delaying the time to peak infection. The slum population sustains greater infection rates under all intervention scenarios in the network that treats slums differently. Vaccination strategy performs better than social distancing strategies in slums.

Conclusions Unique characteristics of slums play a significant role in the spread of infectious diseases. Modeling slums and estimating their impact on epidemics will help policy makers and regulators more accurately prioritize allocation of scarce medical resources and implement public health policies.

Policy Implications Currently, over a billion people reside in slums across the world and this population is expected to double by 2030. This study uses influenza as an example to demonstrate the need to understand the role of slum populations in the spread and containment of infectious diseases.

Strengths and limitations of this study

- We show that the unique attributes of slums must be accounted for in understanding the spread and control of infectious diseases.
- Intervention strategies have been applied one at a time but a combination of them could be used simultaneously to more aggressively control the epidemic.
- This study does not consider age-specific susceptibility or immunity from past infections; all individual persons are assumed to be equally susceptible.
- The disease transmission risk does not change across activity types, e.g. an hour with an infected person at home or at work carries the same risk.
- Co-location based contact time is used as a proxy for physical proximity and short-distance environmentally-mediated transmission.

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INTRODUCTION

Infectious disease is one of the leading causes of human morbidity and mortality worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000 people in the United States (US) are hospitalized with influenza-like illness (ILI) symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the National Institute of Virology has shown that ILI cases are present throughout the year, although they peak in rainy and winter seasons.[3] It carries a significant economic burden through reduced productivity and high costs of health care.[4-7] A CDC study finds that for outpatient and non-medically attended individuals, acute respiratory infections cost 1%-5% of monthly per capita income in India. In contrast, cost of inpatient care can be as high as 6%-34% of monthly per capita income.[8] For developed countries, the annual cost of influenza is estimated to be between $1-$6 million per 100,000 people, according to the World Health Organization.[9]

In 2007, India established an Integrated Disease Surveillance Program (IDSP), which included a network of 12 regional laboratories, to minimize the threat of avian influenza and other highly infectious zoonotic diseases.[10] India faces some unique challenges in surveillance, prevention and control because of the seasonality of influenza at sub-regional levels. This seasonal variation depends upon latitude, monsoon season, humidity and climatic factors of the regions. Acute respiratory infections are estimated to be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13] estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in year 2011, and children under age 5 had the highest incidence of them.

Given that influenza is environmentally-mediated and spreads through close proximity, population density is an important factor in its spread. In India, the average population density is about 1000 people per square mile; in the slums, it can be 10 to 100 times higher.[14] Larger household size and crowding make it easier to transmit infections).[15-18] For example, Baker et al.[16] find that meningococcal disease risk among children doubles with the addition of 2 adolescents or adults (10 years or older) to a 6-room house. Other than overcrowding, slums are characterized by their lack of medical services,[19-20] which makes slum residents highly vulnerable to infectious diseases. Diseases like cholera, malaria, dengue and HIV are common in slums across the world.[21-23]

This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8 million people live in slum areas, as an example city to study the spread and control of influenza. Delhi is an interesting case study. It ranks fourth in the world in urban population, and, among the top 25 largest urban areas, it ranks tenth in population density. Moreover, the results are likely to be generalizable to other slum areas within and outside of India.

This paper is an extension of the work done in Chen et al.[4], which shows that slum populations have a significant effect on influenza transmission in urban areas. Ignoring the influence of slum characteristics underestimates the speed of an outbreak and its extent. However, Chen et al.[4] do not consider any interventions on the epidemic spread. *The focus of this research is to study the effect of different intervention strategies on several subpopulations (slum, age and gender) in two different Delhi networks, i.e., original (referred to as Network 1) and refined (Network 2).*

The original network used in Xia et al.[24] studied the spread and control of influenza in Delhi using Network 1, which did not take into account the special attributes of the slum population, such as larger family sizes and different types of daily activity schedules. Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for slum demographics and slum activities, but did not study intervention strategies. In Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.

The goals of this work focus on understanding the effects of pharmaceutical and non-pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI) include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing measures such as school closure, quarantine and staying home. These effects are studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a scenario where interventions can be applied to a limited number of individuals, we explore how resources should be split between slum and non-slum subpopulations in order to achieve the best outcomes with respect to total infection rate (i.e., the cumulative fraction of a population infected).

METHODS

We use an agent-based modeling (ABM) approach to simulate the spread and containment of influenza in social contact networks of Delhi, India. We compare two networks: one considers slum-specific attributes, and the other does not. In this section, we describe the networks, the disease model for each agent, the interventions, and the heterogeneities of the problem that make ABM uniquely suited to study epidemics. Throughout this manuscript, each agent in the ABM is an individual human.

Social Contact Networks: This study uses two synthetic social networks of Delhi, created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found in Xia et al.[24], Chen et al.[4], Barrett et al[25], Bisset et al.[26] and references therein. The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined network developed in Chen et al.[4], *Network 2*.

Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set of activities of individuals, and the locations of those activities including geo-locations of residential areas, shopping centers, and schools, collected through surveys by MapMyIndia.com. By assigning activity locations to individuals' activities, people are located at particular times at particular geographic coordinates (including office buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between individuals are estimated when each person is deemed to have made contact with a subset of other people simultaneously present at the same location. This gives rise to a synthetic social contact network where network edges represent these contacts.

Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the individuals whose homes reside in the slum polygons. Slum residents' attributes and their daily sets of activities are collected through a ground survey in Delhi slums, by a vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from *MapMechanic.com*. Individuals living in the slum regions are a part of the slum population. All other individuals are part of the non-slum population. Network 2 is a geo-located, and contextualized social contact network of Delhi with slums integrated in it.

Following are the main differences between the original network (Network 1) and the refined network (Network 2). The original social contact network treats the slum regions like any other region in Delhi in terms of assignment of demographics and individual activities, i.e. no special consideration is given to slum residents. The refined Network 2 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific demographics and activities to the individuals whose homes reside inside these polygons. Thus, the number of individuals is the same in both populations. The slum population constitutes about 13% (1.8 million) of the entire Delhi population of 13.8 million people. The main effects of integrating slums is that Network 2 has more home-related contacts due to larger family sizes and more outside contacts due to more daily activities outside home. Also, those individuals who reside outside of slum zones have the same activities in both networks. Overall, there are over 231 million daily interactions between pairs of individuals. Table S1 compares those two networks as well as data sources for slum and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are in the supplementary information (SI)). For example, the average degree increases from 30.4 to 33.4 from Network 1 to Network 2, and the maximum degree increases from 170 to 180. We refer to Chen et al.[4] for more detailed information about the two networks. Several plots of properties and structural characteristics of Networks 1 and 2 are given in Chen et al.[27].

Disease Model: An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. Each node in the network represents an individual, and each edge represents a contact on which the disease can spread. A contact represents possible transmission between two people that are co-located for some duration (based on their activity schedules). This is an approximation to model direct contact and short-distance environmentally-mediated transmission that might include direct physical contact, fomite mediated, and airborne transmission.[28]

We start each epidemic simulation with 20 index cases, randomly chosen. (We find that results are not sensitive to the number of initial infections.) The detailed description of the SEIR model as well as the choices of transmissibility value, R_0, the explicit incubation and exposed periods can be found in the supplementary information. This disease model has been used in other works such as Liao et al.[29], Marathe et al.[30].

The transmissibility value for disease transmission is that for the strong influenza model in Chen et al.[4]. That work used mild, strong, and catastrophic influenza models, so we chose the intermediate transmissibility. This corresponds to base attack rates (i.e., cumulative infection fractions) of 0.42 and 0.48, respectively, in Networks 1 and 2. These rates are generally higher than those in some other studies that either compute experimental attack rates from cases or compute them in modeling studies such as this one. Attack rates used by past researchers for different strains of influenza include Asia [0.22 to 0.50],[31] Southeast Asia [0.11 to 0.31 in children [32]; 0.05 to 0.65 [33]], and India [0.111 to 0.235 [34]; 0.074 to 0.424 [35]; 0.045 to 0.294 [36]; 0.008 to 0.100 [37]; 0.209 for various strains [13]]. The results of Chen et al.[4] indicate that the results here, for this particular transmissibility, will be qualitatively the same for other transmissibilities, but will scale down or up as transmissibility changes in the same direction.

Interventions: This work considers three vaccination scenarios, i.e., vaccinate when cumulative infection rate is 0% (VAX0, i.e. vaccinate on day 1), 1% (VAX1), and 5% (VAX5). Three classes of social distancing strategies are considered: (i) stay-home (SHO) if infected, i.e. eliminate all non-home related contacts but continue to maintain contacts within the household; (ii) close-schools when cumulative infection rate has reached 1% (CS1) and when it has reached 5% (CS5), i.e. eliminate school related contacts; and (iii) (ISO), in which all contacts, including home contacts, of a person are eliminated when a person becomes infectious. For vaccination, five different compliance rates (10%, 30%, 50%, 70%, 90%) and two different vaccine efficacies (30% and 70%) are considered.

VAX0, SHO, ISO are all fairly aggressive interventions because they are implemented either before a person gets infected or immediately upon becoming infectious. These are actions taken at the individual or family level. For example, vaccination before the influenza season or isolating a sick child at home are family decisions. Even CS1 is an aggressive intervention in the sense that this action is taken by government officials based on aggregate school sickness levels—closing schools before any outbreaks is typically not done. From these starting points, vaccinations when 1% or 5% of the population is infected (VAX1, VAX5), and closing schools when 5% of the population is infected are less aggressive treatments (CS5). The five levels of compliance are also variations on aggressiveness in treatments.

These conditions and parameters are consistent with results from other studies and guidelines put out by international organizations. A meta-study of immunization and slums [38] identifies several vaccination-related studies of slums in India. Unfortunately, these studies are for other diseases such as Hepatitis B, measles, mumps, malaria, and typhoid fever. Nonetheless, slum vaccination rates for children over these ailments range from 25% to 69% for full immunity and from 15% to 55% for partial immunity. Vaccination effectiveness for influenza-like illness (ILI) in India was determined to be about 33% to 36%.[39] In 2012-2013, of 1000 pregnant women in Srinagar India, none were vaccinated against influenza.[40] With regard to school closures, the World Health Organization (WHO) states that school closures may be undertaken proactively (before an outbreak) or reactively (after influenza starts to spread).[41] WHO recommends that school closure occur before 1% of the population becomes infected. It also recommends that people (students and staff) stay home when they feel ill. In another meta-study[42], it was found that school closure, effected when 0.1% of the population was infected, was twice as effective in reducing the total attack rate as school closure occurring after 1% of the population was infected. Moreover, the percentage of people infected before school closure was triggered varied between 0.02% to 10% across several studies.

When a susceptible node is vaccinated, its probability of getting infected by an infectious node is scaled down by the efficacy. If it becomes infectious, its probability of infecting susceptible nodes is also scaled down by the efficacy. In other words, both incoming and outgoing infection probabilities of vaccinated individuals are reduced by the vaccine efficacy. Interventions are applied to slum residents, non-slum residents, and the entire region of Delhi.

For each experiment, 25 replicates are simulated for 400 days, and their mean results are reported. The averages are time-point wise averages, e.g. the mean infection rate at day 100 is calculated by taking the average of the 25 infection rates that occur on day 100 of each replicate. Table S2 summarizes all the interventions considered, and Table S3 contains all variables in simulations, including intervention parameters.

Heterogeneities captured: There are several heterogeneous aspects to this problem that motivate the use of an ABM approach: (i) the 298 slum zones have populations that vary by more than four orders of magnitude in size; (ii) the geographic extent of slum zones differ; (iii) the slum zones are located at irregular spatial intervals throughout Delhi; (iv) the activity patterns of people living in slums are different from those in the non-slum region; and (v) each individual interacts with specific others based on co-location.

The implications of these heterogeneities include the following. First, the particular synthetic households that live within slums are predicated on the number of slum zones, their locations, and their spatial geometries. These homes have larger family size and hence more home contacts. Second, slum individuals have different activity patterns which change the co-located contacts of each slum person: that is, with whom they interact and for how long. For example, see the supplemental information of Chen et al.[27]. The average total contact durations by activity type and by slum/non-slum residents are provided, which show that non-slum people have greater contact durations for work, school, and college activities, but less for home and other types. Overall, a slum person has about 50% greater total contact duration per day compared to a non-slum person. The same supplemental shows that in the age range 20 to 60 years (by year), females that live in slums have more contacts per day than their male counterparts. However, females whose homes are outside of slum regions have average number of daily contacts that are below their male counterparts.

RESULTS AND ANALYSIS

Our results are grouped as follows. (1) Comparison of Network 1 and Network 2 for base case and intervention cases. (2) Results for both networks based on demographic classes, such as slum/non-slum, gender, and age groups, for a wider range of intervention strategies. (3) Comparison of Network 1 with the non-slum population of Network 2. (4) Effects of pharmaceutical and non-pharmaceutical interventions for a wide range of parameter values. (5) Effects of different resource allocation strategies.

All differences are tested with the two-sample t-test and they are all statistically significant with p-values smaller than 2.2e-16. The 95% confidence intervals are given for each comparison. Here is a brief summary of selected results with examples of mechanisms, to provide a high-level overview. Details of results follow this summary and these details matter because there are many factors (inputs) in a simulation whose interactions change results.

(1) Ignoring the unique attributes of slums in a population overestimates the benefits of the interventions. For example, in the case of vaccination intervention (efficacy 30% and compliance 30%), the values for the epidemic size (i.e., cumulative percentage of infected), peak infection rate (i.e., maximum percentage of a population infected on any day), and time to peak are 33.1%, 3.0%, and 184 days, respectively, in Network 2, whereas they are 23.3%, 1.34%, and 286 days in Network 1. In relative terms, the epidemic size and peak infection rate are underestimated by 42.2% and 123.2% respectively, while the time to peak is overestimated by 35.7% in Network 1 (see Figures 1, 2 and Table S4). The larger family sizes for slum families in Network 2 and the increased number of edges result in larger outbreaks and faster time to peak infections.

(2) Interventions are more effective in Network 1 than Network 2 for all types of interventions: vaccination, closing schools, staying home, and isolation. These trends also hold over wide ranges of efficacy and compliance (see Figures 3, 4, S1, S2 and S3). Hence, not accounting for slums gives overly optimistic results for the effectiveness of the interventions. The reduced average family size in Network 1 means fewer within-home edges, which slows infection and reduces spreading. Closing schools and staying home interventions do not affect home edges. However, the magnitude of this effect varies with intervention conditions (e.g., compliance rate, time at which intervention is applied).

(3) Cumulative infection rates by subpopulation in Network 2 show that slums sustain greater infection rates than non-slums under all intervention scenarios, sometimes by as much as 44.0%. See Figure 4 and Table S5 for more details. This is due to the greater household sizes in slums.

(4) For Network 2, under a wide range of intervention compliance rates (10% to 90%), the isolation strategy is up to 32% more effective in containing an outbreak than vaccination (for 30% efficacy). Staying home is up to 18% more effective than vaccination at 50% compliance. See Figure 3 and Table S6 for more details. Isolation,

although hard to implement from practical considerations, is most effective because edges to susceptible individuals are removed (isolation also provides a good comparative case). Differences between staying home and vaccination depend on compliance rates.

(5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse effect in slums than in non-slum regions across compliance rates from 10% to 90%. See Figure 4 and Table S7 for more details. Early interventions mean actions are taken when outbreaks are smaller and are therefore more readily contained.

(6) Comparison of Network 1 (Figure 3a) with the non-slum population (Figure 4b) of Network 2 shows that just the presence of slum specific activities and interactions with non-slum population makes social-distancing based interventions less effective in the non-slum regions of Network 2.

(7) A full-factorial design that splits resources between slum and non-slum regions indicates that the most effective intervention is to give vaccines to slums and apply social distancing to non-slums. Applying vaccine and social distancing to slum regions is the next most effective intervention. See Figure 5. By applying social distancing to non-slums, these individuals are kept isolated from slum individuals that are infected. The greatest benefits accrue to the slum populations.

Comparison between Networks 1 and 2: Base case versus interventions

We start with a comparative analysis of the influenza epidemic, with and without interventions, on Network 1 and Network 2 to measure the impact of integrating slums in the population on epidemic measures. Figure 1 shows the average simulation time histories for the base case, and when vaccination is applied randomly to 30% of the population in each network with vaccine efficacy set at 30%. Mean infection rate is the daily fraction of infected individuals. It is the time-point wise average over 25 simulations. For example, the mean infection rate at day 100 is calculated by taking the average of all 25 infection rates. Simulations for other vaccine efficacies and compliance rates give qualitatively similar results. Two sets of those results are shown in the supplemental information, see Figures S1 and S2. Note that Network 1 does not distinguish between slum and non-slum individuals, so the epidemic curve is not split by subpopulation.

Results in Network 2 differ significantly from results in Network 1 for both the base case and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a larger epidemic size and has higher peaks compared to the corresponding epidemic quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to plan, there will be a false sense of security and lack of urgency to implement interventions. For both the base case and the intervention case, ignoring unique characteristics of the slums will result in an underestimation of the infections and the speed of spread.

Figure 1 goes here

For the intervention cases, the time to peak infection decreases by 35.7%, i.e. from 286 days for Network 1 to 184 days for Network 2, meaning an influenza epidemic would peak roughly 100 days earlier than one would expect based on the results from Network 1. For the base case, time to peak infection drops by 20.8%, i.e. 34 days reduction for Network 2 as compared to Network 1.

Percentage changes and differences must be viewed cautiously, and to illustrate this point, we present data for the key parameters in Tables S4 and S8. The difference in the peak infection rate (i.e., the maximum fraction of daily infected individuals during the simulation) between Networks 1 and 2 for the base case is 2.2%, or 47.6% in percentage change (see Table S8). For the intervention case shown in Table S4, the difference between the two networks is less (1.7%), but the percentage change is more (123.2%) because the magnitudes of the peak infection rates are reduced when effective interventions are used. We make note of this here and mainly use the percentage change values in discussing results. For more detailed comparison between vaccination intervention and the base case in Network 1 and Network 2, we refer to Tables S7 and S9 and Figures S4 and S5.

Comparison between Networks 1 and 2 based on individual demographic information

We divide the Delhi population into strata by age, gender, and geographic home location (i.e., slum and non-slum), and analyze mean cumulative infection rates by subpopulation for the two networks. In simulations, individuals are chosen at random in the entire network for vaccination. Various vaccination scenarios are investigated.

Figure 2 displays the cumulative infection rate results. On the x-axis, ‘Total’ refers to the entire population of Delhi. There are three breakdowns of the entire population. ‘Slum’ and ‘Non-slum’ refer to slum and non-slum regions, respectively. ‘Male’ and ‘Female’ denote the total number of males and females in Delhi, respectively. Four age groups are considered: ‘Preschool’ (0-4), ‘School’ (5-18), ‘Adult’ (19-64), and ‘Senior’ (65+). The black lines correspond to the mean cumulative infection rates for the base case. Other curves indicate vaccination strategies under different levels of vaccination rate (v) and vaccine efficacy (α). Two vaccination rates (30%, 50%) and two vaccine efficacy rates (30%, 70%) are shown in the figure.

For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all categories of individuals.

Main manuscript

In Network 1, slum and non-slums are treated the same so the infection rates are identical in Figure 2. However, all scenarios in Network 2 show a higher burden of disease on the slum population. This is due to the fact that slum households have larger family size and more contacts on average than households in non-slum areas, see Chen et al.[27] As shown later, we find similar patterns of infection in slum and non-slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.

The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums results in overestimation of the benefits of interventions in terms of reduction in the mean cumulative infection rate and peak infection rate, as well as the time to peak. This optimism holds for slum, non-slum and total population under various levels of vaccination rates and efficacy rates in Network 2. See Table S10 for more detailed comparison of results between slum and non-slum in Network 2.

Figure 2 goes here

Comparison between Networks 1 and 2 across a wide range of intervention strategies

Next, we consider a variety of intervention strategies for comparative analysis. We consider vaccination, school closure, stay home, and isolation strategies. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at home (SHO) strategy, all non-home activities and interactions are eliminated but all contacts within the household are maintained. Under isolation (ISO) an individual has no contact with other individuals (even home interactions are eliminated). The stay-at-home and isolation interventions are implemented for compliant infectious individuals, after they become infectious, for the entire infectious duration.

Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a wide range of intervention strategies. For each strategy, five different compliance rates are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers are the actual number of infected individuals. Darker colors correspond to higher infection rates. Note that compliance rate is simply the vaccination rate for strategies VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire population. The 'Base' values do not vary with compliance because the base case has no intervention. Note that all heat maps in this paper use the same color scheme so that colors can be compared across figures.

Since Network 1 does not distinguish between slum and non-slum populations, we only compare the two networks for the whole of Delhi. The general pattern is similar for both networks. However, all interventions have a larger effect on Network 1 under the same compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0, stay-home, and isolation strategies in Network 1 as compared to those for Network 2.

Figure 3 goes here

At a high level, among all intervention strategies, early vaccination (VAX0 and VAX1), social isolation (ISO), and stay home (SHO) are more effective than the other strategies, and this is more readily observed at higher compliance rates. For these more effective strategies, the interventions per person are implemented right after (or very shortly after) the person is infected. For example, SHO is implemented immediately after a person becomes infectious. Thus, a person that becomes infectious can infect their family members, but if these other members become infectious, then they, too, will be confined to home. Thus, home-bound people can infect their family members, but no one beyond their family (for 100% compliance). As compliance rate increases, this effect approaches, roughly, a "family-based" isolation intervention (similar to ISO), consistent with the results in Figure 3 and in subsequent results.

Effect of vaccination versus social distancing on slum and non-slum subpopulations

We now compare the impact of vaccination and social distancing on slum and non-slum subpopulations from Network 2. Social distancing interventions are close-schools, stay-home, and isolation.

The mean cumulative infection rates (and actual numbers of infections underneath) for each compliance level are shown in the heat maps in Figure 4 for slum and non-slum populations in Network 2. The axis labels are identical to those in Figure 3, as is the color scheme of the cells. The base case values are constant since there is no intervention and hence no compliance. Darker colors correspond to higher infection rates.

Compared to the base case, all interventions reduce infection rates to some extent. As the compliance rate increases, infection rates drop for all interventions. Infection rates drop to zero in slum and non-slum regions at a compliance level of 70% or higher, under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce the infection rates significantly, and this effect increases with compliance rate.

The following observations can be made from Figure 4. Social distancing, i.e. SHO, at low and intermediate compliance and CS at all compliance levels, are less effective in slum regions as compared to non-slum regions. This is because CS only eliminates school interactions for those attending school, and there are fewer school edges in slums compared to non-slum areas, as shown in Figure S6. The effectiveness of CS in slums is mitigated by the greater average number and duration of interactions at home in slums as compared to non-slums (see Figure S6 and Chen et al.[27]). Thus, if a person is sick, there is a greater chance of transmitting contagion to family members, who then may have activities outside of school, thus circumventing the CS intervention. At high compliance, SHO is effective because all interactions outside home (including school) are eliminated.[27]

These observations are also supported by Figure S7, which contains numbers of edges used to transmit contagion for a base-case run of Figure 1. There are several effects that bear on the above observations. First, in the cases of activities “work”, “other”, and “school”, the number of edges transmitting contagion from slums to non-slums is greater than the reverse: from non-slum to slum. Second, in two of these three activity categories, there is more slum to non-slum transmissions than slum to slum transmissions. Edges of transmission for slum dwellers is dominated by home interactions. The infected homes in slums serve as launching points to drive disease to non-slums through slum to non-slum interactions. (There are no ``mixed’’ edges at homes, and shopping and college activities have low levels of slum activity because of socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but we now return to Figure 4.

Isolation works well at 30% or higher compliance rates, but it is a much harder strategy to implement, especially in slums. However, it is considered here for comparative analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as compliance increases. However, close-school is generally less effective because this intervention removes only a fraction of interactions for a fraction of the population, i.e. school aged children. Simulations were also run for 70% vaccine efficacy. Since results are qualitatively similar for those parameters, these plots are provided in Figure S3.

Figure 4 goes here

Comparison between Network 1 and non-slum areas of Network 2

Note that Network 1 treats all parts of the region as non-slum, i.e. all individuals follow non-slum activities and demographics. In order to capture the additional disease risk to the non-slum population that arises from the interactions with the slum population, we compare Network 1 in Figure 3a with the non-slum population of Network 2 in Figure 4b. In base case, the additional disease risk to the non-slum population goes up from 42% to 45%. However, the beneficial effects of social distancing strategies drop by a large amount, e.g. close school strategies are 5-20% less effective in the non-slum areas of Network 2. This effect changes non-linearly with the compliance rate. As compliance rate goes up, the difference between performance of Network 1 and non-slum parts of Network 2 goes up in CS1 and CS5. This implies that in Network 2, non-slum population requires much higher levels of compliance to achieve the same results as in Network 1. This difference is less stark for vaccination based interventions, i.e. VAX0, VAX1 and VAX5. This is expected since the effect of vaccination is less dependent on interactions; it is only through herd immunity that interactions come into play.

Constrained resource allocation among slum and non-slum areas

We consider a specific scenario under Network 2. If only a limited number of vaccines are available, and only a certain fraction of individuals can be kept home during an epidemic, how should these interventions be applied to the slum and non-slum regions so that the epidemic can be controlled effectively? Given that slum residents' attributes differ from those of non-slum residents, is there a strategy that works better in slums than in non-slum areas? The total population in Delhi is about 13.8 million, which includes about 1.8 million slum residents. We assume that only 10% of the total population can be covered by interventions, half through vaccination and the other half through stay home. Enough vaccines are available to cover 5% of the total population (i.e. 692,183 vaccinated, corresponding to about 38.25% of slum or 5.75% of non-slum population), and 5% of the individuals can stay home (692,183 individuals; this is applied to only the infected individuals). Note that an individual may receive a vaccine and also stay at home if this individual, in spite of being vaccinated, gets infected.

We consider 4 different ways of applying interventions to 10% of the total population: (i) apply both interventions to slums, i.e. give all vaccines to slums and apply SHO only in the slums (VsSs); (ii) apply all interventions to non-slum areas (VnSn); (iii) give vaccines to slums and SHO to non-slums (VsSn) and (iv) give vaccines to non-slums and apply SHO to slums (VnSs).

For both types of intervention, the same number of individuals is chosen randomly from slum or non-slum areas. 10% of the total Delhi population amounts to 76.5% of slum population, 11.5% of the non-slum population, or a combination of 38.25% of the slum and 5.75% of the non-slum population (i.e. half from slums and half from non-slums). Figure 5 shows the mean cumulative infection rates, as well as the number of infected from the entire population of Delhi, the slums, and non-slum areas under each of the four scenarios. The first 3 columns refer to Network 2 and the last column shows results for Network 1. Since Network 1 does not distinguish between slum and non-slum areas, the infection rates in each subpopulation remain the same as for the total population.

Comparison of the last two columns in Figure 5 indicates that the non-slum population in Network 2 faces 3-5% additional disease risk compared to Network 1 in all cases. This is primarily driven by the increased interactions within slum populations and between slum and non-slum populations in Network 2.

In Figure 5, all four intervention strategies produce essentially the same total attack rates (around 43% to 44%), a drop of 4% to 5% over the base case. The dominant effect on Network 2, is the benefits that primarily accrue to the slum population for the VsSs and VsSn strategies because they drive down the fraction of infected slum residents from 0.74 to 0.55 or 0.58. Also, as described in the context of Figures 4 and S6 above, social distancing of the non-slum residents helps to isolate them from the infected slum residents. Results such as these may be helpful to policy makers in breaking the poverty trap in economically poor regions.[43]

Also, the strategy of vaccinating non-slums and social distancing slums (VnSs) is not as effective as the interventions in rows 1 and 2 of Figure 5. This is a counterintuitive result, since the density of population is much higher in the slums, which may lead to the belief that social distancing in slums will break up the dense clusters. However, a careful examination shows that keeping slum residents home is not an effective social distancing strategy because their family size is, on average, almost 3 times the family size of non-slum households.[27] The high level of mixing at home makes social distancing ineffective in slums unless the infected individual is completely isolated. However, complete isolation is not viable in slum areas where the entire household may live in a single room.

Figure 5 goes here

DISCUSSION

With slum populations expected to grow to 2 billion by 2030,[44] it is becoming increasingly urgent to understand how to control the spread of infectious diseases in slum areas and measure its effect on urban populations. To our knowledge, a detailed study of interventions to control influenza epidemics in slums, using an agent-based simulation model, has never been done before. Slum conditions are important for a city beyond the direct effects of disease transmission. For example, civil wars may be precipitated or exacerbated by disease outbreaks because they decrease social health and welfare.[45]

Even though slum regions contain only 13% of the total population of Delhi, Chen et al.[4] show that omitting their attributes leads to underestimation of the overall infection rate and the peak infection rate of the epidemic. This paper extends that work by evaluating the differential impact of interventions on slum and non-slum regions. Various vaccination and social distancing strategies are analyzed under different scenarios that show that the slum population is more prone to infections under the same control measures. Furthermore, taking account of slum populations significantly alters the disease dynamics in the *entire* population. Differences in key measures are demonstrated between the cases of accounting for slum populations and not: e.g., a 100% increase in the peak attack rate in some cases when slum regions' characteristics are taken into account, compared to the case when they are ignored.

Figure 4, which compares infections in slum with non-slum areas, shows that at very high compliance rates, some interventions can be equally effective in both slums and non-slums. However, such high compliance rates are typically not feasible due to practical realities on the ground, and also because they require timely diagnosis of infected cases. For SHO to be effective, the coverage rate needs to be 70% or more in both slums and non-slums, and the diagnosis of the infected individuals needs to be correct and immediate. In other words, effective control of a contagious epidemic in a

high-density place like Delhi, would require either early and drastic action (e.g. ISO) or a highly compliant set of individuals, or a combination of these features.

This work overall demonstrates the power of agent-based and population modeling to evaluate complicated interaction-based epidemiological phenomena. Clearly, there are limitations to this work (several are itemized below). But these agent and population approaches provide a platform for adding additional complexity. All of the figures demonstrate that quantitative results depend on complicated interplay among inputs. These results are important because they inform policy decisions. An equally important benefit of this type of work, but not often stated, is developing intuition about epidemic dynamics (in this case, with the effects of slums), to enable decision makers to reason about nuanced interactions among effects to a degree that is hard to obtain with other approaches that lack this level of detail.

Despite the detailed modeling effort, there are limitations of this work and areas for improvement in the future. For example: (1) Examination of different population level base attack rates derived from different transmission probabilities. (2) Different susceptibilities and infectivity for individual agents; e.g., based on age. (3) Effects of asymptomatic infections (although we have addressed this to some extent with compliance and efficacy of interventions). (4) Seasonal effects.[46-47] (5) Effects of immunity for an individual from previous infections (in previous seasons). (6) Evaluation of interaction of different strains from season to season. (7) Comparison of tropical versus subtropical factors. (8) Evaluation of a specific outbreak scenario. (9) Impact of sickness on absenteeism from work and its economic ramifications. (10) Effects on rural versus urban populations. (11) Using combinations of interventions rather than one at a time; this was only done here in Figure 5. However, to disambiguate results, it is prudent to first examine individual interventions. (12) Effect of changing disease transmission rate for different activity types. (13) Effect of changing contact times at different locations. (14) To capture close-proximity transmission, one could use actual physical proximity. Here, we use colocation. Finally, just as changes in modeling details can change model results, so, too, changes in the conditions in actual outbreaks can change results; some of these factors are listed above. It is essentially impossible to capture all of these effects—many of which are unknown—down to the level of individual humans.

Public health implications: This research demonstrates that modeling slum populations is important, not only for understanding disease dynamics, but also for designing effective control measures. Ignoring the influence of slum characteristics on their urban environment will significantly underestimate the speed of an outbreak and its extent, and hence will lead to misguided interventions by public health officials and policy planners. Lessons from this research can be applied in the field and observations collected from the field can provide valuable data to improve the models and validate the results. For example, our results show that a slum resident has about 50% greater total contact duration per day compared to a non-slum resident. This makes social distancing based interventions more taxing in the slum population. Public health policy makers may want to subsidize pharmaceutical resources for the slum population to make them more affordable. Similarly, we find women in slums have a higher number of contacts per day than their male counterparts whereas in non-slum regions, women have a fewer number of daily contacts than their male counterparts. This kind of information can be used to prioritize the distribution of limited resources, e.g. women could be given preference over males for vaccination in slum areas. This research provides simulation-based evidence that in general social distancing strategies are ineffective in slums because of a large number of contacts at home. Unless one applies complete isolation, which is not feasible in slums, just staying at home still keeps a large number of contacts and pathways of spread intact.

Contributorship statement

AA, SE, CJK, AM, MM, SS, AV designed and conceived the study. SC carried out the experiments and simulations. SC, CJK, AM performed data analysis. CJK, BL, AM, MM, EKN, MLW helped with reviewing the results and writing the paper.

Competing Interests

There are no competing interests.

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Data Sharing Statement

Data pertaining to figures and statistical analysis are partially provided in the supplementary file, and also can be obtained by contacting the corresponding author through email.

Main manuscript

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Main manuscript

FIGURE 1: Epidemic curves for base case and vaccination case. Each time point in the curve is an average over 25 replicates. The vaccines are given randomly to 30% of the entire population and the vaccine efficacy is 30%. For Network 2, epidemic curves are shown for total population and slum and non-slum subpopulations. 'Intervene Total' refers to the epidemic curve of the entire Delhi population when the vaccine intervention is applied. 'Intervene Slum' refers to the epidemic curve for just the slum population, and 'Intervene Non-slum' refers to the epidemic curve for just the non-slum population for the intervention case. Epidemic curves for a variety of compliances and efficacies are reported in Figures S1 and S2.

FIGURE 2: Mean cumulative infection rates for different subgroups in the two networks. Two vaccination rates (v = 30%, 50%) and two vaccine efficacy rates (α = 30%, 70%) are considered. Individuals are chosen at random in the entire network for vaccination on day 0. Mean infection rates are calculated within each group. The last several lines in the plot for Network 1 are overlapping at the bottom because the mean infection rates are almost zero under those scenarios. 'Total' refers to the entire population of Delhi. 'Slum' and 'Non-slum' refer to slum and non-slum regions, respectively. 'Male' and 'Female' denote the total number of males and females in Delhi, respectively. Age groups are denoted by 'Preschool', 'School', 'Adult', and 'Senior'.

(a) Total Delhi Network 1 (b) Total Delhi Network 2

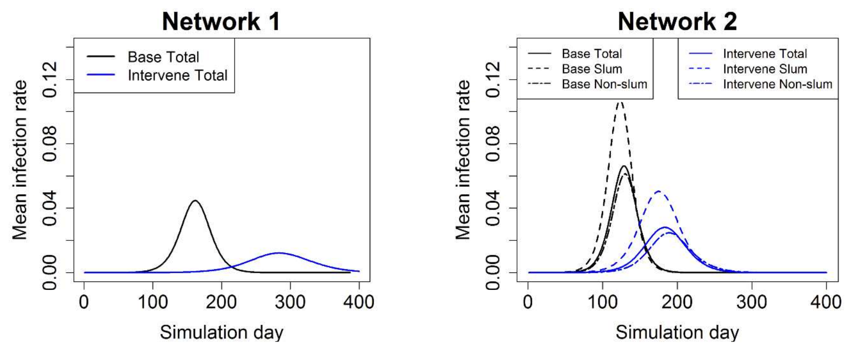
Figure 3. Mean cumulative infection rates under different interventions for Network 1 and Network 2. The larger font numbers are fractions of populations that are infected and the smaller font numbers are counts of infected individuals. Colors of the boxes correspond to the values of the large numbers (i.e., fractions of infected), and the same scheme is used for both plots for comparisons—and for all plots in this paper. Five different compliance rates are examined (10%, 30%, 50%, 70% and 90%), and 4 types of intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when the cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5) of the total population. The vaccine efficacy is set at 30%. For close-schools, two trigger points are used: when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected at random from the entire Delhi population, and the cumulative infection rates are calculated for each network.

(a) Slum (b) Non-slum

Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond to higher infection rates. The smaller font numbers are counts of infected individuals. The vaccination efficacy is fixed at 30%. Five different compliance rates (10%, 30%, 50%, 70% and 90%) and 4 types of

intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population, and the mean infection rates are calculated separately for the slum and non-slum subpopulations. Although not reported here, qualitatively similar results are found for other transmission rates, as well as for higher vaccine efficacy (70%). Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals.

FIGURE 5: Mean cumulative infection rates for each category listed on the x-axis, for Network 2 and Network 1, under four different intervention scenarios. The color scheme of the boxes are based on the large values in the boxes—the cumulative infection rates. Darker colors correspond to higher infection rates. Smaller font values are the number of infected individuals. The vaccine efficacy is set at 30%. VsSs refers to the case when vaccines and social distancing are both applied to slum residents; VnSn refers to the case when vaccines and social distancing are applied to non-slum residents. Similarly, VsSn means vaccines are given to slums and stay home is applied to non-slums; and VnSs means vaccines are given to non-slums and stay home is applied to slums. Base refers to the case where no intervention is applied. The smaller-font numbers under the infection rates show the actual number of infected individuals in each category listed on the x-axis.



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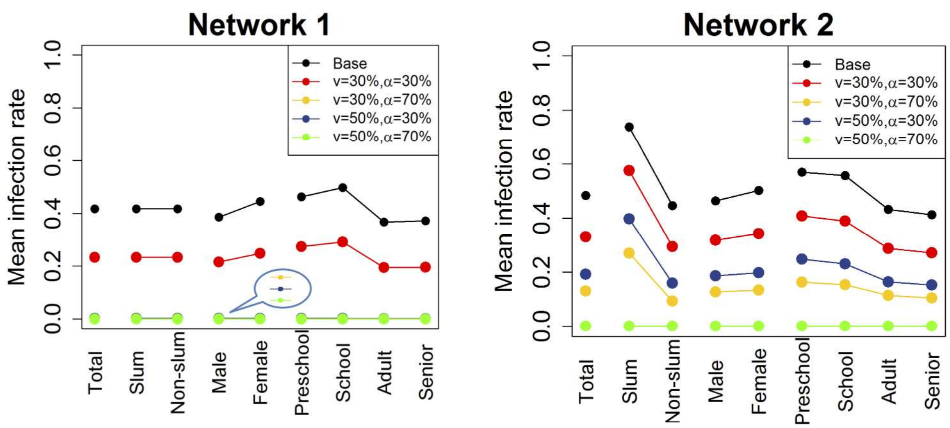

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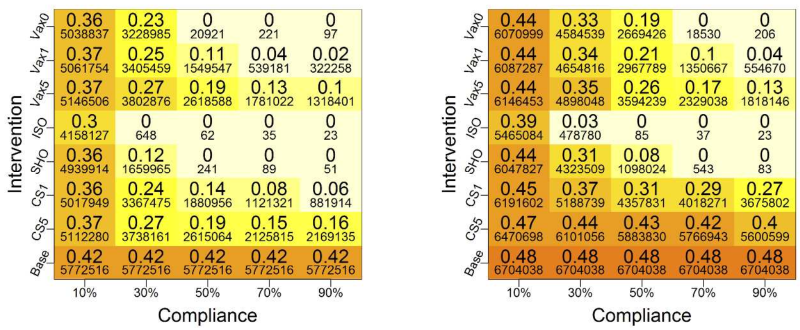

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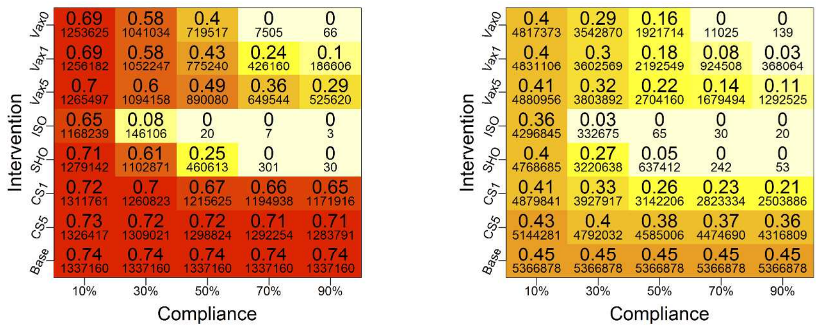

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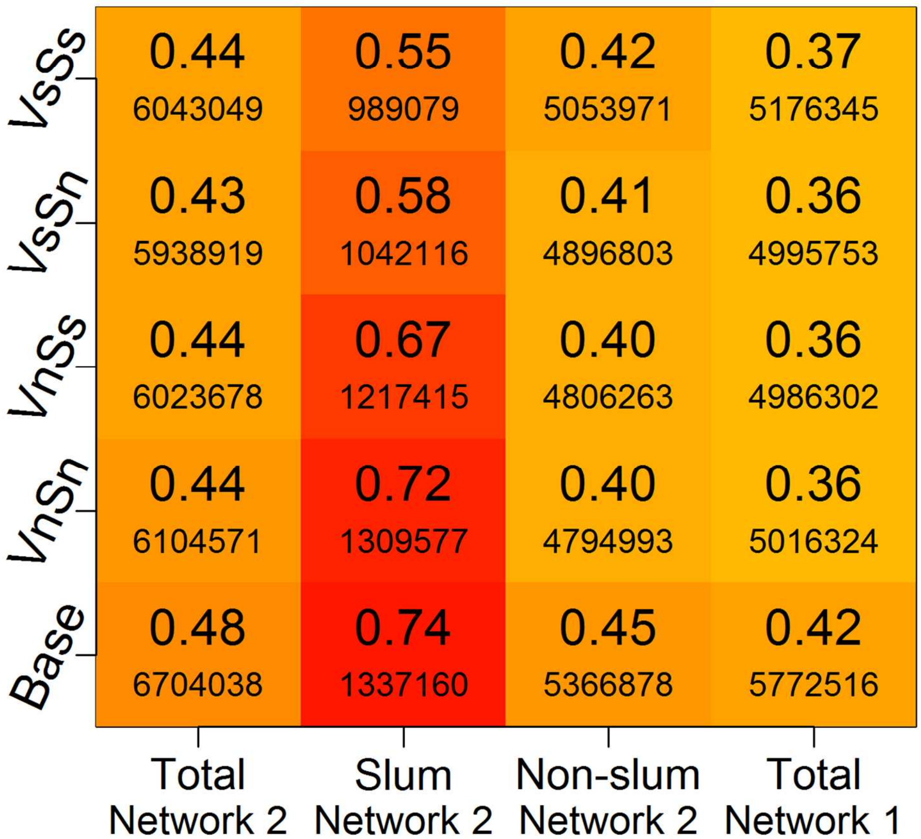

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Supplemental Information

Disparities in Spread and Control of Influenza in Slums of Delhi

A. Adiga, S. Chu, S. Eubank, S. Gupta, C. J. Kuhlman, B. Lewis, A. Marathe, M. Marathe, E. K. Nordberg, S. Swarup, A. Vullikanti and M. L. Wilson

Supplemental Information

Presentation of Results.

For each set of input parameters, 25 replicates were run using agent-based simulation and the results presented are the average values over the 25 replicates. Also, 95% confidence intervals (CIs) are given when appropriate.

Comparisons Between Network 1 and Network 2.

Table S1 shows some differences between network1 and network 2 due to their different ways of modeling slum population. Note that these two networks are the same ones as those used in Chen et al.[1]. Further comparisons between the two networks are found in Chen et al.[2].

Table S1. Comparison of two networks as well as data sources for slum and non-slum Delhi, India.

	Network 1		Network 2	
	Slum	Non-slum	Slum	Non-slum
Population Size	0	13.8 million	1.8 million	12 million
Average Household Size of Slum Region	5.2		15.5	
Daily Activities	33,890,156		39,077,861	
Number of Edges	210,428,521		231,258,772	
Average Degree	30.4		33.4	
Maximum Degree	170		180	
Data Sources	MapMyIndia.com		MapMyIndia.com Indiamart.com MapMechanic.com	

Network 2 contains 298 slum zones, while network 1 models the whole population as non-slum. For network 1, the non-slum demographics and activities data is collected by survey through MapMyIndia.com. While for slum population, we collected additional data by Indiamart.com and MapMechanic.com for slum demographics and activities as well as slum polygons. More detailed demographic and activity differences can be found in the Chen et al.[1]

Terminology and Abbreviations for Interventions.

Table S2 contains abbreviations for different interventions and their meanings. Stay-at-home (SHO) and social isolation (ISO) interventions are applied to a person immediately after they become infected, while close-schools (CS) and vaccinations (VAX) may be applied after a specified fraction of the total population has been infected.

Table S2: Summary of abbreviations for interventions and their meanings.

Supplemental Information

Abbreviation	Definition
CS	Close-schools: School-related interactions are eliminated.
CSx	Close-schools is implemented after the total fraction of the population that has been infected reaches x.
ISO	Social isolation: a person who is socially isolated does not interact with any other person, even people in their home. Isolation is triggered only after a person becomes infectious.
SHO	Stay at home: All out-of-the-home activities for this person are eliminated, and this person only interacts with others at home. Stay at home is triggered only after a person becomes infectious.
VAX	Vaccination: a person who is vaccinated has a reduced probability of contracting the virus.
VAXx	Vaccination of an individual occurs after the total fraction of the population that has been infected reaches x.

Table S3 contains the variables used in simulations. The transmissibility corresponds to strong flu in Chen et al.[1] For vaccination, efficacy is either 30% or 70%. That is, for 30% efficacy, a person who gets vaccinated has reduced their susceptibility to infection by 30%.

Table S3: Summary of parameters and values used in simulations.

Category	Values
Networks of Delhi	Network 1 (does not model slums); Network 2 (models slums).
Seeding	20 people selected randomly over the entire population at time 0 as index cases.
Transmissibility	0.000027.
Intervention approaches.	Base case (no intervention); close-schools (CS); stay-home (SHO); isolation (ISO); vaccination (VAX).
Intervention/compliance rates.	10%, 30%, 50%, 70%, 90%.
Efficacy of vaccination intervention.	30%, 70%.
Intervention trigger time	Cumulative infection rate reaches 0%, 1% and 5%.
Simulation replicates	25

The Agent Epidemic States and Disease Model.

An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. An infectious person spreads the disease to each susceptible neighbor independently with a probability referred to as the transmission probability, given by

$$p = \lambda\,(1 - (1 - \tau)^{\Delta t}),$$

where λ is a scaling factor to lower the probability (e.g., in the case of vaccination), τ is the transmissibility and Δt is the duration of interaction in minutes. Durations of contact are labels on the network edges. A susceptible person undergoes independent trials from all of its neighbors that are infectious. The transmission probability is a function of the number and duration of contacts.[3] This is selected to simulate an Influenza model resulting in a R_0=1.26 (cumulative attack rate 42%, corresponding to a transmissibility of 0.000027 per minute of contact time) for Network 1, and R_0=1.39 (cumulative attack rate 48%) for Network 2.[4] This transmissibility value is used uniformly throughout this study and corresponds to the probability at which an infectious node infects a susceptible node per minute of contact.

At each time (day), if an infectious person infects a susceptible person, the susceptible person transitions to the exposed (or incubating) state. The exposed person has contracted Influenza but cannot yet spread it to others. The incubation period is assigned per person, according to the following distribution: 1 day (30%); 2 days (50%); 3 days (20%). At the end of the exposed or incubation period, the person switches to an infected state. The duration of infectiousness is assigned per person, according to the distribution: 3 days (30%); 4 days (40%); 5 days (20%); 6 days (10%). After the infectious period, the person recovers and stays healthy for the simulation period. This sequence of state transitions is irreversible and is the only possible disease progression.

Epidemic Curves for Other Interventions, for Varying Efficacy and Compliances.

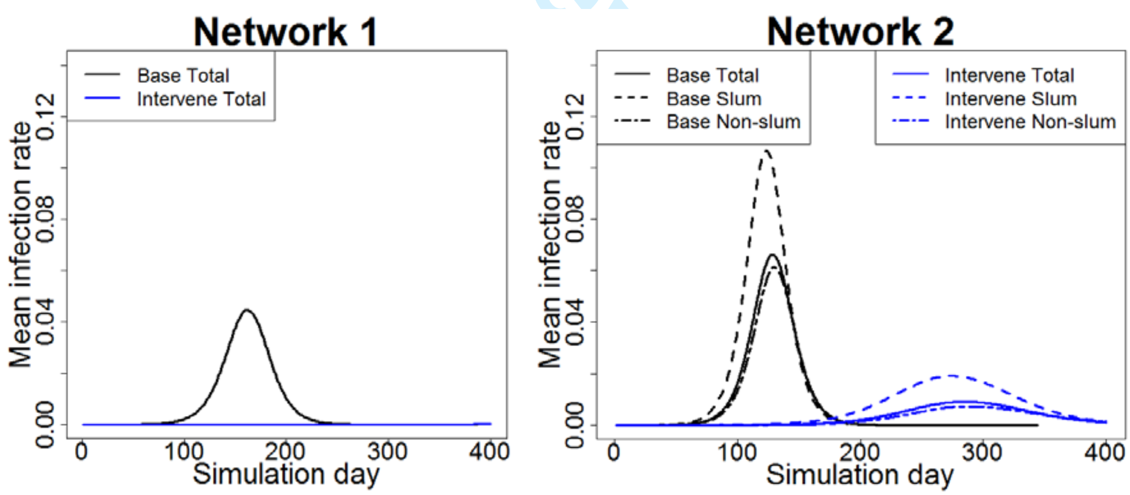


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

Supplemental Information

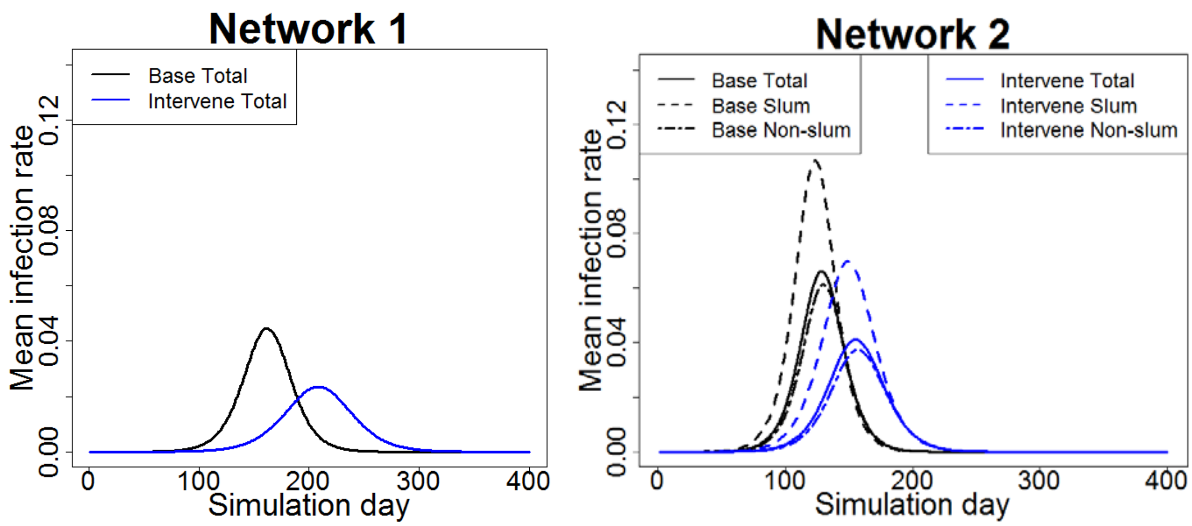
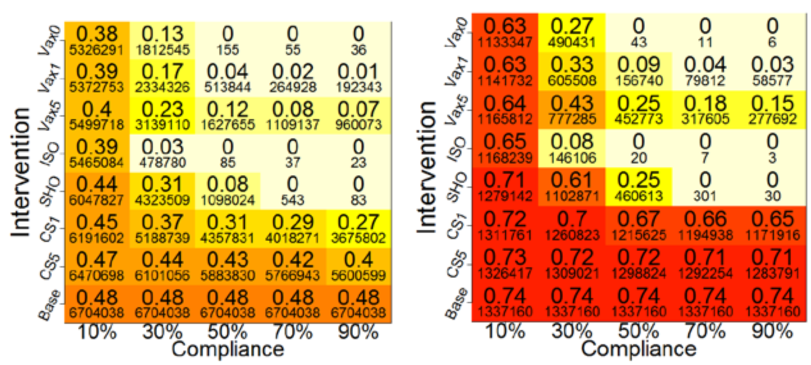


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.



(a) Total Delhi (b) Slum (c) Non-slum

Figure S3. Heat map of mean cumulative infection rates in Delhi, and slum and non-slum regions under different intervention strategies for Network 2. The vaccination efficacy is fixed at 70%. Five different compliance rates, i.e., 10%, 30%, 50%, 70% and 90% and 4 types of intervention strategies, i.e. vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO), are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used i.e. when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population and the mean cumulative infection rates are calculated separately for the total population, and slum and non-slum subpopulations. Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals. Darker colors correspond to higher infection rates.

Tabulations of Basic Results: Comparisons between Networks 1 and 2 for Compliance of 30% and Efficacy of 30%.

Table S4 shows results when 30% of the population that is selected uniformly at random is vaccinated with a vaccine that is 30% effective. The contrast between the two populations is even greater when considering interventions. The peak infection rate of the entire population increases by 123.2% (95% CI: 122.7%-123.7%) in Network 2 compared to Network 1 for the intervention, versus 47.6% difference between the networks in Table S8. The time to peak decreases by 35.7% (95% CI: 32.9%-38.8%) in Network 2 compared to that in Network 1, for the intervention case, compared to only 20.84% percentage change between the two Networks for the base case in Table S8. The cumulative infection rate (or attack rate) is also underestimated, which is 42.2% (95% CI: 41.5%-42.8%) greater on average in Network 2 compared to Network 1 for the intervention case. Hence, the differences between key epidemic results for Networks 1 and 2 that are generated for the intervention case are even more pronounced than they are for the base case. These values are all statistically significant.

Table S4: Comparisons of key epidemic parameters for Networks 1 and 2 for a vaccination intervention before the epidemic starts (VAX0), where the vaccine efficacy is 30% and the compliance rate is 30%.

Vaccination	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	286	184	102 (95% CI: 94-111)	35.7% (95% CI: 32.9%-38.8%)
Peak Infection Rate	1.34%	2.99%	1.65% (95% CI: 1.64%-1.66%)	123.19% (95% CI: 122.69%-123.65%)
Cumulative Infection Rate	23.3%	33.1%	9.82% (95% CI: 9.67%-9.96%)	42.17% (95% CI: 41.51%-42.77%)

Table S5 shows the effect of delay in applying interventions. The numbers show the percentage difference in cumulative infection rate in slums and non-slums of Network 2 for the specified interventions and compliance rates at different trigger levels. For example, the value 30.55% at 0.1% compliance means that for intervention close-schools, where this intervention is implemented after 5% of the total population is infected, the fraction of people in slums that get infected is 30.55% greater than the fraction of non-slum residents who get infected.

Table S5. Differences of epidemic size between slum and non-slum regions for Network 2 for base case (no intervention); close-schools (CS) after 1% total outbreak fraction (CS1) and after 5% total outbreak fraction (CS5); stay at home (SHO); social isolation (ISO); vaccination (VAX) after 1% total outbreak fraction (VAX1) and after 5% total outbreak fraction (VAX5), under various compliance rates. The vaccination efficacy is 30%.

Compliance	Base	CS5	CS1	SHO	ISO	VAX5	VAX1
0.1	29.30%	30.55%	31.94%	31.06%	28.85%	29.37%	29.27%
0.3	29.30%	32.52%	37.03%	34.18%	5.31%	28.85%	28.21%

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0.5	29.30%	33.67%	41.07%	20.16%	0.00%	26.72%	24.62%
0.7	29.30%	34.23%	42.57%	0.01%	0.00%	21.94%	15.87%
0.9	29.30%	35.07%	43.95%	0.00%	0.00%	18.31%	7.25%

Table S6 examines the difference in effects of interventions on the cumulative infection rate in Network 2. These data use both the stay home (SHO) and the isolation (ISO) interventions as base cases. Each entry represents the difference between the cumulative infection rates for the specified pharmaceutical interventions and SHO or ISO. For example, 18.03% means that the cumulative infection rate for vaccinating after 5% of the population is infected, is 18.03% greater than that for the intervention of SHO; 31.92% means that the cumulative infection rate for vaccinating after 5% of the population is infected is 31.92% greater than that for the intervention of ISO. Thus, the larger the magnitude of a positive number, the greater the effectiveness of SHO or ISO compared to the specified pharmaceutical intervention.

Table S6. Differences in epidemic size between stay at home (SHO) interventions, social isolation (ISO) interventions and pharmaceutical interventions (VAX0, VAX1, VAX5), under various compliance rates. The compliance rate and efficacy for vaccination is 30% and 30%, respectively.

Compliance	Vax5-SHO	Vax1-SHO	Vax0-SHO	VAX5-ISO	VAX1-ISO	VAX0-ISO
0.1	0.71%	0.29%	0.17%	4.92%	4.49%	4.38%
0.3	4.15%	2.39%	1.89%	31.92%	30.17%	29.66%
0.5	18.03%	13.51%	11.35%	25.96%	21.44%	19.28%
0.7	16.82%	9.75%	0.13%	16.82%	9.76%	0.13%
0.9	13.13%	4.01%	0.00%	13.13%	4.01%	0.00%

Effect of intervention on Network 2, With and Without Interventions.

The comparison between vaccination intervention and the base case in Network 2 is detailed in Table S7 below.

In Network 2, for the total population, vaccination delays the time to peak infection by 43.27% (95% CI: 40.14%-46.41%) relatively, from 128 to 184 days on average, while the peak infection rate is reduced by about 3.88% from 2.99% to 6.87% on average (56.47% relatively with 95% CI: 56.35%-56.56%). The total infection rate is reduced by 15.31% from 33.12% to 48.43% (31.62% relatively with 95% CI: 31.57%-31.67%).

In slum regions in Network 2, vaccination delays the time to peak infection by 43.09% (95% CI: 39.78%-46.4%) relatively, from 123 to 176 days on average, while the peak infection rate is reduced by about 5.70% from 5.42% to 11.12% on average (51.26% relatively with 95% CI: 50.88%-51.64%). The total infection rate in slums is reduced by 16.35% from 57.53% to 73.88% (22.13% relatively with 95% CI: 22.07% to 22.19%).

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In non-slum regions in Network 2, the time to peak is delayed by 43.44% (95% CI: 40.32%-46.56%) relatively, from 130 to 186 days on average, while the peak infection rate is reduced by about 3.68% from 2.69% to 6.36% on average (57.79% relatively with 95% CI: 57.64%-57.94%). The total infection rate in non-slums is reduced by 15.16% from 44.60% to 29.45% (33.98% relatively with 95% CI: 33.93% -34.03%).

Table S7: Comparisons between the base and vaccination cases for Network 2. The three parameters (time to peak, peak infection rate and cumulative infection rate) are broken out, and for each, values for the total population, and slum and non-slum subpopulations are given. The vaccination rate is 30% and efficacy is 30% for those receiving the vaccine.

Network 2, Time to Peak	Base	Vaccination	Compare-absolute	Compare-Relative
Total	128	184	55 (95% CI: 51-59)	43.27% (95% CI: 40.14%-46.41%)
Slum	123	176	53 (95% CI: 49-57)	43.09% (95% CI: 39.78%-46.4%)
Non-Slum	130	186	56 (95% CI: 52-60)	43.44% (95% CI: 40.32% - 46.56%)

Network 2, Peak Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	6.87%	2.99%	-3.88% (95% CI: -3.870% -3.884%)	-56.46% (95% CI: -56.35% -56.56%)
Slum	11.12%	5.42%	-5.70% (95% CI: -5.66% -5.74%)	-51.26% (95% CI: -50.88% -51.64%)
Non-Slum	6.36%	2.69%	-3.68% (95% CI: -3.67% -3.69%)	-57.79% (95% CI: -57.64% -57.94%)

Network 2, Cumulative Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	48.43%	33.12%	-15.31% (95% CI: -15.29% -15.34%)	-31.62% (95% CI: -31.57% -31.67%)
Slum	73.88%	57.53%	-16.35% (95% CI: -16.30% -16.39%)	-22.13% (95% CI: -22.07% -22.19%)
Non-Slum	44.60%	29.45%	-15.16% 95% CI: (-15.14% -15.18%)	-33.98% (95% CI: -33.93% -34.03%)

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Table S8 summarizes differences in key epidemic parameters for Networks 1 and 2 for the base case with no interventions. The peak infection rate is the maximum fraction of individuals who are infected on any day, the time to peak is the day on which the peak infection rate occurs, and cumulative infection rate is the cumulative fraction of individuals who get infected in the epidemic. Under the base case, the peak infection rate in Network 2 is 47.6% (95% CI: 47.4%-47.8%) greater compared to that in Network 1 (47.6%=(6.87%-4.65%)/4.65%). The time to peak infection for Network 2 is decreased by 20.8% (95% CI: 19.2%-22.7%) compared to that in Network 1. The cumulative infection rate (or attack rate) is also underestimated under Network 1 by 16.1% (95% CI: 16.1%-16.2%) compared to Network 2. These results, presented in the main paper, are tabulated here in Table S8 for convenience and comparison.

Table S8: Comparisons of key epidemic parameters for Networks 1 and 2 for the base case.

Base	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	162	128	34 (95% CI: 31-37)	20.84% (95% CI: 19.19%-22.71%)
Peak Infection Rate	4.65%	6.87%	2.215% (95% CI: 2.206%-2.224%)	47.6% (95% CI: 47.4%-47.8%)
Cumulative Infection Rate	41.70%	48.43%	6.73% (95% CI: 6.71%-6.75%)	16.1% (95% CI: 16.1%-16.2%)

Effect of intervention on Network 1, With and Without Interventions.

In Network 1, vaccination delays the time to peak infection by 76.41%, from 162 to 286 days on average, with 95% CI: 71.53%-81.28%. The peak infection rate is reduced by 3.3121 percentage points, from 1.34% to 4.65%, which is a relative percentage difference (RPD) of -71.20%, with 95% CI: -71.02% to -71.38%. These and cumulative infection rate data are given in Table S9.

Table S9: Comparisons of a vaccination intervention (30% vaccination rate, 30% efficacy of a vaccination) with the base case in Network 1 Delhi.

Network 1,Total	Base	Vaccination	Compare-absolute	Compare-relative
Time to Peak	162	286	124 (95% CI: 116-132)	76.41% (95% CI: 71.53%-81.28%)
Peak Infection Rate	4.65%	1.34%	3.31% (95% CI: 3.30%-3.32%)	71.20% (95% CI: 71.02%-71.38)
Cumulative Infection Rate	41.7%	23.3%	18.40% (95% CI: 18.25%-18.55%)	44.13% (95% CI: 43.77%-44.48%)

Tables S7 and S9 show that, generally, Network 1 is more responsive to intervention than Network 2. In Network 1, the percentage changes in time-to-peak, peak infection rate, and cumulative infection rate, due to intervention, are 76.4%, -71.2%, and -44.1%,

respectively. For Network 2, these values are 43.3%, -56.5%, and -31.6%, respectively. The reason for lower impact in Network 2 is the greater connectivity of households in slums, which helps drive the contagion.

Effect of interventions on slum and non-slum subpopulations of Network 2, compared to the base case.

The data used in comparing key outbreak parameters in slum and non-slum regions are taken from Table S7, and the corresponding epidemic curves are in Figure 1. The percentage change in peak infection rate due to intervention in slum (-51.3%) and non-slum (-57.8%) regions in Network 2, are comparable, although the magnitudes of the peak infections in slums are about twice those in the non-slum regions. For the cumulative infection rates, the relative drop from the intervention is greater for the non-slum (-34.0% vs. -22.1%) population than it is for the slum population, but the absolute drop is about the same (-16.3% vs. -15.1%).

Table S10: Comparison of results between slum and non-slum in Network 2. The input data is the same as in Table S7.

Network 2, **Base**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	123	130	7(95% CI: 4-9)	5.26% (95% CI: 3.37%-7.16%)
Peak Infection Rate	1.12%	6.36%	4.76% (95% CI: 4.72%-4.80%)	42.79% (95% CI: 42.46%-43.14%)
Cumulative infection rate	73.88%	44.60%	29.25% (95% CI: 29.25% - 29.31%)	39.63% (95% CI: 39.59%-39.67%)

Network 2, **Vaccination**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	176	186	10(95% CI: 5-15)	5.23% (95% CI: 2.58%-8.46%)
Peak Infection Rate	5.42%	2.69%	2.74% (95% CI: 2.71% - 2.76%)	50.46% (95% CI: 50.06%-50.86%)
Cumulative infection rate	57.53%	29.45%	28.08% (95% CI: 28.04%-28.12%)	48.82% (95% CI: 48.74%-48.89%)

Figure S4 contains the percentage changes between the base case and intervention case for Networks 1 and 2 for the three parameters in the legend, and further breaks down Network 2 into slum and non-slum subpopulations. This plot provides a summary of differences between the base and intervention cases. For all four conditions considered, the intervention reduces the severity of an epidemic. It delays the time when the infection peaks, and reduces the peak infection and the cumulative infection rates. Note that the intervention has a larger effect on the epidemics when applied to Network 1, as consistent with Figure 1.

Supplemental Information

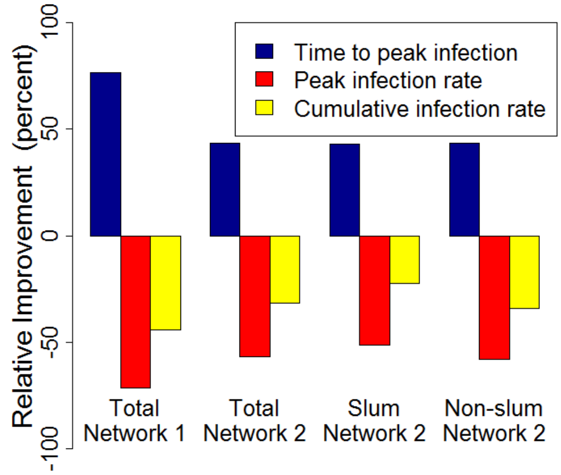


Figure S4: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 than Network 2, while, for Network 2, it is slightly more effective for the non-slum population than slum. Details of the data associated with this plot are provided in Tables S7 and S9.

Figure S5 provides the same data in as in Figure S7, but now the data are provided as absolute differences, rather than as percentage changes. (There are three separate plots owing to the different ranges in absolute differences. Qualitatively, the time to peak infection (blue bars) does not change between the two networks and the two subpopulations of Network 2 (Figure S4 versus Figure S5(a)). However, the red bars in Figure S4 are qualitatively different from those in Figure S5(b), when considering absolute changes. That is, the magnitude of the percentage change in peak infection rate between the base and intervention cases is greatest in Network 1 (Figure S4, red bars), while in Figure S5(b), it is least on an absolute change basis. Similarly, the slum population in Network 2 shows the least percentage change in Figure S4, but the greatest absolute change in Figure S5(b). Rankings of the subpopulations in Network 2 is also reversed for cumulative infection rate: the percentage change is greatest in the non-slum region, while it is greatest for the slum regions in absolute terms.

Supplemental Information

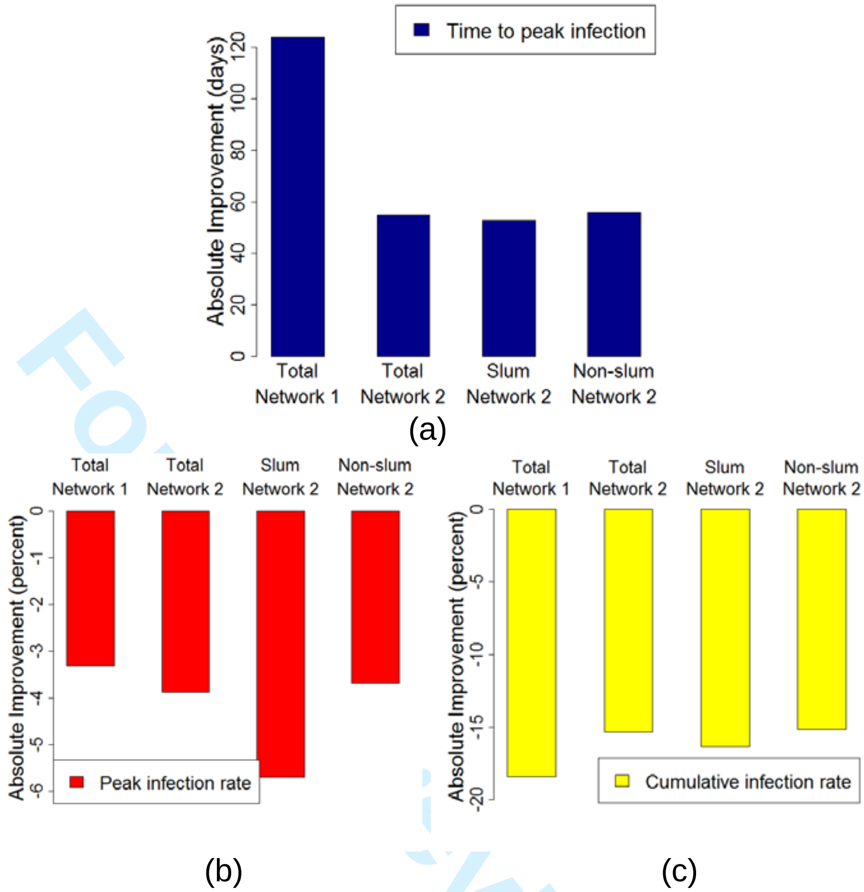
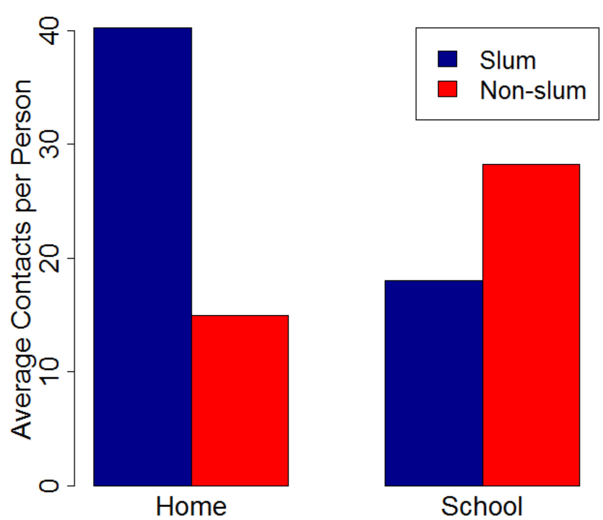


Figure S5: Comparison of absolute difference in improvement; the relative differences are shown in Figure S7. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S7 and S9.

Evaluation of Network 2 Home and School Contacts.



Supplemental Information

Figure S6: Comparison of average contacts per person in slum and non-slum regions for home and school activity types in Network 2.

Evaluation of Network 2 Edges Transmitting Infection.

Figure S7 provides counts of edges used to transmit infection for a base case simulation in Network 2 of Figure 1 of the main text. Edges are broken down by activity types of people who are interacting during transmission. Data are also broken down by the classifications of individuals interacting (e.g., slum and nonslum, see legend).

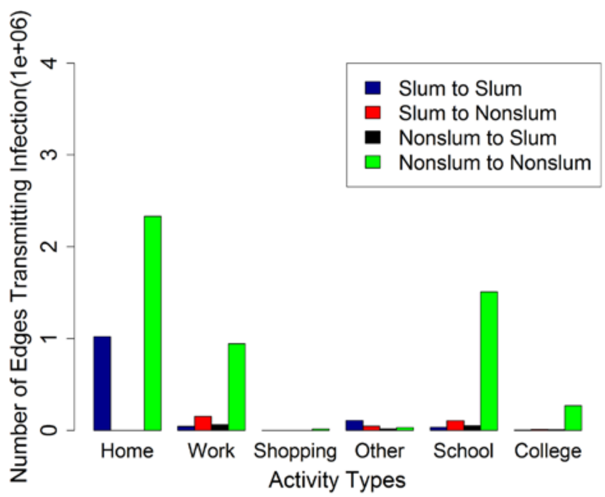


Figure S7. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater than nonslum-to-slum ones because once infection gets into a slum household, it may spread within the household more (because there are more people and connections). Thus, a slum household carries more infection to its interactions with nonslum people. The "Other" activity category, like home activity, shows more edges carrying infection for slum-to-slum interactions than slum-to-nonslum, which is consistent with Figures S4 and S6 of Chen et al.[2], where further network characteristics are given.

Supplemental Information

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Main manuscript

Disparities in Spread and Control of Influenza in Slums of Delhi: Findings From An Agent-Based Modeling Study

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Main manuscript

ABSTRACT

Objectives This research studies the role of slums in the spread and control of infectious diseases in the National Capital Territory of India, Delhi, using a detailed social contact network of its residents.

Methods We use an agent-based model to study the spread of influenza in Delhi through person-to-person contact. Two different networks are used; one in which slum and non-slum regions are treated the same and the other in which 298 slum zones are identified. In the second network, slum-specific demographics and activities are assigned to the individuals whose homes reside inside these zones. The main effects of integrating slums is that the network has more home-related contacts due to larger family sizes and more outside contacts due to more daily activities outside home. Various vaccination and social distancing interventions are applied to control the spread of influenza.

Results Simulation based results show that when slum attributes are ignored, the effectiveness of vaccination can be overestimated by 30%-55%, in terms of reducing the peak number of infections and the size of the epidemic, and in delaying the time to peak infection. The slum population sustains greater infection rates under all intervention scenarios in the network that treats slums differently. Vaccination strategy performs better than social distancing strategies in slums.

Conclusions Unique characteristics of slums play a significant role in the spread of infectious diseases. Modeling slums and estimating their impact on epidemics will help policy makers and regulators more accurately prioritize allocation of scarce medical resources and implement public health policies.

Policy Implications Currently, over a billion people reside in slums across the world and this population is expected to double by 2030. This study uses influenza as an example to demonstrate the need to understand the role of slum populations in the spread and containment of infectious diseases.

Strengths and limitations of this study

- We show that the unique attributes of slums must be accounted for in understanding the spread and control of infectious diseases.
- We demonstrate that the granularity afforded by the agent-based model enables extraction of subpopulations, and subsets of interactions, to help interpret results.
- This study does not consider age-specific susceptibility or immunity from past infections; all individual persons are assumed to be equally susceptible.
- The disease transmission risk does not change across activity types, e.g. an hour with an infected person at home or at work carries the same risk.
- Co-location based contact time is used as a proxy for physical proximity and short-distance environmentally-mediated transmission.

Main manuscript

INTRODUCTION

Infectious disease is one of the leading causes of human morbidity and mortality worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000 people in the United States (US) are hospitalized with influenza-like illness (ILI) symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the National Institute of Virology has shown that ILI cases are present throughout the year, although they peak in rainy and winter seasons.[3] It carries a significant economic burden through reduced productivity and high costs of health care.[4-7] A CDC study finds that for outpatient and non-medically attended individuals, acute respiratory infections cost 1%-5% of monthly per capita income in India. In contrast, cost of inpatient care can be as high as 6%-34% of monthly per capita income.[8] For developed countries, the annual cost of influenza is estimated to be between $1-$6 million per 100,000 people, according to the World Health Organization.[9]

In 2007, India established an Integrated Disease Surveillance Program (IDSP), which included a network of 12 regional laboratories, to minimize the threat of avian influenza and other highly infectious zoonotic diseases.[10] India faces some unique challenges in surveillance, prevention and control because of the seasonality of influenza at sub-regional levels. This seasonal variation depends upon latitude, monsoon season, humidity and climatic factors of the regions. Acute respiratory infections are estimated to be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13] estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in year 2011, and children under age 5 had the highest incidence of them.

Given that influenza is environmentally-mediated and spreads through close proximity, population density is an important factor in its spread. In India, the average population density is about 1000 people per square mile; in the slums, it can be 10 to 100 times higher.[14] Larger household size and crowding make it easier to transmit infections).[15-18] For example, Baker et al.[16] find that meningococcal disease risk among children doubles with the addition of 2 adolescents or adults (10 years or older) to a 6-room house. Other than overcrowding, slums are characterized by their lack of medical services,[19-20] which makes slum residents highly vulnerable to infectious diseases. Diseases like cholera, malaria, dengue and HIV are common in slums across the world.[21-23]

This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8 million people live in slum areas, as an example city to study the spread and control of influenza. Delhi is an interesting case study. It ranks fourth in the world in urban population, and, among the top 25 largest urban areas, it ranks tenth in population density. Moreover, the results are likely to be generalizable to other slum areas within and outside of India.

Main manuscript

This paper is an extension of the work done in Chen et al.[4], which shows that slum populations have a significant effect on influenza transmission in urban areas. Ignoring the influence of slum characteristics underestimates the speed of an outbreak and its extent. However, Chen et al.[4] do not consider any interventions on the epidemic spread. *The focus of this research is to study the effect of different intervention strategies on several subpopulations (slum, age and gender) in two different Delhi networks, i.e., original (referred to as Network 1) and refined (Network 2).*

The original network used in Xia et al.[24] studied the spread and control of influenza in Delhi using Network 1, which did not take into account the special attributes of the slum population, such as larger family sizes and different types of daily activity schedules. Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for slum demographics and slum activities, but did not study intervention strategies. In Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.

The goals of this work focus on understanding the effects of pharmaceutical and non-pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI) include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing measures such as school closure, quarantine and staying home. These effects are studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a scenario where interventions can be applied to a limited number of individuals, we explore how resources should be split between slum and non-slum subpopulations in order to achieve the best outcomes with respect to total infection rate (i.e., the cumulative fraction of a population infected).

METHODS

We use an agent-based modeling (ABM) approach to simulate the spread and containment of influenza in social contact networks of Delhi, India. We compare two networks: one considers slum-specific attributes, and the other does not. In this section, we describe the networks, the disease model for each agent, the interventions, and the heterogeneities of the problem that make ABM uniquely suited to study epidemics. Throughout this manuscript, each agent in the ABM is an individual human.

Social Contact Networks: This study uses two synthetic social networks of Delhi, created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found in Xia et al.[24], Chen et al.[4], Barrett et al[25], Bisset et al.[26] and references therein. The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined network developed in Chen et al.[4], *Network 2*.

Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set of activities of individuals, and the locations of those activities including geo-locations of residential areas, shopping centers, and schools, collected through surveys by MapMyIndia.com. By assigning activity locations to individuals' activities, people are located at particular times at particular geographic coordinates (including office buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between individuals are estimated when each person is deemed to have made contact with a subset of other people simultaneously present at the same location. This gives rise to a synthetic social contact network where network edges represent these contacts.

Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the individuals whose homes reside in the slum polygons. Slum residents' attributes and their daily sets of activities are collected through a ground survey in Delhi slums, by a vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from *MapMechanic.com*. Individuals living in the slum regions are a part of the slum population. All other individuals are part of the non-slum population. Network 2 is a geo-located, and contextualized social contact network of Delhi with slums integrated in it.

Following are the main differences between the original network (Network 1) and the refined network (Network 2). The original social contact network treats the slum regions like any other region in Delhi in terms of assignment of demographics and individual activities, i.e. no special consideration is given to slum residents. The refined Network 2 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific demographics and activities to the individuals whose homes reside inside these polygons. Thus, the number of individuals is the same in both populations. The slum population constitutes about 13% (1.8 million) of the entire Delhi population of 13.8 million people. The main effects of integrating slums is that Network 2 has more home-related contacts due to larger family sizes and more outside contacts due to more daily activities outside home. Also, those individuals who reside outside of slum zones have the same activities in both networks. Overall, there are over 231 million daily interactions between pairs of individuals. Table S1 compares those two networks as well as data sources for slum and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are in the supplementary information (SI)). For example, the average degree increases from 30.4 to 33.4 from Network 1 to Network 2, and the maximum degree increases from 170 to 180. We refer to Chen et al.[4] for more detailed information about the two networks. Several plots of properties and structural characteristics of Networks 1 and 2 are given in Chen et al.[27].

Disease Model: An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. Each node in the network represents an individual, and each edge represents a contact on which the disease can spread. A contact represents possible transmission between two people that are co-located for some duration (based on their activity schedules). This is an approximation to model direct contact and short-distance environmentally-mediated transmission that might include direct physical contact, fomite mediated, and airborne transmission.[28]

We start each epidemic simulation with 20 index cases, randomly chosen. (We find that results are not sensitive to the number of initial infections.) The detailed description of the SEIR model as well as the choices of transmissibility value, R_0, the explicit incubation and exposed periods can be found in the supplementary information. This disease model has been used in other works such as Liao et al.[29], Marathe et al.[30].

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The transmissibility value for disease transmission is that for the strong influenza model in Chen et al.[4]. That work used mild, strong, and catastrophic influenza models, so we chose the intermediate transmissibility. This corresponds to base attack rates (i.e., cumulative infection fractions) of 0.42 and 0.48, respectively, in Networks 1 and 2. These rates are generally higher than those in some other studies that either compute experimental attack rates from cases or compute them in modeling studies such as this one. Attack rates used by past researchers for different strains of influenza include Asia [0.22 to 0.50],[31] Southeast Asia [0.11 to 0.31 in children [32]; 0.05 to 0.65 [33]], and India [0.111 to 0.235 [34]; 0.074 to 0.424 [35]; 0.045 to 0.294 [36]; 0.008 to 0.100 [37]; 0.209 for various strains [13]]. The results of Chen et al.[4] indicate that the results here, for this particular transmissibility, will be qualitatively the same for other transmissibilities, but will scale down or up as transmissibility changes in the same direction.

Interventions: This work considers three vaccination scenarios, i.e., vaccinate when cumulative infection rate is 0% (VAX0, i.e. vaccinate on day 1), 1% (VAX1), and 5% (VAX5). Three classes of social distancing strategies are considered: (i) stay-home (SHO) if infected, i.e. eliminate all non-home related contacts but continue to maintain contacts within the household; (ii) close-schools when cumulative infection rate has reached 1% (CS1) and when it has reached 5% (CS5), i.e. eliminate school related contacts; and (iii) (ISO), in which all contacts, including home contacts, of a person are eliminated when a person becomes infectious. For vaccination, five different compliance rates (10%, 30%, 50%, 70%, 90%) and two different vaccine efficacies (30% and 70%) are considered.

VAX0, SHO, ISO are all fairly aggressive interventions because they are implemented either before a person gets infected or immediately upon becoming infectious. These are actions taken at the individual or family level. For example, vaccination before the influenza season or isolating a sick child at home are family decisions. Even CS1 is an aggressive intervention in the sense that this action is taken by government officials based on aggregate school sickness levels—closing schools before any outbreaks is typically not done. From these starting points, vaccinations when 1% or 5% of the population is infected (VAX1, VAX5), and closing schools when 5% of the population is infected are less aggressive treatments (CS5). The five levels of compliance are also variations on aggressiveness in treatments.

These conditions and parameters are consistent with results from other studies and guidelines put out by international organizations. A meta-study of immunization and slums [38] identifies several vaccination-related studies of slums in India. Unfortunately, these studies are for other diseases such as Hepatitis B, measles, mumps, malaria, and typhoid fever. Nonetheless, slum vaccination rates for children over these ailments range from 25% to 69% for full immunity and from 15% to 55% for partial immunity. Vaccination effectiveness for influenza-like illness (ILI) in India was determined to be about 33% to 36%.[39] In 2012-2013, of 1000 pregnant women in Srinagar India, none were vaccinated against influenza.[40] With regard to school closures, the World Health

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Organization (WHO) states that school closures may be undertaken proactively (before an outbreak) or reactively (after influenza starts to spread).[41] WHO recommends that school closure occur before 1% of the population becomes infected. It also recommends that people (students and staff) stay home when they feel ill. In another meta-study[42], it was found that school closure, effected when 0.1% of the population was infected, was twice as effective in reducing the total attack rate as school closure occurring after 1% of the population was infected. Moreover, the percentage of people infected before school closure was triggered varied between 0.02% to 10% across several studies.

When a susceptible node is vaccinated, its probability of getting infected by an infectious node is scaled down by the efficacy. If it becomes infectious, its probability of infecting susceptible nodes is also scaled down by the efficacy. In other words, both incoming and outgoing infection probabilities of vaccinated individuals are reduced by the vaccine efficacy. Interventions are applied to slum residents, non-slum residents, and the entire region of Delhi.

For each experiment, 25 replicates are simulated for 400 days, and their mean results are reported. The averages are time-point wise averages, e.g. the mean infection rate at day 100 is calculated by taking the average of the 25 infection rates that occur on day 100 of each replicate. Table S2 summarizes all the interventions considered, and Table S3 contains all variables in simulations, including intervention parameters.

Heterogeneities captured: There are several heterogeneous aspects to this problem that motivate the use of an ABM approach: (i) the 298 slum zones have populations that vary by more than four orders of magnitude in size; (ii) the geographic extent of slum zones differ; (iii) the slum zones are located at irregular spatial intervals throughout Delhi; (iv) the activity patterns of people living in slums are different from those in the non-slum region; and (v) each individual interacts with specific others based on co-location.

The implications of these heterogeneities include the following. First, the particular synthetic households that live within slums are predicated on the number of slum zones, their locations, and their spatial geometries. These homes have larger family size and hence more home contacts. Second, slum individuals have different activity patterns which change the co-located contacts of each slum person: that is, with whom they interact and for how long. For example, see the supplemental information of Chen et al.[27]. The average total contact durations by activity type and by slum/non-slum residents are provided, which show that non-slum people have greater contact durations for work, school, and college activities, but less for home and other types. Overall, a slum person has about 50% greater total contact duration per day compared to a non-slum person. The same supplemental shows that in the age range 20 to 60 years (by year), females that live in slums have more contacts per day than their male counterparts. However, females whose homes are outside of slum regions have average number of daily contacts that are below their male counterparts.

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RESULTS AND ANALYSIS

Our results are grouped as follows. (1) Comparison of Network 1 and Network 2 for base case and intervention cases. (2) Results for both networks based on demographic classes, such as slum/non-slum, gender, and age groups, for a wider range of intervention strategies. (3) Comparison of Network 1 with the non-slum population of Network 2. (4) Effects of pharmaceutical and non-pharmaceutical interventions for a wide range of parameter values. (5) Effects of different resource allocation strategies.

All differences are tested with the two-sample t-test and they are all statistically significant with p-values smaller than 2.2e-16. The 95% confidence intervals are given for each comparison. Here is a brief summary of selected results with examples of mechanisms, to provide a high-level overview. Details of results follow this summary and these details matter because there are many factors (inputs) in a simulation whose interactions change results.

(1) Ignoring the unique attributes of slums in a population overestimates the benefits of the interventions. For example, in the case of vaccination intervention (efficacy 30% and compliance 30%), the values for the epidemic size (i.e., cumulative percentage of infected), peak infection rate (i.e., maximum percentage of a population infected on any day), and time to peak are 33.1%, 3.0%, and 184 days, respectively, in Network 2, whereas they are 23.3%, 1.34%, and 286 days in Network 1. In relative terms, the epidemic size and peak infection rate are underestimated by 42.2% and 123.2% respectively, while the time to peak is overestimated by 35.7% in Network 1 (see Figures 1, 2 and Table S4). The larger family sizes for slum families in Network 2 and the increased number of edges result in larger outbreaks and faster time to peak infections.

(2) Interventions are more effective in Network 1 than Network 2 for all types of interventions: vaccination, closing schools, staying home, and isolation. These trends also hold over wide ranges of efficacy and compliance (see Figures 3, 4, S1, S2 and S3). Hence, not accounting for slums gives overly optimistic results for the effectiveness of the interventions. The reduced average family size in Network 1 means fewer within-home edges, which slows infection and reduces spreading. Closing schools and staying home interventions do not affect home edges. However, the magnitude of this effect varies with intervention conditions (e.g., compliance rate, time at which intervention is applied).

(3) Cumulative infection rates by subpopulation in Network 2 show that slums sustain greater infection rates than non-slums under all intervention scenarios, sometimes by as much as 44.0%. See Figure 4 and Table S5 for more details. This is due to the greater household sizes in slums.

(4) For Network 2, under a wide range of intervention compliance rates (10% to 90%), the isolation strategy is up to 32% more effective in containing an outbreak than vaccination (for 30% efficacy). Staying home is up to 18% more effective than

vaccination at 50% compliance. See Figure 3 and Table S6 for more details. Isolation, although hard to implement from practical considerations, is most effective because edges to susceptible individuals are removed (isolation also provides a good comparative case). Differences between staying home and vaccination depend on compliance rates.

(5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse effect in slums than in non-slum regions across compliance rates from 10% to 90%. See Figure 4 and Table S7 for more details. Early interventions mean actions are taken when outbreaks are smaller and are therefore more readily contained.

(6) Comparison of Network 1 (Figure 3a) with the non-slum population (Figure 4b) of Network 2 shows that just the presence of slum specific activities and interactions with non-slum population makes social-distancing based interventions less effective in the non-slum regions of Network 2.

(7) A full-factorial design that splits resources between slum and non-slum regions indicates that the most effective intervention is to give vaccines to slums and apply social distancing to non-slums. Applying vaccine and social distancing to slum regions is the next most effective intervention. See Figure 5. By applying social distancing to non-slums, these individuals are kept isolated from slum individuals that are infected. The greatest benefits accrue to the slum populations.

Comparison between Networks 1 and 2: Base case versus interventions

We start with a comparative analysis of the influenza epidemic, with and without interventions, on Network 1 and Network 2 to measure the impact of integrating slums in the population on epidemic measures. Figure 1 shows the average simulation time histories for the base case, and when vaccination is applied randomly to 30% of the population in each network with vaccine efficacy set at 30%. Mean infection rate is the daily fraction of infected individuals. It is the time-point wise average over 25 simulations. For example, the mean infection rate at day 100 is calculated by taking the average of all 25 infection rates. Simulations for other vaccine efficacies and compliance rates give qualitatively similar results. Two sets of those results are shown in the supplemental information, see Figures S1 and S2. Note that Network 1 does not distinguish between slum and non-slum individuals, so the epidemic curve is not split by subpopulation.

Results in Network 2 differ significantly from results in Network 1 for both the base case and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a larger epidemic size and has higher peaks compared to the corresponding epidemic quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to plan, there will be a false sense of security and lack of urgency to implement interventions. For both the base case and the intervention case, ignoring unique characteristics of the slums will result in an underestimation of the infections and the speed of spread.

Figure 1 goes here

For the intervention cases, the time to peak infection decreases by 35.7%, i.e. from 286 days for Network 1 to 184 days for Network 2, meaning an influenza epidemic would peak roughly 100 days earlier than one would expect based on the results from Network 1. For the base case, time to peak infection drops by 20.8%, i.e. 34 days reduction for Network 2 as compared to Network 1.

Percentage changes and differences must be viewed cautiously, and to illustrate this point, we present data for the key parameters in Tables S4 and S8. The difference in the peak infection rate (i.e., the maximum fraction of daily infected individuals during the simulation) between Networks 1 and 2 for the base case is 2.2%, or 47.6% in percentage change (see Table S8). For the intervention case shown in Table S4, the difference between the two networks is less (1.7%), but the percentage change is more (123.2%) because the magnitudes of the peak infection rates are reduced when effective interventions are used. We make note of this here and mainly use the percentage change values in discussing results. For more detailed comparison between vaccination intervention and the base case in Network 1 and Network 2, we refer to Tables S7 and S9 and Figures S4 and S5.

Comparison between Networks 1 and 2 based on individual demographic information

We divide the Delhi population into strata by age, gender, and geographic home location (i.e., slum and non-slum), and analyze mean cumulative infection rates by subpopulation for the two networks. In simulations, individuals are chosen at random in the entire network for vaccination. Various vaccination scenarios are investigated.

Figure 2 displays the cumulative infection rate results. On the x-axis, ‘Total’ refers to the entire population of Delhi. There are three breakdowns of the entire population. ‘Slum’ and ‘Non-slum’ refer to slum and non-slum regions, respectively. ‘Male’ and ‘Female’ denote the total number of males and females in Delhi, respectively. Four age groups are considered: ‘Preschool’ (0-4), ‘School’ (5-18), ‘Adult’ (19-64), and ‘Senior’ (65+). The black lines correspond to the mean cumulative infection rates for the base case. Other curves indicate vaccination strategies under different levels of vaccination rate (v) and vaccine efficacy (α). Two vaccination rates (30%, 50%) and two vaccine efficacy rates (30%, 70%) are shown in the figure.

For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate

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of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all categories of individuals.

In Network 1, slum and non-slums are treated the same so the infection rates are identical in Figure 2. However, all scenarios in Network 2 show a higher burden of disease on the slum population. This is due to the fact that slum households have larger family size and more contacts on average than households in non-slum areas, see Chen et al.[27] As shown later, we find similar patterns of infection in slum and non-slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.

The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums results in overestimation of the benefits of interventions in terms of reduction in the mean cumulative infection rate and peak infection rate, as well as the time to peak. This optimism holds for slum, non-slum and total population under various levels of vaccination rates and efficacy rates in Network 2. See Table S10 for more detailed comparison of results between slum and non-slum in Network 2.

Figure 2 goes here

Comparison between Networks 1 and 2 across a wide range of intervention strategies

Next, we consider a variety of intervention strategies for comparative analysis. We consider vaccination, school closure, stay home, and isolation strategies. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at home (SHO) strategy, all non-home activities and interactions are eliminated but all contacts within the household are maintained. Under isolation (ISO) an individual has no contact with other individuals (even home interactions are eliminated). The stay-at-home and isolation interventions are implemented for compliant infectious individuals, after they become infectious, for the entire infectious duration.

Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a wide range of intervention strategies. For each strategy, five different compliance rates are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers are the actual number of infected individuals. Darker colors correspond to higher infection rates. Note that compliance rate is simply the vaccination rate for strategies VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire population. The 'Base' values do not vary with compliance because the base case has no intervention. Note that all heat maps in this paper use the same color scheme so that colors can be compared across figures.

Since Network 1 does not distinguish between slum and non-slum populations, we only compare the two networks for the whole of Delhi. The general pattern is similar for both networks. However, all interventions have a larger effect on Network 1 under the same compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0, stay-home, and isolation strategies in Network 1 as compared to those for Network 2.

Figure 3 goes here

At a high level, among all intervention strategies, early vaccination (VAX0 and VAX1), social isolation (ISO), and stay home (SHO) are more effective than the other strategies, and this is more readily observed at higher compliance rates. For these more effective strategies, the interventions per person are implemented right after (or very shortly after) the person is infected. For example, SHO is implemented immediately after a person becomes infectious. Thus, a person that becomes infectious can infect their family members, but if these other members become infectious, then they, too, will be confined to home. Thus, home-bound people can infect their family members, but no one beyond their family (for 100% compliance). As compliance rate increases, this effect approaches, roughly, a “family-based” isolation intervention (similar to ISO), consistent with the results in Figure 3 and in subsequent results.

Effect of vaccination versus social distancing on slum and non-slum subpopulations

We now compare the impact of vaccination and social distancing on slum and non-slum subpopulations from Network 2. Social distancing interventions are close-schools, stay-home, and isolation.

The mean cumulative infection rates (and actual numbers of infections underneath) for each compliance level are shown in the heat maps in Figure 4 for slum and non-slum populations in Network 2. The axis labels are identical to those in Figure 3, as is the color scheme of the cells. The base case values are constant since there is no intervention and hence no compliance. Darker colors correspond to higher infection rates.

Compared to the base case, all interventions reduce infection rates to some extent. As the compliance rate increases, infection rates drop for all interventions. Infection rates drop to zero in slum and non-slum regions at a compliance level of 70% or higher, under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce the infection rates significantly, and this effect increases with compliance rate.

The following observations can be made from Figure 4. Social distancing, i.e. SHO, at low and intermediate compliance and CS at all compliance levels, are less effective in slum regions as compared to non-slum regions. This is because CS only eliminates school interactions for those attending school, and there are fewer school edges in slums compared to non-slum areas, as shown in Figure S6. The effectiveness of CS in slums is mitigated by the greater average number and duration of interactions at home in slums as compared to non-slums (see Figure S6 and Chen et al.[27]). Thus, if a person is sick, there is a greater chance of transmitting contagion to family members, who then may have activities outside of school, thus circumventing the CS intervention. At high compliance, SHO is effective because all interactions outside home (including school) are eliminated.[27]

These observations are also supported by Figure S7, which contains numbers of edges used to transmit contagion for a base-case run of Figure 1. There are several effects that bear on the above observations. First, in the cases of activities "work", "other", and "school", the number of edges transmitting contagion from slums to non-slums is greater than the reverse: from non-slum to slum. Second, in two of these three activity categories, there is more slum to non-slum transmissions than slum to slum transmissions. Edges of transmission for slum dwellers is dominated by home interactions. The infected homes in slums serve as launching points to drive disease to non-slums through slum to non-slum interactions. (There are no ``mixed'' edges at homes, and shopping and college activities have low levels of slum activity because of socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but we now return to Figure 4.

Isolation works well at 30% or higher compliance rates, but it is a much harder strategy to implement, especially in slums. However, it is considered here for comparative analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as compliance increases. However, close-school is generally less effective because this intervention removes only a fraction of interactions for a fraction of the population, i.e. school aged children. Simulations were also run for 70% vaccine efficacy. Since results are qualitatively similar for those parameters, these plots are provided in Figure S3.

Figure 4 goes here

Comparison between Network 1 and non-slum areas of Network 2

Note that Network 1 treats all parts of the region as non-slum, i.e. all individuals follow non-slum activities and demographics. In order to capture the additional disease risk to the non-slum population that arises from the interactions with the slum population, we compare Network 1 in Figure 3a with the non-slum population of Network 2 in Figure 4b. In base case, the additional disease risk to the non-slum population goes up from 42% to 45%. However, the beneficial effects of social distancing strategies drop by a large amount, e.g. close school strategies are 5-20% less effective in the non-slum areas of Network 2. This effect changes non-linearly with the compliance rate. As compliance rate goes up, the difference between performance of Network 1 and non-slum parts of Network 2 goes up in CS1 and CS5. This implies that in Network 2, non-slum population requires much higher levels of compliance to achieve the same results as in Network 1. This difference is less stark for vaccination based interventions, i.e. VAX0, VAX1 and VAX5. This is expected since the effect of vaccination is less dependent on interactions; it is only through herd immunity that interactions come into play.

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Constrained resource allocation among slum and non-slum areas

We consider a specific scenario under Network 2. If only a limited number of vaccines are available, and only a certain fraction of individuals can be kept home during an epidemic, how should these interventions be applied to the slum and non-slum regions so that the epidemic can be controlled effectively? Given that slum residents' attributes differ from those of non-slum residents, is there a strategy that works better in slums than in non-slum areas? The total population in Delhi is about 13.8 million, which includes about 1.8 million slum residents. We assume that only 10% of the total population can be covered by interventions, half through vaccination and the other half through stay home. Enough vaccines are available to cover 5% of the total population (i.e. 692,183 vaccinated, corresponding to about 38.25% of slum or 5.75% of non-slum population), and 5% of the individuals can stay home (692,183 individuals; this is applied to only the infected individuals). Note that an individual may receive a vaccine and also stay at home if this individual, in spite of being vaccinated, gets infected.

We consider 4 different ways of applying interventions to 10% of the total population: (i) apply both interventions to slums, i.e. give all vaccines to slums and apply SHO only in the slums (VsSs); (ii) apply all interventions to non-slum areas (VnSn); (iii) give vaccines to slums and SHO to non-slums (VsSn) and (iv) give vaccines to non-slums and apply SHO to slums (VnSs).

For both types of intervention, the same number of individuals is chosen randomly from slum or non-slum areas. 10% of the total Delhi population amounts to 76.5% of slum population, 11.5% of the non-slum population, or a combination of 38.25% of the slum and 5.75% of the non-slum population (i.e. half from slums and half from non-slums). Figure 5 shows the mean cumulative infection rates, as well as the number of infected from the entire population of Delhi, the slums, and non-slum areas under each of the four scenarios. The first 3 columns refer to Network 2 and the last column shows results for Network 1. Since Network 1 does not distinguish between slum and non-slum areas, the infection rates in each subpopulation remain the same as for the total population.

Comparison of the last two columns in Figure 5 indicates that the non-slum population in Network 2 faces 3-5% additional disease risk compared to Network 1 in all cases. This is primarily driven by the increased interactions within slum populations and between slum and non-slum populations in Network 2.

In Figure 5, all four intervention strategies produce essentially the same total attack rates (around 43% to 44%), a drop of 4% to 5% over the base case. The dominant effect on Network 2, is the benefits that primarily accrue to the slum population for the VsSs and VsSn strategies because they drive down the fraction of infected slum residents from 0.74 to 0.55 or 0.58. Also, as described in the context of Figures 4 and S6 above, social distancing of the non-slum residents helps to isolate them from the infected slum residents. Results such as these may be helpful to policy makers in breaking the poverty trap in economically poor regions.[43]

Also, the strategy of vaccinating non-slums and social distancing slums (VnSs) is not as effective as the interventions in rows 1 and 2 of Figure 5. This is a counterintuitive result, since the density of population is much higher in the slums, which may lead to the belief that social distancing in slums will break up the dense clusters. However, a careful examination shows that keeping slum residents home is not an effective social distancing strategy because their family size is, on average, almost 3 times the family size of non-slum households.[27] The high level of mixing at home makes social distancing ineffective in slums unless the infected individual is completely isolated. However, complete isolation is not viable in slum areas where the entire household may live in a single room.

Figure 5 goes here

DISCUSSION

With slum populations expected to grow to 2 billion by 2030,[44] it is becoming increasingly urgent to understand how to control the spread of infectious diseases in slum areas and measure its effect on urban populations. To our knowledge, a detailed study of interventions to control influenza epidemics in slums, using an agent-based simulation model, has never been done before. Slum conditions are important for a city beyond the direct effects of disease transmission. For example, civil wars may be precipitated or exacerbated by disease outbreaks because they decrease social health and welfare.[45]

Even though slum regions contain only 13% of the total population of Delhi, Chen et al.[4] show that omitting their attributes leads to underestimation of the overall infection rate and the peak infection rate of the epidemic. This paper extends that work by evaluating the differential impact of interventions on slum and non-slum regions. Various vaccination and social distancing strategies are analyzed under different scenarios that show that the slum population is more prone to infections under the same control measures. Furthermore, taking account of slum populations significantly alters the disease dynamics in the *entire* population. Differences in key measures are demonstrated between the cases of accounting for slum populations and not: e.g., a 100% increase in the peak attack rate in some cases when slum regions' characteristics are taken into account, compared to the case when they are ignored.

Figure 4, which compares infections in slum with non-slum areas, shows that at very high compliance rates, some interventions can be equally effective in both slums and non-slums. However, such high compliance rates are typically not feasible due to practical realities on the ground, and also because they require timely diagnosis of infected cases. For SHO to be effective, the coverage rate needs to be 70% or more in both slums and non-slums, and the diagnosis of the infected individuals needs to be correct and immediate. In other words, effective control of a contagious epidemic in a

high-density place like Delhi, would require either early and drastic action (e.g. ISO) or a highly compliant set of individuals, or a combination of these features.

This work overall demonstrates the power of agent-based and population modeling to evaluate complicated interaction-based epidemiological phenomena. Clearly, there are limitations to this work (several are itemized below). But these agent and population approaches provide a platform for adding additional complexity. All of the figures demonstrate that quantitative results depend on complicated interplay among inputs. These results are important because they inform policy decisions. An equally important benefit of this type of work, but not often stated, is developing intuition about epidemic dynamics (in this case, with the effects of slums), to enable decision makers to reason about nuanced interactions among effects to a degree that is hard to obtain with other approaches that lack this level of detail. However, we believe that other modeling approaches may also be valuable in understanding epidemic dynamics in slum populations.

Despite the detailed modeling effort, there are limitations of this work and areas for improvement in the future. For example: (1) Examination of different population level base attack rates derived from different transmission probabilities. (2) Different susceptibilities and infectivity for individual agents; e.g., based on age. (3) Effects of asymptomatic infections (although we have addressed this to some extent with compliance and efficacy of interventions). (4) Seasonal effects.[46-47] (5) Effects of immunity for an individual from previous infections (in previous seasons). (6) Evaluation of interaction of different strains from season to season. (7) Comparison of tropical versus subtropical factors. (8) Evaluation of a specific outbreak scenario. (9) Impact of sickness on absenteeism from work and its economic ramifications. (10) Effects on rural versus urban populations. (11) Using combinations of interventions rather than one at a time; this was only done here in Figure 5. However, to disambiguate results, it is prudent to first examine individual interventions. (12) Effect of changing disease transmission rate for different activity types. (13) Effect of changing contact times at different locations. (14) To capture close-proximity transmission, one could use actual physical proximity. Here, we use colocation. Finally, just as changes in modeling details can change model results, so, too, changes in the conditions in actual outbreaks can change results; some of these factors are listed above. It is essentially impossible to capture all of these effects—many of which are unknown—down to the level of individual humans.

Public health implications: This research demonstrates that modeling slum populations is important, not only for understanding disease dynamics, but also for designing effective control measures. Ignoring the influence of slum characteristics on their urban environment will significantly underestimate the speed of an outbreak and its extent, and hence will lead to misguided interventions by public health officials and policy planners. Lessons from this research can be applied in the field and observations collected from the field can provide valuable data to improve the models and validate the results. For example, our results show that a slum resident has about 50% greater total contact duration per day compared to a non-slum resident. This makes social distancing based interventions more taxing in the slum population. Public health policy makers may want to subsidize pharmaceutical resources for the slum population to make them more affordable. Similarly, we find women in slums have a higher number of contacts per day than their male counterparts whereas in non-slum regions, women have a fewer number of daily contacts than their male counterparts. This kind of information can be used to prioritize the distribution of limited resources, e.g. women could be given preference over males for vaccination in slum areas. This research provides simulation-based evidence that in general social distancing strategies are ineffective in slums because of a large number of contacts at home. Unless one applies complete isolation, which is not feasible in slums, just staying at home still keeps a large number of contacts and pathways of spread intact.

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Contributorship statement

AA, SE, CJK, AM, MM, SS, AV designed and conceived the study. SC carried out the experiments and simulations. SC, CJK, AM performed data analysis. CJK, BL, AM, MM, EKN, MLW helped with reviewing the results and writing the paper.

Competing Interests

There are no competing interests.

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Data Sharing Statement

Data pertaining to figures and statistical analysis are partially provided in the supplementary file, and also can be obtained by contacting the corresponding author through email.

Main manuscript

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FIGURE 1: Epidemic curves for base case and vaccination case. Each time point in the curve is an average over 25 replicates. The vaccines are given randomly to 30% of the entire population and the vaccine efficacy is 30%. For Network 2, epidemic curves are shown for total population and slum and non-slum subpopulations. 'Intervene Total' refers to the epidemic curve of the entire Delhi population when the vaccine intervention is applied. 'Intervene Slum' refers to the epidemic curve for just the slum population, and 'Intervene Non-slum' refers to the epidemic curve for just the non-slum population for the intervention case. Epidemic curves for a variety of compliances and efficacies are reported in Figures S1 and S2.

FIGURE 2: Mean cumulative infection rates for different subgroups in the two networks. Two vaccination rates (v = 30%, 50%) and two vaccine efficacy rates (α = 30%, 70%) are considered. Individuals are chosen at random in the entire network for vaccination on day 0. Mean infection rates are calculated within each group. The last several lines in the plot for Network 1 are overlapping at the bottom because the mean infection rates are almost zero under those scenarios. 'Total' refers to the entire population of Delhi. 'Slum' and 'Non-slum' refer to slum and non-slum regions, respectively. 'Male' and 'Female' denote the total number of males and females in Delhi, respectively. Age groups are denoted by 'Preschool', 'School', 'Adult', and 'Senior'.

(a) Total Delhi Network 1 (b) Total Delhi Network 2

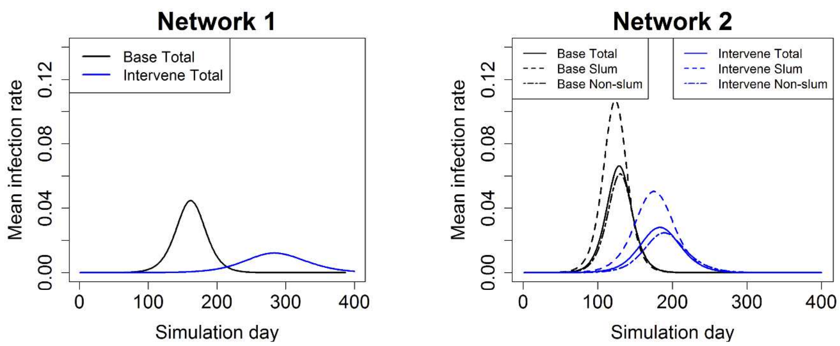
Figure 3. Mean cumulative infection rates under different interventions for Network 1 and Network 2. The larger font numbers are fractions of populations that are infected and the smaller font numbers are counts of infected individuals. Colors of the boxes correspond to the values of the large numbers (i.e., fractions of infected), and the same scheme is used for both plots for comparisons—and for all plots in this paper. Five different compliance rates are examined (10%, 30%, 50%, 70% and 90%), and 4 types of intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when the cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5) of the total population. The vaccine efficacy is set at 30%. For close-schools, two trigger points are used: when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected at random from the entire Delhi population, and the cumulative infection rates are calculated for each network.

(a) Slum (b) Non-slum

Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond to higher infection rates. The smaller font numbers are counts of infected individuals. The vaccination efficacy is fixed at 30%. Five different compliance rates (10%, 30%, 50%, 70% and 90%) and 4 types of

intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population, and the mean infection rates are calculated separately for the slum and non-slum subpopulations. Although not reported here, qualitatively similar results are found for other transmission rates, as well as for higher vaccine efficacy (70%). Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals.

FIGURE 5: Mean cumulative infection rates for each category listed on the x-axis, for Network 2 and Network 1, under four different intervention scenarios. The color scheme of the boxes are based on the large values in the boxes—the cumulative infection rates. Darker colors correspond to higher infection rates. Smaller font values are the number of infected individuals. The vaccine efficacy is set at 30%. VsSs refers to the case when vaccines and social distancing are both applied to slum residents; VnSn refers to the case when vaccines and social distancing are applied to non-slum residents. Similarly, VsSn means vaccines are given to slums and stay home is applied to non-slums; and VnSs means vaccines are given to non-slums and stay home is applied to slums. Base refers to the case where no intervention is applied. The smaller-font numbers under the infection rates show the actual number of infected individuals in each category listed on the x-axis.



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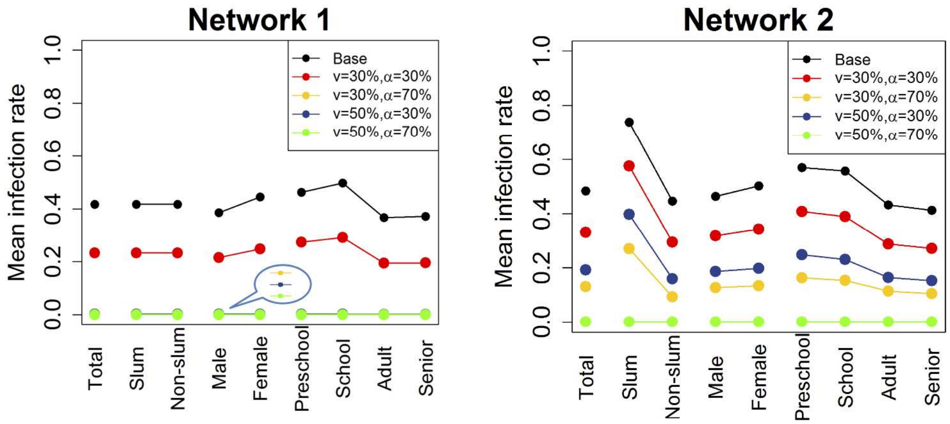

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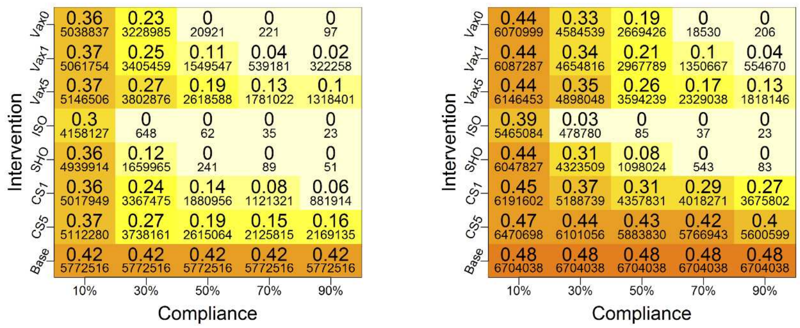

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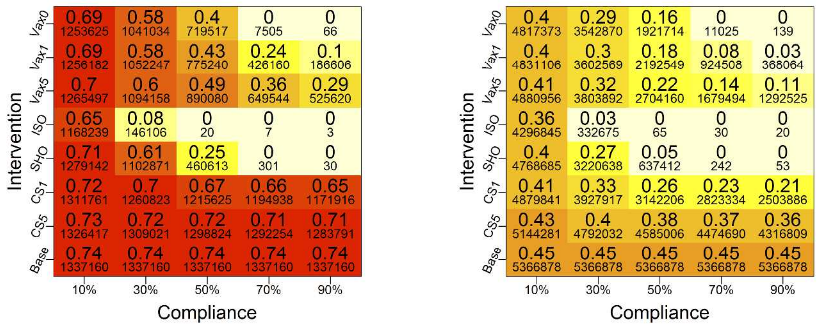

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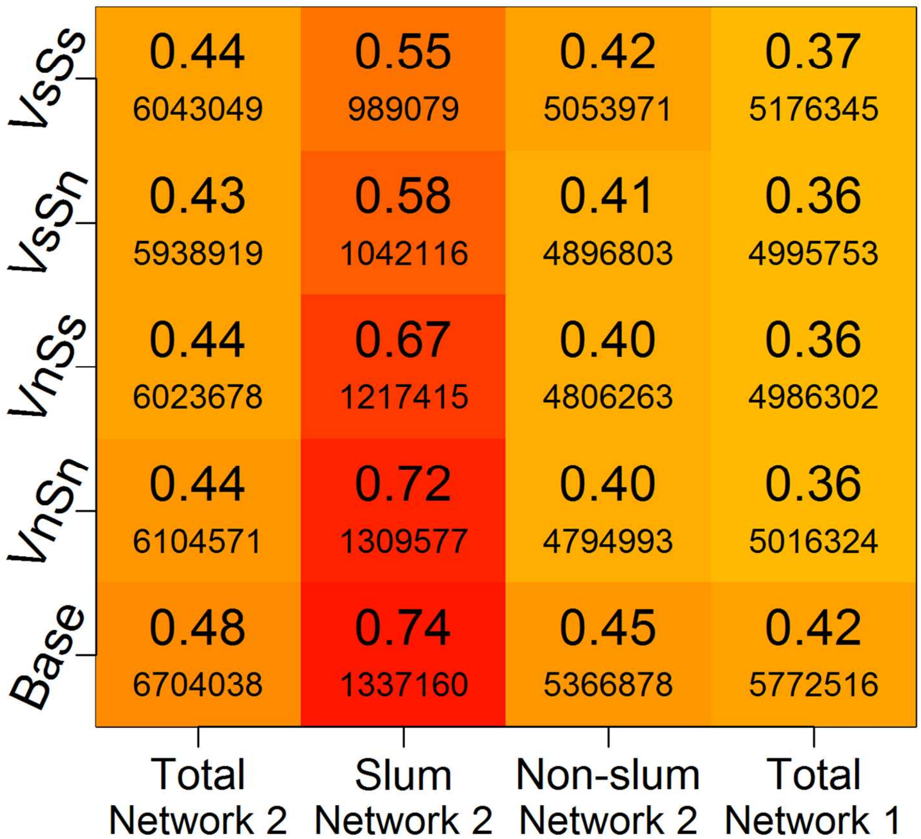

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Supplemental Information

Disparities in Spread and Control of Influenza in Slums of Delhi: Findings From An Agent-Based Modeling Study

A. Adiga, S. Chu, S. Eubank, C. J. Kuhlman, B. Lewis, A. Marathe, M. Marathe, E. K. Nordberg, S. Swarup, A. Vullikanti and M. L. Wilson

Supplemental Information

Presentation of Results.

For each set of input parameters, 25 replicates were run using agent-based simulation and the results presented are the average values over the 25 replicates. Also, 95% confidence intervals (CIs) are given when appropriate.

Comparisons Between Network 1 and Network 2.

Table S1 shows some differences between network1 and network 2 due to their different ways of modeling slum population. Note that these two networks are the same ones as those used in Chen et al.[1]. Further comparisons between the two networks are found in Chen et al.[2].

Table S1. Comparison of two networks as well as data sources for slum and non-slum Delhi, India.

	Network 1		Network 2	
	Slum	Non-slum	Slum	Non-slum
Population Size	0	13.8 million	1.8 million	12 million
Average Household Size of Slum Region	5.2		15.5	
Daily Activities	33,890,156		39,077,861	
Number of Edges	210,428,521		231,258,772	
Average Degree	30.4		33.4	
Maximum Degree	170		180	
Data Sources	MapMyIndia.com		MapMyIndia.com Indiamart.com MapMechanic.com	

Network 2 contains 298 slum zones, while network 1 models the whole population as non-slum. For network 1, the non-slum demographics and activities data is collected by survey through MapMyIndia.com. While for slum population, we collected additional data by Indiamart.com and MapMechanic.com for slum demographics and activities as well as slum polygons. More detailed demographic and activity differences can be found in the Chen et al.[1]

Terminology and Abbreviations for Interventions.

Table S2 contains abbreviations for different interventions and their meanings. Stay-at-home (SHO) and social isolation (ISO) interventions are applied to a person immediately after they become infected, while close-schools (CS) and vaccinations (VAX) may be applied after a specified fraction of the total population has been infected.

Table S2: Summary of abbreviations for interventions and their meanings.

Supplemental Information

Abbreviation	Definition
CS	Close-schools: School-related interactions are eliminated.
CSx	Close-schools is implemented after the total fraction of the population that has been infected reaches x.
ISO	Social isolation: a person who is socially isolated does not interact with any other person, even people in their home. Isolation is triggered only after a person becomes infectious.
SHO	Stay at home: All out-of-the-home activities for this person are eliminated, and this person only interacts with others at home. Stay at home is triggered only after a person becomes infectious.
VAX	Vaccination: a person who is vaccinated has a reduced probability of contracting the virus.
VAXx	Vaccination of an individual occurs after the total fraction of the population that has been infected reaches x.

Table S3 contains the variables used in simulations. The transmissibility corresponds to strong flu in Chen et al.[1] For vaccination, efficacy is either 30% or 70%. That is, for 30% efficacy, a person who gets vaccinated has reduced their susceptibility to infection by 30%.

Table S3: Summary of parameters and values used in simulations.

Category	Values
Networks of Delhi	Network 1 (does not model slums); Network 2 (models slums).
Seeding	20 people selected randomly over the entire population at time 0 as index cases.
Transmissibility	0.000027.
Intervention approaches.	Base case (no intervention); close-schools (CS); stay-home (SHO); isolation (ISO); vaccination (VAX).
Intervention/compliance rates.	10%, 30%, 50%, 70%, 90%.
Efficacy of vaccination intervention.	30%, 70%.
Intervention trigger time	Cumulative infection rate reaches 0%, 1% and 5%.
Simulation replicates	25

The Agent Epidemic States and Disease Model.

An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. An infectious person spreads the disease to each susceptible neighbor independently with a probability referred to as the transmission probability, given by

$$p = \lambda \left(1 - (1 - \tau)^{\Delta t}\right),$$

where λ is a scaling factor to lower the probability (e.g., in the case of vaccination), τ is the transmissibility and Δt is the duration of interaction in minutes. Durations of contact are labels on the network edges. A susceptible person undergoes independent trials from all of its neighbors that are infectious. The transmission probability is a function of the number and duration of contacts.[3] This is selected to simulate an Influenza model resulting in a R_0=1.26 (cumulative attack rate 42%, corresponding to a transmissibility of 0.000027 per minute of contact time) for Network 1, and R_0=1.39 (cumulative attack rate 48%) for Network 2.[4] This transmissibility value is used uniformly throughout this study and corresponds to the probability at which an infectious node infects a susceptible node per minute of contact.

At each time (day), if an infectious person infects a susceptible person, the susceptible person transitions to the exposed (or incubating) state. The exposed person has contracted Influenza but cannot yet spread it to others. The incubation period is assigned per person, according to the following distribution: 1 day (30%); 2 days (50%); 3 days (20%). At the end of the exposed or incubation period, the person switches to an infected state. The duration of infectiousness is assigned per person, according to the distribution: 3 days (30%); 4 days (40%); 5 days (20%); 6 days (10%). After the infectious period, the person recovers and stays healthy for the simulation period. This sequence of state transitions is irreversible and is the only possible disease progression.

Epidemic Curves for Other Interventions, for Varying Efficacy and Compliances.

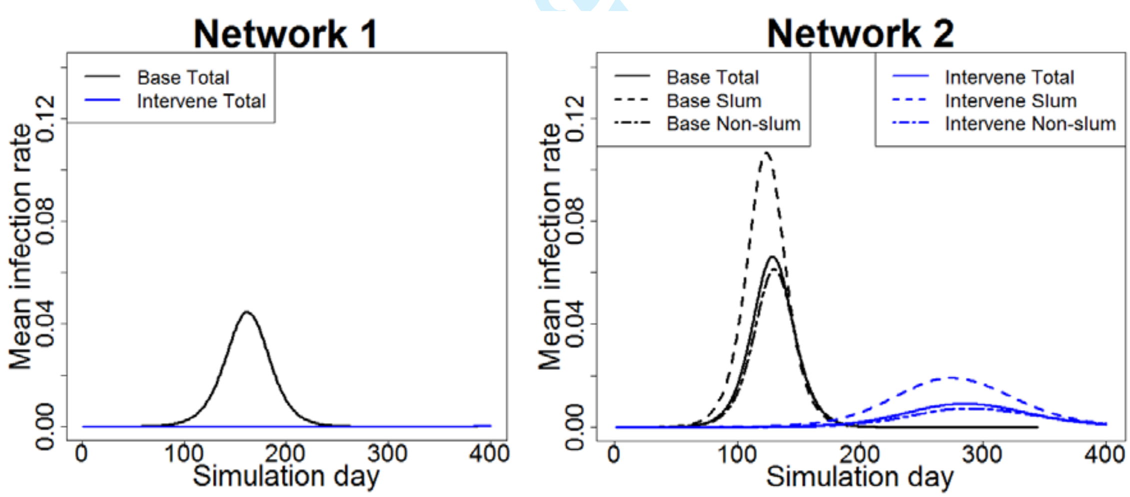


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

Supplemental Information

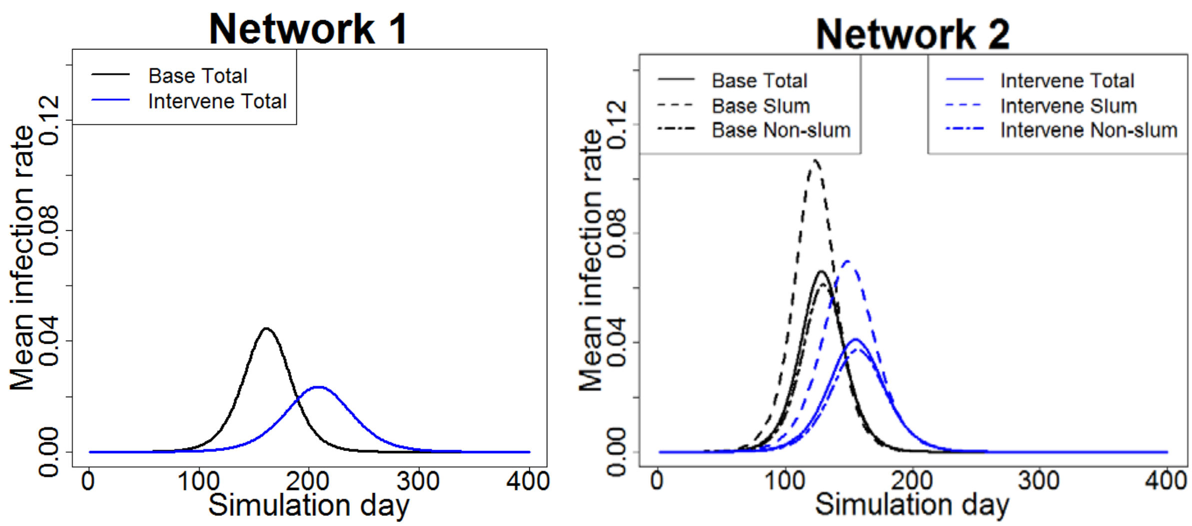
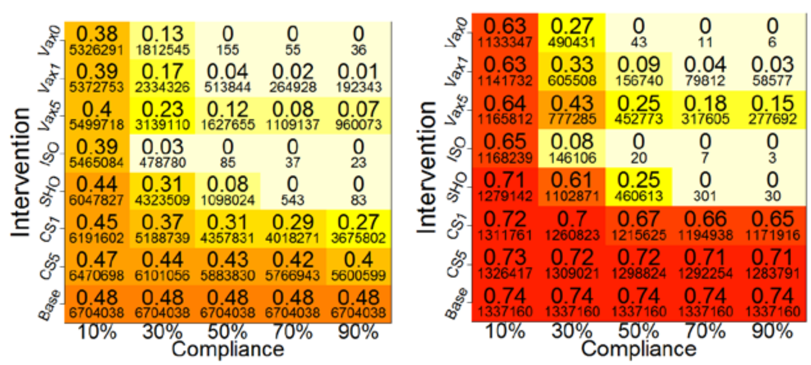


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.



(a) Total Delhi (b) Slum (c) Non-slum

Figure S3. Heat map of mean cumulative infection rates in Delhi, and slum and non-slum regions under different intervention strategies for Network 2. The vaccination efficacy is fixed at 70%. Five different compliance rates, i.e., 10%, 30%, 50%, 70% and 90% and 4 types of intervention strategies, i.e. vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO), are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used i.e. when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population and the mean cumulative infection rates are calculated separately for the total population, and slum and non-slum subpopulations. Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals. Darker colors correspond to higher infection rates.

Supplemental Information

Tabulations of Basic Results: Comparisons between Networks 1 and 2 for Compliance of 30% and Efficacy of 30%.

Table S4 shows results when 30% of the population that is selected uniformly at random is vaccinated with a vaccine that is 30% effective. The contrast between the two populations is even greater when considering interventions. The peak infection rate of the entire population increases by 123.2% (95% CI: 122.7%-123.7%) in Network 2 compared to Network 1 for the intervention, versus 47.6% difference between the networks in Table S8. The time to peak decreases by 35.7% (95% CI: 32.9%-38.8%) in Network 2 compared to that in Network 1, for the intervention case, compared to only 20.84% percentage change between the two Networks for the base case in Table S8. The cumulative infection rate (or attack rate) is also underestimated, which is 42.2% (95% CI: 41.5%-42.8%) greater on average in Network 2 compared to Network 1 for the intervention case. Hence, the differences between key epidemic results for Networks 1 and 2 that are generated for the intervention case are even more pronounced than they are for the base case. These values are all statistically significant.

Table S4: Comparisons of key epidemic parameters for Networks 1 and 2 for a vaccination intervention before the epidemic starts (VAX0), where the vaccine efficacy is 30% and the compliance rate is 30%.

Vaccination	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	286	184	102 (95% CI: 94-111)	35.7% (95% CI: 32.9%-38.8%)
Peak Infection Rate	1.34%	2.99%	1.65% (95% CI: 1.64%-1.66%)	123.19% (95% CI: 122.69%-123.65%)
Cumulative Infection Rate	23.3%	33.1%	9.82% (95% CI: 9.67%-9.96%)	42.17% (95% CI: 41.51%-42.77%)

Table S5 shows the effect of delay in applying interventions. The numbers show the percentage difference in cumulative infection rate in slums and non-slums of Network 2 for the specified interventions and compliance rates at different trigger levels. For example, the value 30.55% at 0.1% compliance means that for intervention close-schools, where this intervention is implemented after 5% of the total population is infected, the fraction of people in slums that get infected is 30.55% greater than the fraction of non-slum residents who get infected.

Table S5. Differences of epidemic size between slum and non-slum regions for Network 2 for base case (no intervention); close-schools (CS) after 1% total outbreak fraction (CS1) and after 5% total outbreak fraction (CS5); stay at home (SHO); social isolation (ISO); vaccination (VAX) after 1% total outbreak fraction (VAX1) and after 5% total outbreak fraction (VAX5), under various compliance rates. The vaccination efficacy is 30%.

Compliance	Base	CS5	CS1	SHO	ISO	VAX5	VAX1
0.1	29.30%	30.55%	31.94%	31.06%	28.85%	29.37%	29.27%
0.3	29.30%	32.52%	37.03%	34.18%	5.31%	28.85%	28.21%

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0.5	29.30%	33.67%	41.07%	20.16%	0.00%	26.72%	24.62%
0.7	29.30%	34.23%	42.57%	0.01%	0.00%	21.94%	15.87%
0.9	29.30%	35.07%	43.95%	0.00%	0.00%	18.31%	7.25%

Table S6 examines the difference in effects of interventions on the cumulative infection rate in Network 2. These data use both the stay home (SHO) and the isolation (ISO) interventions as base cases. Each entry represents the difference between the cumulative infection rates for the specified pharmaceutical interventions and SHO or ISO. For example, 18.03% means that the cumulative infection rate for vaccinating after 5% of the population is infected, is 18.03% greater than that for the intervention of SHO; 31.92% means that the cumulative infection rate for vaccinating after 5% of the population is infected is 31.92% greater than that for the intervention of ISO. Thus, the larger the magnitude of a positive number, the greater the effectiveness of SHO or ISO compared to the specified pharmaceutical intervention.

Table S6. Differences in epidemic size between stay at home (SHO) interventions, social isolation (ISO) interventions and pharmaceutical interventions (VAX0, VAX1, VAX5), under various compliance rates. The compliance rate and efficacy for vaccination is 30% and 30%, respectively.

Compliance	Vax5-SHO	Vax1-SHO	Vax0-SHO	VAX5-ISO	VAX1-ISO	VAX0-ISO
0.1	0.71%	0.29%	0.17%	4.92%	4.49%	4.38%
0.3	4.15%	2.39%	1.89%	31.92%	30.17%	29.66%
0.5	18.03%	13.51%	11.35%	25.96%	21.44%	19.28%
0.7	16.82%	9.75%	0.13%	16.82%	9.76%	0.13%
0.9	13.13%	4.01%	0.00%	13.13%	4.01%	0.00%

Effect of intervention on Network 2, With and Without Interventions.

The comparison between vaccination intervention and the base case in Network 2 is detailed in Table S7 below.

In Network 2, for the total population, vaccination delays the time to peak infection by 43.27% (95% CI: 40.14%-46.41%) relatively, from 128 to 184 days on average, while the peak infection rate is reduced by about 3.88% from 2.99% to 6.87% on average (56.47% relatively with 95% CI: 56.35%-56.56%). The total infection rate is reduced by 15.31% from 33.12% to 48.43% (31.62% relatively with 95% CI: 31.57%-31.67%).

In slum regions in Network 2, vaccination delays the time to peak infection by 43.09% (95% CI: 39.78%-46.4%) relatively, from 123 to 176 days on average, while the peak infection rate is reduced by about 5.70% from 5.42% to 11.12% on average (51.26% relatively with 95% CI: 50.88%-51.64%). The total infection rate in slums is reduced by 16.35% from 57.53% to 73.88% (22.13% relatively with 95% CI: 22.07% to 22.19%).

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In non-slum regions in Network 2, the time to peak is delayed by 43.44% (95% CI: 40.32%-46.56%) relatively, from 130 to 186 days on average, while the peak infection rate is reduced by about 3.68% from 2.69% to 6.36% on average (57.79% relatively with 95% CI: 57.64%-57.94%). The total infection rate in non-slums is reduced by 15.16% from 44.60% to 29.45% (33.98% relatively with 95% CI: 33.93% -34.03%).

Table S7: Comparisons between the base and vaccination cases for Network 2. The three parameters (time to peak, peak infection rate and cumulative infection rate) are broken out, and for each, values for the total population, and slum and non-slum subpopulations are given. The vaccination rate is 30% and efficacy is 30% for those receiving the vaccine.

Network 2, Time to Peak	Base	Vaccination	Compare-absolute	Compare-Relative
Total	128	184	55 (95% CI: 51-59)	43.27% (95% CI: 40.14%-46.41%)
Slum	123	176	53 (95% CI: 49-57)	43.09% (95% CI: 39.78%-46.4%)
Non-Slum	130	186	56 (95% CI: 52-60)	43.44% (95% CI: 40.32% - 46.56%)

Network 2, Peak Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	6.87%	2.99%	-3.88% (95% CI: -3.870% -3.884%)	-56.46% (95% CI: -56.35% -56.56%)
Slum	11.12%	5.42%	-5.70% (95% CI: -5.66% -5.74%)	-51.26% (95% CI: -50.88% -51.64%)
Non-Slum	6.36%	2.69%	-3.68% (95% CI: -3.67% -3.69%)	-57.79% (95% CI: -57.64% -57.94%)

Network 2, Cumulative Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	48.43%	33.12%	-15.31% (95% CI: -15.29% -15.34%)	-31.62% (95% CI: -31.57% -31.67%)
Slum	73.88%	57.53%	-16.35% (95% CI: -16.30% -16.39%)	-22.13% (95% CI: -22.07% -22.19%)
Non-Slum	44.60%	29.45%	-15.16% 95% CI: (-15.14% -15.18%)	-33.98% (95% CI: -33.93% -34.03%)

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Table S8 summarizes differences in key epidemic parameters for Networks 1 and 2 for the base case with no interventions. The peak infection rate is the maximum fraction of individuals who are infected on any day, the time to peak is the day on which the peak infection rate occurs, and cumulative infection rate is the cumulative fraction of individuals who get infected in the epidemic. Under the base case, the peak infection rate in Network 2 is 47.6% (95% CI: 47.4%-47.8%) greater compared to that in Network 1 (47.6%=(6.87%-4.65%)/4.65%). The time to peak infection for Network 2 is decreased by 20.8% (95% CI: 19.2%-22.7%) compared to that in Network 1. The cumulative infection rate (or attack rate) is also underestimated under Network 1 by 16.1% (95% CI: 16.1%-16.2%) compared to Network 2. These results, presented in the main paper, are tabulated here in Table S8 for convenience and comparison.

Table S8: Comparisons of key epidemic parameters for Networks 1 and 2 for the base case.

Base	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	162	128	34 (95% CI: 31-37)	20.84% (95% CI: 19.19%-22.71%)
Peak Infection Rate	4.65%	6.87%	2.215% (95% CI: 2.206%-2.224%)	47.6% (95% CI: 47.4%-47.8%)
Cumulative Infection Rate	41.70%	48.43%	6.73% (95% CI: 6.71%-6.75%)	16.1% (95% CI: 16.1%-16.2%)

Effect of intervention on Network 1, With and Without Interventions.

In Network 1, vaccination delays the time to peak infection by 76.41%, from 162 to 286 days on average, with 95% CI: 71.53%-81.28%. The peak infection rate is reduced by 3.3121 percentage points, from 1.34% to 4.65%, which is a relative percentage difference (RPD) of -71.20%, with 95% CI: -71.02% to -71.38%. These and cumulative infection rate data are given in Table S9.

Table S9: Comparisons of a vaccination intervention (30% vaccination rate, 30% efficacy of a vaccination) with the base case in Network 1 Delhi.

Network 1,Total	Base	Vaccination	Compare-absolute	Compare-relative
Time to Peak	162	286	124 (95% CI: 116-132)	76.41% (95% CI: 71.53%-81.28%)
Peak Infection Rate	4.65%	1.34%	3.31% (95% CI: 3.30%-3.32%)	71.20% (95% CI: 71.02%-71.38)
Cumulative Infection Rate	41.7%	23.3%	18.40% (95% CI: 18.25%-18.55%)	44.13% (95% CI: 43.77%-44.48%)

Tables S7 and S9 show that, generally, Network 1 is more responsive to intervention than Network 2. In Network 1, the percentage changes in time-to-peak, peak infection rate, and cumulative infection rate, due to intervention, are 76.4%, -71.2%, and -44.1%,

respectively. For Network 2, these values are 43.3%, -56.5%, and -31.6%, respectively. The reason for lower impact in Network 2 is the greater connectivity of households in slums, which helps drive the contagion.

Effect of interventions on slum and non-slum subpopulations of Network 2, compared to the base case.

The data used in comparing key outbreak parameters in slum and non-slum regions are taken from Table S7, and the corresponding epidemic curves are in Figure 1. The percentage change in peak infection rate due to intervention in slum (-51.3%) and non-slum (-57.8%) regions in Network 2, are comparable, although the magnitudes of the peak infections in slums are about twice those in the non-slum regions. For the cumulative infection rates, the relative drop from the intervention is greater for the non-slum (-34.0% vs. -22.1%) population than it is for the slum population, but the absolute drop is about the same (-16.3% vs. -15.1%).

Table S10: Comparison of results between slum and non-slum in Network 2. The input data is the same as in Table S7.

Network 2, **Base**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	123	130	7(95% CI: 4-9)	5.26% (95% CI: 3.37%-7.16%)
Peak Infection Rate	1.12%	6.36%	4.76% (95% CI: 4.72%-4.80%)	42.79% (95% CI: 42.46%-43.14%)
Cumulative infection rate	73.88%	44.60%	29.25% (95% CI: 29.25% - 29.31%)	39.63% (95% CI: 39.59%-39.67%)

Network 2, **Vaccination**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	176	186	10(95% CI: 5-15)	5.23% (95% CI: 2.58%-8.46%)
Peak Infection Rate	5.42%	2.69%	2.74% (95% CI: 2.71% - 2.76%)	50.46% (95% CI: 50.06%-50.86%)
Cumulative infection rate	57.53%	29.45%	28.08% (95% CI: 28.04%-28.12%)	48.82% (95% CI: 48.74%-48.89%)

Figure S4 contains the percentage changes between the base case and intervention case for Networks 1 and 2 for the three parameters in the legend, and further breaks down Network 2 into slum and non-slum subpopulations. This plot provides a summary of differences between the base and intervention cases. For all four conditions considered, the intervention reduces the severity of an epidemic. It delays the time when the infection peaks, and reduces the peak infection and the cumulative infection rates. Note that the intervention has a larger effect on the epidemics when applied to Network 1, as consistent with Figure 1.

Supplemental Information

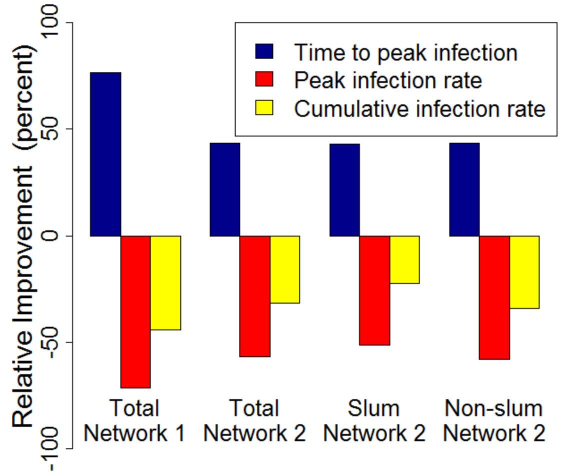


Figure S4: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 than Network 2, while, for Network 2, it is slightly more effective for the non-slum population than slum. Details of the data associated with this plot are provided in Tables S7 and S9.

Figure S5 provides the same data in as in Figure S7, but now the data are provided as absolute differences, rather than as percentage changes. (There are three separate plots owing to the different ranges in absolute differences. Qualitatively, the time to peak infection (blue bars) does not change between the two networks and the two subpopulations of Network 2 (Figure S4 versus Figure S5(a)). However, the red bars in Figure S4 are qualitatively different from those in Figure S5(b), when considering absolute changes. That is, the magnitude of the percentage change in peak infection rate between the base and intervention cases is greatest in Network 1 (Figure S4, red bars), while in Figure S5(b), it is least on an absolute change basis. Similarly, the slum population in Network 2 shows the least percentage change in Figure S4, but the greatest absolute change in Figure S5(b). Rankings of the subpopulations in Network 2 is also reversed for cumulative infection rate: the percentage change is greatest in the non-slum region, while it is greatest for the slum regions in absolute terms.

Supplemental Information

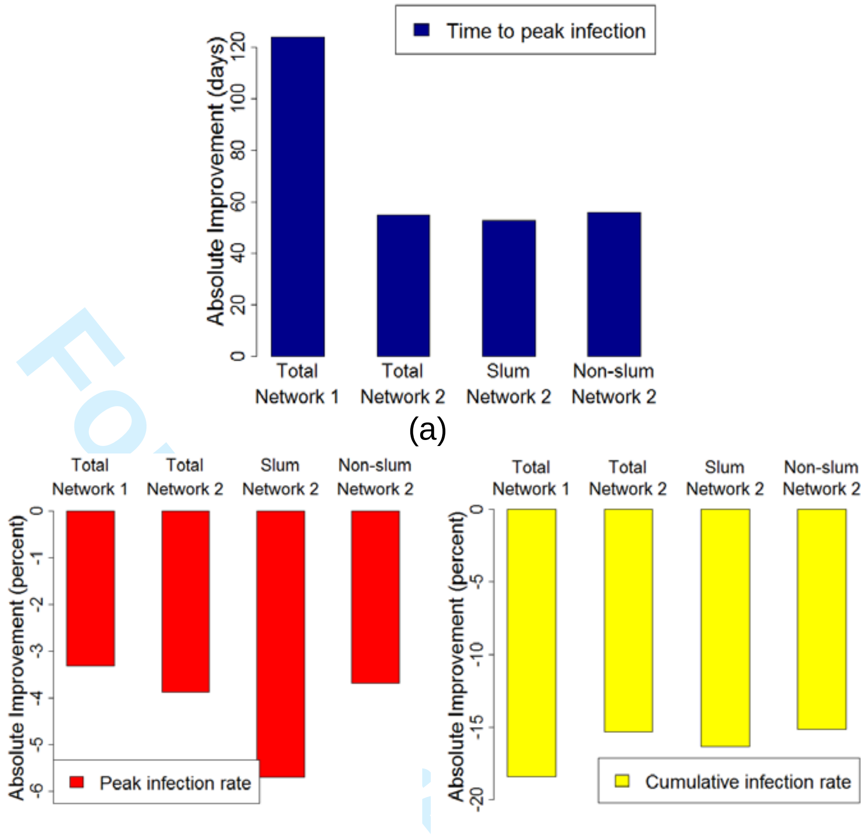
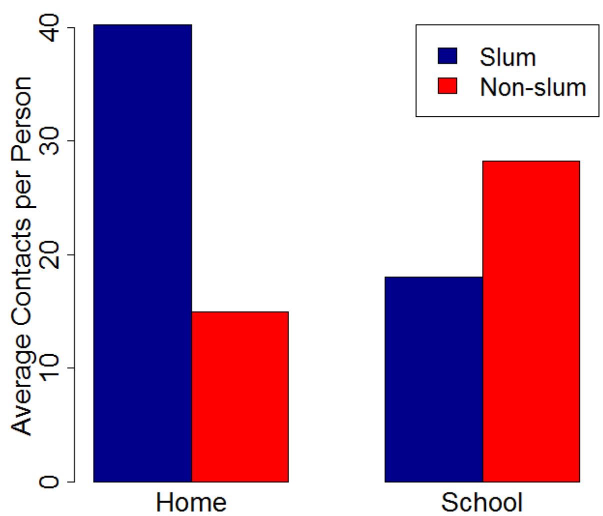


Figure S5: Comparison of absolute difference in improvement; the relative differences are shown in Figure S7. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S7 and S9.

Evaluation of Network 2 Home and School Contacts.



Supplemental Information

Figure S6: Comparison of average contacts per person in slum and non-slum regions for home and school activity types in Network 2.

Evaluation of Network 2 Edges Transmitting Infection.

Figure S7 provides counts of edges used to transmit infection for a base case simulation in Network 2 of Figure 1 of the main text. Edges are broken down by activity types of people who are interacting during transmission. Data are also broken down by the classifications of individuals interacting (e.g., slum and nonslum, see legend).

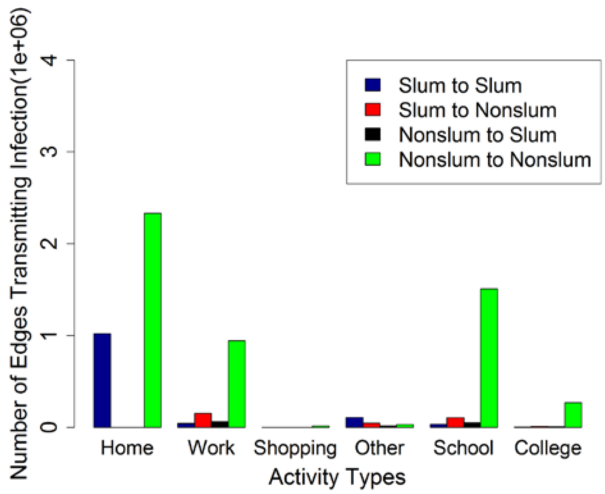


Figure S7. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater than nonslum-to-slum ones because once infection gets into a slum household, it may spread within the household more (because there are more people and connections). Thus, a slum household carries more infection to its interactions with nonslum people. The "Other" activity category, like home activity, shows more edges carrying infection for slum-to-slum interactions than slum-to-nonslum, which is consistent with Figures S4 and S6 of Chen et al.[2], where further network characteristics are given.

Supplemental Information

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Main manuscript

Disparities in Spread and Control of Influenza in Slums of Delhi: Findings From An Agent-Based Modeling Study

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Main manuscript

ABSTRACT

Objectives This research studies the role of slums in the spread and control of infectious diseases in the National Capital Territory of India, Delhi, using a detailed social contact network of its residents.

Methods We use an agent-based model to study the spread of influenza in Delhi through person-to-person contact. Two different networks are used; one in which slum and non-slum regions are treated the same and the other in which 298 slum zones are identified. In the second network, slum-specific demographics and activities are assigned to the individuals whose homes reside inside these zones. The main effects of integrating slums is that the network has more home-related contacts due to larger family sizes and more outside contacts due to more daily activities outside home. Various vaccination and social distancing interventions are applied to control the spread of influenza.

Results Simulation based results show that when slum attributes are ignored, the effectiveness of vaccination can be overestimated by 30%-55%, in terms of reducing the peak number of infections and the size of the epidemic, and in delaying the time to peak infection. The slum population sustains greater infection rates under all intervention scenarios in the network that treats slums differently. Vaccination strategy performs better than social distancing strategies in slums.

Conclusions Unique characteristics of slums play a significant role in the spread of infectious diseases. Modeling slums and estimating their impact on epidemics will help policy makers and regulators more accurately prioritize allocation of scarce medical resources and implement public health policies.

Strengths and limitations of this study

- We show that the unique attributes of slums must be accounted for in understanding the spread and control of infectious diseases.
- We demonstrate that the granularity afforded by the agent-based model enables extraction of subpopulations, and subsets of interactions, to help interpret results.
- This study does not consider age-specific susceptibility or immunity from past infections; all individual persons are assumed to be equally susceptible.
- The disease transmission risk does not change across activity types, e.g. an hour with an infected person at home or at work carries the same risk.
- Co-location based contact time is used as a proxy for physical proximity and short-distance environmentally-mediated transmission.

INTRODUCTION

Main manuscript

Infectious disease is one of the leading causes of human morbidity and mortality worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000 people in the United States (US) are hospitalized with influenza-like illness (ILI) symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the National Institute of Virology has shown that ILI cases are present throughout the year, although they peak in rainy and winter seasons.[3] It carries a significant economic burden through reduced productivity and high costs of health care.[4-7] A CDC study finds that for outpatient and non-medically attended individuals, acute respiratory infections cost 1%-5% of monthly per capita income in India. In contrast, cost of inpatient care can be as high as 6%-34% of monthly per capita income.[8] For developed countries, the annual cost of influenza is estimated to be between $1-$6 million per 100,000 people, according to the World Health Organization.[9]

In 2007, India established an Integrated Disease Surveillance Program (IDSP), which included a network of 12 regional laboratories, to minimize the threat of avian influenza and other highly infectious zoonotic diseases.[10] India faces some unique challenges in surveillance, prevention and control because of the seasonality of influenza at sub-regional levels. This seasonal variation depends upon latitude, monsoon season, humidity and climatic factors of the regions. Acute respiratory infections are estimated to be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13] estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in year 2011, and children under age 5 had the highest incidence of them.

Given that influenza is environmentally-mediated and spreads through close proximity, population density is an important factor in its spread. In India, the average population density is about 1000 people per square mile; in the slums, it can be 10 to 100 times higher.[14] Larger household size and crowding make it easier to transmit infections).[15-18] For example, Baker et al.[16] find that meningococcal disease risk among children doubles with the addition of 2 adolescents or adults (10 years or older) to a 6-room house. Other than overcrowding, slums are characterized by their lack of medical services,[19-20] which makes slum residents highly vulnerable to infectious diseases. Diseases like cholera, malaria, dengue and HIV are common in slums across the world.[21-23]

This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8 million people live in slum areas, as an example city to study the spread and control of influenza. Delhi is an interesting case study. It ranks fourth in the world in urban population, and, among the top 25 largest urban areas, it ranks tenth in population density. Although Delhi is our target population, the results are likely to be useful in studying other slum areas within and outside of India because of the wide range of intervention types and parameter values examined.

This paper is an extension of the work done in Chen et al.[4], which shows that slum populations have a significant effect on influenza transmission in urban areas. Ignoring the influence of slum characteristics underestimates the speed of an outbreak and its extent. However, Chen et al.[4] do not consider any interventions on the epidemic spread. *The focus of this research is to study the effect of different intervention strategies on several subpopulations (slum, age and gender) in two different Delhi networks, i.e., original (referred to as Network 1) and refined (Network 2).*

The original network used in Xia et al.[24] studied the spread and control of influenza in Delhi using Network 1, which did not take into account the special attributes of the slum population, such as larger family sizes and different types of daily activity schedules. Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for slum demographics and slum activities, but did not study intervention strategies. In Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.

The goals of this work focus on understanding the effects of pharmaceutical and non-pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI) include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing measures such as school closure, quarantine and staying home. These effects are studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a scenario where interventions can be applied to a limited number of individuals, we explore how resources should be split between slum and non-slum subpopulations in order to achieve the best outcomes with respect to total infection rate (i.e., the cumulative fraction of a population infected).

METHODS

We use an agent-based modeling (ABM) approach to simulate the spread and containment of influenza in social contact networks of Delhi, India. We compare two networks: one considers slum-specific attributes, and the other does not. In this section, we describe the networks, the disease model for each agent, the interventions, and the heterogeneities of the problem that make ABM uniquely suited to study epidemics. Throughout this manuscript, each agent in the ABM is an individual human.

Social Contact Networks: This study uses two synthetic social networks of Delhi, created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found in Xia et al.[24], Chen et al.[4], Barrett et al.[25], Bisset et al.[26] and references therein. The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined network developed in Chen et al.[4], *Network 2.*

It is important to note that while the social contact networks are inputs in epidemiological simulations, these networks are not specified directly. Rather, these networks are the outputs of population generation methods that are overviewed below and cited immediately above, and include activity surveys and demographic data, both inside and outside of slums. Thus, the topologies of the networks arise from the population generation process, and its inputs.

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Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set of activities of individuals, and the locations of those activities including geo-locations of residential areas, shopping centers, and schools, collected through surveys by MapMyIndia.com. By assigning activity locations to individuals' activities, people are located at particular times at particular geographic coordinates (including office buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between individuals are estimated when each person is deemed to have made contact with a subset of other people simultaneously present at the same location. This gives rise to a synthetic social contact network where network edges represent these contacts.

Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the individuals whose homes reside in the slum polygons. Slum residents' attributes and their daily sets of activities are collected through a ground survey in Delhi slums, by a vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from *MapMechanic.com*. Individuals living in the slum regions are a part of the slum population. All other individuals are part of the non-slum population. Network 2 is a geo-located, and contextualized social contact network of Delhi with slums integrated in it.

Following are the main differences between the original network (Network 1) and the refined network (Network 2). The original social contact Network 1 treats the slum regions like any other region in Delhi in terms of assignment of demographics and individual activities, i.e. no special consideration is given to slum residents. The refined Network 2 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific demographics and activities to the individuals whose homes reside inside these polygons. Thus, the number of individuals is the same in both populations. The slum population constitutes about 13% (1.8 million) of the entire Delhi population of 13.8 million people. The main effects of integrating slums is that Network 2 has more home-related contacts due to larger family sizes and more outside contacts due to more daily activities outside home. Also, those individuals who reside outside of slum zones have the same activities in both networks (but their contacts may change if their interactions include slum residents). Overall, there are over 231 million daily interactions between pairs of individuals. Table S1 compares those two networks as well as data sources for slum and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are in the supplementary information (SI)). For example, the average degree increases from 30.4 to 33.4 from Network 1 to Network 2, and the maximum degree increases from 170 to 180. We refer to Chen et al.[4] for more detailed information about the two networks. Several plots of properties and structural characteristics of Networks 1 and 2 are given in Chen et al.[27].

Disease Model: An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. Each node in the network represents an individual, and each edge represents a contact on which the disease can spread. A contact represents possible transmission between two people that are co-located for some duration (based on their activity schedules). This is an approximation to model direct contact and short-distance environmentally-mediated transmission that might include direct physical contact, fomite mediated, and airborne transmission.[28]

We start each epidemic simulation with 20 index cases, randomly chosen. (We find that results are not sensitive to the number of initial infections.) The detailed description of the SEIR model as well as the choices of transmissibility value, $R_{0,}$ the explicit incubation and exposed periods can be found in the supplementary information. This disease model has been used in other works such as Liao et al.[29], Marathe et al.[30].

The transmissibility value for disease transmission is that for the strong influenza model in Chen et al.[4]. That work used mild, strong, and catastrophic influenza models, so we chose the intermediate transmissibility. This corresponds to base attack rates (i.e., cumulative infection fractions) of 0.42 and 0.48, respectively, in Networks 1 and 2. These rates are generally higher than those in some other studies that either compute experimental attack rates from cases or compute them in modeling studies such as this one. Attack rates used by past researchers for different strains of influenza include Asia [0.22 to 0.50],[31] Southeast Asia [0.11 to 0.31 in children [32]; 0.05 to 0.65 [33]], and India [0.111 to 0.235 [34]; 0.074 to 0.424 [35]; 0.045 to 0.294 [36]; 0.008 to 0.100 [37]; 0.209 for various strains [13]]. The results of Chen et al.[4] indicate that the results here, for this particular transmissibility, will be qualitatively the same for other transmissibilities, but will scale down or up as transmissibility changes in the same direction.

Interventions: This work considers three vaccination scenarios, i.e., vaccinate when cumulative infection rate is 0% (VAX0, i.e. vaccinate on day 1), 1% (VAX1), and 5% (VAX5). Three classes of social distancing strategies are considered: (i) stay-home (SHO) if infected, i.e. eliminate all non-home related contacts but continue to maintain contacts within the household; (ii) close-schools when cumulative infection rate has reached 1% (CS1) and when it has reached 5% (CS5), i.e. eliminate school related contacts; and (iii) (ISO), in which all contacts, including home contacts, of a person are eliminated when a person becomes infectious. For vaccination, five different compliance rates (10%, 30%, 50%, 70%, 90%) and two different vaccine efficacies (30% and 70%) are considered.

VAX0, SHO, ISO are all fairly aggressive interventions because they are implemented either before a person gets infected or immediately upon becoming infectious. These are actions taken at the individual or family level. For example, vaccination before the influenza season or isolating a sick child at home are family decisions. Even CS1 is an aggressive intervention in the sense that this action is taken by government officials based on aggregate school sickness levels—closing schools before any outbreaks is typically not done. From these starting points, vaccinations when 1% or 5% of the population is infected (VAX1, VAX5), and closing schools when 5% of the population is infected (CS5) are less aggressive treatments. The five levels of compliance are also variations on aggressiveness in treatments.

These conditions and parameters are consistent with results from other studies and guidelines put out by international organizations. A meta-study of immunization and slums [38] identifies several vaccination-related studies of slums in India. Unfortunately, these studies are for other diseases such as Hepatitis B, measles, mumps, malaria, and typhoid fever. Nonetheless, slum vaccination rates for children over these ailments range from 25% to 69% for full immunity and from 15% to 55% for partial immunity. Vaccination effectiveness for influenza-like illness (ILI) in India was determined to be about 33% to 36%.[39] In 2012-2013, of 1000 pregnant women in Srinagar India, none were vaccinated against influenza.[40] With regard to school closures, the World Health Organization (WHO) states that school closures may be undertaken proactively (before an outbreak) or reactively (after influenza starts to spread).[41] WHO recommends that school closure occur before 1% of the population becomes infected. It also recommends that people (students and staff) stay home when they feel ill. In another meta-study[42], it was found that school closure, effected when 0.1% of the population was infected, was twice as effective in reducing the total attack rate as school closure occurring after 1% of the population was infected. Moreover, the percentage of people infected before school closure was triggered varied between 0.02% to 10% across several studies.

When a susceptible node is vaccinated, its probability of getting infected by an infectious node is scaled down by the efficacy. If it becomes infectious, its probability of infecting susceptible nodes is also scaled down by the efficacy. In other words, both incoming and outgoing infection probabilities of vaccinated individuals are reduced by the vaccine efficacy. Interventions are applied to slum residents, non-slum residents, and the entire region of Delhi.

For each experiment, 25 replicates are simulated for 400 days, and their mean results are reported. The averages are time-point wise averages, e.g. the mean infection rate at day 100 is calculated by taking the average of the 25 infection rates that occur on day 100 of each replicate. Table S2 summarizes all the interventions considered, and Table S3 contains all variables in simulations, including intervention parameters.

Heterogeneities captured: There are several heterogeneous aspects to this problem that motivate the use of an ABM approach: (i) the 298 slum zones have populations that vary by more than four orders of magnitude in size; (ii) the geographic extent of slum zones differ; (iii) the slum zones are located at irregular spatial intervals throughout Delhi; (iv) the activity patterns of people living in slums are different from those in the non-slum region; and (v) each individual interacts with specific others based on co-location.

The implications of these heterogeneities include the following. First, the particular synthetic households that live within slums are predicated on the number of slum zones, their locations, and their spatial geometries. These homes have larger family size and hence more home contacts. Second, slum individuals have different activity patterns which change the co-located contacts of each slum person: that is, with whom they interact and for how long. For example, see the supplemental information of Chen et al.[27]. The average total contact durations by activity type and by slum/non-slum residents are provided, which show that non-slum people have greater contact durations for work, school, and college activities, but less for home and other types.

Overall, a slum person has about 50% greater total contact duration per day compared to a non-slum person. The same supplemental shows that in the age range 20 to 60 years (by year), females that live in slums have more contacts per day than their male counterparts. However, females whose homes are outside of slum regions have average number of daily contacts that are below their male counterparts.

RESULTS AND ANALYSIS

Our results are grouped as follows. (1) Comparison of Network 1 and Network 2 for base case and intervention cases. (2) Results for both networks based on demographic classes, such as slum/non-slum, gender, and age groups, for a wider range of intervention strategies. (3) Comparison of Network 1 with the non-slum population of Network 2. (4) Effects of pharmaceutical and non-pharmaceutical interventions for a wide range of parameter values. (5) Effects of different resource allocation strategies.

All differences are tested with the two-sample t-test and they are all statistically significant with p-values smaller than 2.2e-16. The 95% confidence intervals are given for each comparison. Here is a brief summary of selected results with examples of mechanisms, to provide a high-level overview. Details of results follow this summary and these details matter because there are many factors (inputs) in a simulation whose interactions change results.

(1) Ignoring the unique attributes of slums in a population overestimates the benefits of the interventions. For example, in the case of vaccination intervention (efficacy 30% and compliance 30%), the values for the epidemic size (i.e., cumulative percentage of infected), peak infection rate (i.e., maximum percentage of a population infected on any day), and time to peak are 33.1%, 3.0%, and 184 days, respectively, in Network 2, whereas they are 23.3%, 1.34%, and 286 days in Network 1. In relative terms, the epidemic size and peak infection rate are underestimated by 42.2% and 123.2% respectively, while the time to peak is overestimated by 35.7% in Network 1 (see Figures 1, 2 and Table S4). The larger family sizes for slum families in Network 2 and the increased number of edges result in larger outbreaks and faster time to peak infections.

(2) Interventions are more effective in Network 1 than Network 2 for all types of interventions: vaccination, closing schools, staying home, and isolation. These trends also hold over wide ranges of efficacy and compliance (see Figures 3, 4, S1, S2 and S3). Hence, not accounting for slums gives overly optimistic results for the effectiveness of the interventions. The reduced average family size in Network 1 means fewer within-home edges, which slows infection and reduces spreading. Closing schools and staying home interventions do not affect home edges. However, the magnitude of this effect varies with intervention conditions (e.g., compliance rate, time at which intervention is applied).

(3) Cumulative infection rates by subpopulation in Network 2 show that slums sustain greater infection rates than non-slums under all intervention scenarios, sometimes by as

much as 44.0%. See Figure 4 and Table S5 for more details. This is due to the greater household sizes in slums.

(4) For Network 2, under a wide range of intervention compliance rates (10% to 90%), the isolation strategy is up to 32% more effective in containing an outbreak than vaccination (for 30% efficacy). Staying home is up to 18% more effective than vaccination at 50% compliance. See Figure 3 and Table S6 for more details. Isolation, although hard to implement from practical considerations, is most effective because edges to susceptible individuals are removed (isolation also provides a good comparative case). Differences between staying home and vaccination depend on compliance rates.

(5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse effect in slums than in non-slum regions across compliance rates from 10% to 90%. See Figure 4 and Table S7 for more details. Early interventions mean actions are taken when outbreaks are smaller and are therefore more readily contained.

(6) Comparison of Network 1 (Figure 3a) with the non-slum population (Figure 4b) of Network 2 shows that just the presence of slum specific activities and interactions with non-slum population makes social-distancing based interventions less effective in the non-slum regions of Network 2.

(7) A full-factorial design that splits resources between slum and non-slum regions indicates that the most effective intervention is to give vaccines to slums and apply social distancing to non-slums. Applying vaccine and social distancing to slum regions is the next most effective intervention. See Figure 5. By applying social distancing to non-slums, these individuals are kept isolated from slum individuals that are infected. The greatest benefits accrue to the slum populations.

Comparison between Networks 1 and 2: Base case versus interventions

We start with a comparative analysis of the influenza epidemic, with and without interventions, on Network 1 and Network 2, to measure the impact of integrating slums in the population on epidemic measures. Figure 1 shows the average simulation time histories for the base case, and when vaccination is applied randomly to 30% of the population in each network with vaccine efficacy set at 30%. Mean infection rate is the daily fraction of infected individuals. It is the time-point wise average over 25 simulations. For example, the mean infection rate at day 100 is calculated by taking the average of all 25 infection rates. Simulations for other vaccine efficacies and compliance rates give qualitatively similar results. Two sets of those results are shown in the supplemental information, see Figures S1 and S2. Note that Network 1 does not distinguish between slum and non-slum individuals, so the epidemic curve is not split by subpopulation.

Results in Network 2 differ significantly from results in Network 1 for both the base case and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a larger epidemic size and has higher peaks compared to the corresponding epidemic quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to plan, there will be a false sense of security and lack of urgency to implement interventions. For both the base case and the intervention case, ignoring unique characteristics of the slums will result in an underestimation of the infections and the speed of spread.

Figure 1 goes here

For the intervention cases, the time to peak infection decreases by 35.7%, i.e. from 286 days for Network 1 to 184 days for Network 2, meaning an influenza epidemic would peak roughly 100 days earlier than one would expect based on the results from Network 1. For the base case, time to peak infection drops by 20.8%, i.e. 34 days reduction for Network 2 as compared to Network 1.

Percentage changes and differences must be viewed cautiously, and to illustrate this point, we present data for the key parameters in Tables S4 and S8. The difference in the peak infection rate (i.e., the maximum fraction of daily infected individuals during the simulation) between Networks 1 and 2 for the base case is 2.2%, or 47.6% in percentage change (see Table S8). For the intervention case shown in Table S4, the difference between the two networks is less (1.7%), but the percentage change is more (123.2%) because the magnitudes of the peak infection rates are reduced when effective interventions are used. We make note of this here and mainly use the percentage change values in discussing results. For more detailed comparison between vaccination intervention and the base case in Network 1 and Network 2, we refer to Tables S7 and S9 and Figures S4 and S5.

Comparison between Networks 1 and 2 based on individual demographic information

We divide the Delhi population into strata by age, gender, and geographic home location (i.e., slum and non-slum), and analyze mean cumulative infection rates by subpopulation for the two networks. In simulations, individuals are chosen at random in the entire network for vaccination. Various vaccination scenarios are investigated.

Figure 2 displays the cumulative infection rate results. On the x-axis, ‘Total’ refers to the entire population of Delhi. There are three breakdowns of the entire population. ‘Slum’ and ‘Non-slum’ refer to slum and non-slum regions, respectively. ‘Male’ and ‘Female’ denote the total number of males and females in Delhi, respectively. Four age groups are considered: ‘Preschool’ (0-4), ‘School’ (5-18), ‘Adult’ (19-64), and ‘Senior’ (65+). The black lines correspond to the mean cumulative infection rates for the base case. Other curves indicate vaccination strategies under different levels of vaccination rate (v) and vaccine efficacy (α). Two vaccination rates (30%, 50%) and two vaccine efficacy rates (30%, 70%) are shown in the figure.

For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all categories of individuals.

In Network 1, slum and non-slums are treated the same so the infection rates are identical in Figure 2. However, all scenarios in Network 2 show a higher burden of disease on the slum population. This is due to the fact that slum households have larger family size and more contacts on average than households in non-slum areas, see Chen et al.[27] As shown later, we find similar patterns of infection in slum and non-slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.

The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums results in overestimation of the benefits of interventions in terms of reduction in the mean cumulative infection rate and peak infection rate, as well as the time to peak. This optimism holds for slum, non-slum and total population under various levels of vaccination rates and efficacy rates in Network 2. See Table S10 for more detailed comparison of results between slum and non-slum in Network 2.

Figure 2 goes here

Comparison between Networks 1 and 2 across a wide range of intervention strategies

Next, we consider a variety of intervention strategies for comparative analysis. We consider vaccination, school closure, stay home, and isolation strategies. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at home (SHO) strategy, all non-home activities and interactions are eliminated but all contacts within the household are maintained. Under isolation (ISO) an individual has no contact with other individuals (even home interactions are eliminated). The stay-at-home and isolation interventions are implemented for compliant infectious individuals, after they become infectious, for the entire infectious duration.

Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a wide range of intervention strategies. For each strategy, five different compliance rates are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers are the actual number of infected individuals. Darker colors correspond to higher infection rates. Note that compliance rate is simply the vaccination rate for strategies

VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire population. The 'Base' values do not vary with compliance because the base case has no intervention. Note that all heat maps in this paper use the same color scheme so that colors can be compared across figures.

Since Network 1 does not distinguish between slum and non-slum populations, we only compare the two networks for the whole of Delhi. The general pattern is similar for both networks. However, all interventions have a larger effect on Network 1 under the same compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0, stay-home, and isolation strategies in Network 1 as compared to those for Network 2.

Figure 3 goes here

At a high level, among all intervention strategies, early vaccination (VAX0 and VAX1), social isolation (ISO), and stay home (SHO) are more effective than the other strategies, and this is more readily observed at higher compliance rates. For these more effective strategies, the interventions per person are implemented right after (or very shortly after) the person is infected. For example, SHO is implemented immediately after a person becomes infectious. Thus, a person that becomes infectious can infect their family members, but if these other members become infectious, then they, too, will be confined to home. Thus, home-bound people can infect their family members, but no one beyond their family (for 100% compliance). As compliance rate increases, this effect approaches, roughly, a "family-based" isolation intervention (similar to ISO), consistent with the results in Figure 3 and in subsequent results.

Effect of vaccination versus social distancing on slum and non-slum subpopulations

We now compare the impact of vaccination and social distancing on slum and non-slum subpopulations from Network 2. Social distancing interventions are close-schools, stay-home, and isolation.

The mean cumulative infection rates (and actual numbers of infections underneath) for each compliance level are shown in the heat maps in Figure 4 for slum and non-slum populations in Network 2. The axis labels are identical to those in Figure 3, as is the color scheme of the cells. The base case values are constant since there is no intervention and hence no compliance. Darker colors correspond to higher infection rates.

Compared to the base case, all interventions reduce infection rates to some extent. As the compliance rate increases, infection rates drop for all interventions. Infection rates drop to zero in slum and non-slum regions at a compliance level of 70% or higher, under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce the infection rates significantly, and this effect increases with compliance rate.

The following observations can be made from Figure 4. Social distancing, i.e. SHO, at low and intermediate compliance and CS at all compliance levels, are less effective in slum regions as compared to non-slum regions. This is because CS only eliminates school interactions for those attending school, and there are fewer school edges in slums compared to non-slum areas, as shown in Figure S6. The effectiveness of CS in slums is mitigated by the greater average number and duration of interactions at home in slums as compared to non-slums (see Figure S6 and Chen et al.[27]). Thus, if a person is sick, there is a greater chance of transmitting contagion to family members, who then may have activities outside of school, thus circumventing the CS intervention. At high compliance, SHO is effective because all interactions outside home (including school) are eliminated.[27]

These observations are also supported by Figure S7, which contains numbers of edges used to transmit contagion for a base-case run of Figure 1. There are several effects that bear on the above observations. First, in the cases of activities “work”, “other”, and “school”, the number of edges transmitting contagion from slums to non-slums is greater than the reverse: from non-slum to slum. Second, in two of these three activity categories, there is more slum to non-slum transmissions than slum to slum transmissions. Edges of transmission for slum dwellers is dominated by home interactions. The infected homes in slums serve as launching points to drive disease to non-slums through slum to non-slum interactions. (There are no ``mixed'' edges at homes, and shopping and college activities have low levels of slum activity because of socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but we now return to Figure 4.

Isolation works well at 30% or higher compliance rates, but it is a much harder strategy to implement, especially in slums. However, it is considered here for comparative analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as compliance increases. However, close-school is generally less effective because this intervention removes only a fraction of interactions for a fraction of the population, i.e. school aged children. Simulations were also run for 70% vaccine efficacy. Since results are qualitatively similar for those parameters, these plots are provided in Figure S3.

Figure 4 goes here

Comparison between Network 1 and non-slum areas of Network 2

Note that Network 1 treats all parts of the region as non-slum, i.e. all individuals follow non-slum activities and demographics. In order to capture the additional disease risk to the non-slum population that arises from the interactions with the slum population, we compare Network 1 in Figure 3a with the non-slum population of Network 2 in Figure 4b. In base case, the additional disease risk to the non-slum population goes up from 42% to 45%. However, the beneficial effects of social distancing strategies drop by a large amount, e.g. close school strategies are 5-20% less effective in the non-slum areas of Network 2. This effect changes non-linearly with the compliance rate. As compliance rate goes up, the difference between performance of Network 1 and non-slum parts of Network 2 goes up in CS1 and CS5. This implies that in Network 2, non-slum population requires much higher levels of compliance to achieve the same results as in Network 1. This difference is less stark for vaccination based interventions, i.e. VAX0, VAX1 and VAX5. This is expected since the effect of vaccination is less dependent on interactions; it is only through herd immunity that interactions come into play.

Constrained resource allocation among slum and non-slum areas

We consider a specific scenario under Network 2. If only a limited number of vaccines are available, and only a certain fraction of individuals can be kept home during an epidemic, how should these interventions be applied to the slum and non-slum regions so that the epidemic can be controlled effectively? Given that slum residents' attributes differ from those of non-slum residents, is there a strategy that works better in slums than in non-slum areas? The total population in Delhi is about 13.8 million, which includes about 1.8 million slum residents. We assume that only 10% of the total population can be covered by interventions, half through vaccination and the other half through stay home. Enough vaccines are available to cover 5% of the total population (i.e. 692,183 vaccinated, corresponding to about 38.25% of slum or 5.75% of non-slum population), and 5% of the individuals can stay home (692,183 individuals; this is applied to only the infected individuals). Note that an individual may receive a vaccine and also stay at home if this individual, in spite of being vaccinated, gets infected.

We consider 4 different ways of applying interventions to 10% of the total population: (i) apply both interventions to slums, i.e. give all vaccines to slums and apply SHO only in the slums (VsSs); (ii) apply all interventions to non-slum areas (VnSn); (iii) give vaccines to slums and SHO to non-slums (VsSn) and (iv) give vaccines to non-slums and apply SHO to slums (VnSs).

For both types of intervention, the same number of individuals is chosen randomly from slum or non-slum areas. 10% of the total Delhi population amounts to 76.5% of slum population, 11.5% of the non-slum population, or a combination of 38.25% of the slum and 5.75% of the non-slum population (i.e. half from slums and half from non-slums). Figure 5 shows the mean cumulative infection rates, as well as the number of infected from the entire population of Delhi, the slums, and non-slum areas under each of the four scenarios. The first 3 columns refer to Network 2 and the last column shows results for Network 1. Since Network 1 does not distinguish between slum and non-slum areas, the infection rates in each subpopulation remain the same as for the total population.

Comparison of the last two columns in Figure 5 indicates that the non-slum population in Network 2 faces 3-5% additional disease risk compared to Network 1 in all cases. This is primarily driven by the increased interactions within slum populations and between slum and non-slum populations in Network 2.

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In Figure 5, all four intervention strategies produce essentially the same total attack rates (around 43% to 44%), a drop of 4% to 5% over the base case. The dominant effect on Network 2, is the benefits that primarily accrue to the slum population for the VsSs and VsSn strategies because they drive down the fraction of infected slum residents from 0.74 to 0.55 or 0.58. Also, as described in the context of Figures 4 and S6 above, social distancing of the non-slum residents helps to isolate them from the infected slum residents. Results such as these may be helpful to policy makers in breaking the poverty trap in economically poor regions.[43]

Also, the strategy of vaccinating non-slums and social distancing slums (VnSs) is not as effective as the interventions in rows 1 and 2 of Figure 5. This is a counterintuitive result, since the density of population is much higher in the slums, which may lead to the belief that social distancing in slums will break up the dense clusters. However, a careful examination shows that keeping slum residents home is not an effective social distancing strategy because their family size is, on average, almost 3 times the family size of non-slum households.[27] The high level of mixing at home makes social distancing ineffective in slums unless the infected individual is completely isolated. However, complete isolation is not viable in slum areas where the entire household may live in a single room.

Figure 5 goes here

DISCUSSION

With slum populations expected to grow to 2 billion by 2030,[44] it is becoming increasingly urgent to understand how to control the spread of infectious diseases in slum areas and measure its effect on urban populations. To our knowledge, a detailed study of interventions to control influenza epidemics in slums, using an agent-based simulation model, has never been done before. Slum conditions are important for a city beyond the direct effects of disease transmission. For example, civil wars may be precipitated or exacerbated by disease outbreaks because they decrease social health and welfare.[45]

Even though slum regions contain only 13% of the total population of Delhi, Chen et al.[4] show that omitting their attributes leads to underestimation of the overall infection rate and the peak infection rate of the epidemic. This paper extends that work by evaluating the differential impact of interventions on slum and non-slum regions. Various vaccination and social distancing strategies are analyzed under different scenarios that show that the slum population is more prone to infections under the same control measures. Furthermore, taking account of slum populations significantly alters the disease dynamics in the *entire* population. Differences in key measures are demonstrated between the cases of accounting for slum populations and not: e.g., a 100% increase in the peak attack rate in some cases when slum regions' characteristics are taken into account, compared to the case when they are ignored.

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Figure 4, which compares infections in slum with non-slum areas, shows that at very high compliance rates, some interventions can be equally effective in both slums and non-slums. However, such high compliance rates are typically not feasible due to practical realities on the ground, and also because they require timely diagnosis of infected cases. For SHO to be effective, the coverage rate needs to be 70% or more in both slums and non-slums, and the diagnosis of the infected individuals needs to be correct and immediate. In other words, effective control of a contagious epidemic in a high-density place like Delhi would require either early and drastic action (e.g. ISO) or a highly compliant set of individuals, or a combination of these features.

This work overall demonstrates the power of agent-based and population modeling to evaluate complicated interaction-based epidemiological phenomena. Clearly, there are limitations to this work (several are itemized below). But these agent and population approaches provide a platform for adding additional complexity. All of the figures demonstrate that quantitative results depend on complicated interplay among inputs. These results are important because they inform policy decisions. An equally important benefit of this type of work, but not often stated, is developing intuition about epidemic dynamics (in this case, with the effects of slums), to enable decision makers to reason about nuanced interactions among effects to a degree that is hard to obtain with other approaches that lack this level of detail. However, we believe that other modeling approaches may also be valuable in understanding epidemic dynamics in slum populations.

Despite the detailed modeling effort, there are limitations of this work and areas for improvement in the future. For example, this model assumes that both slum and non-slum individuals have the same level of immunity. This may not be true for seasonal infections. Previous researchers have argued that individuals who live in smaller family sizes, who have access to household amenities and maintain a high level of personal cleanliness, face declining microbial exposure which can modify their immune response and reduce their level of tolerance to respiratory infections.[46] Slum households characterized by larger family size and overcrowding, are likely to encounter much higher microbial exposure and therefore may be protected by their greater immunity.[16-17]

Areas for future work include: (1) Examination of different population level base attack rates derived from different transmission probabilities. (2) Different susceptibilities and infectivity for individual agents; e.g., based on age. (3) Effects of asymptomatic infections (although we have addressed this to some extent with compliance and efficacy of interventions). (4) Seasonal effects.[47-48] (5) Effects of immunity for an individual from previous infections (in previous seasons). (6) Evaluation of interaction of different strains from season to season. (7) Comparison of tropical versus subtropical factors. (8) Evaluation of a specific outbreak scenario. (9) Impact of sickness on absenteeism from work and its economic ramifications. (10) Effects on rural versus urban populations. (11) Using combinations of interventions rather than one at a time;

this was only done here in Figure 5. However, to disambiguate results, it is prudent to first examine individual interventions. (12) Effect of changing disease transmission rate for different activity types. (13) Effect of changing contact times at different locations. (14) To capture close-proximity transmission, one could use actual physical proximity. Here, we use colocation. Finally, just as changes in modeling details can change model results, so, too, changes in the conditions in actual outbreaks can change results; some of these factors are listed above. It is essentially impossible to capture all of these effects—many of which are unknown—down to the level of individual humans.

Public health implications: This research demonstrates that modeling slum populations is important, not only for understanding disease dynamics, but also for designing effective control measures. Ignoring the influence of slum characteristics on their urban environment will significantly underestimate the speed of an outbreak and its extent, and hence will lead to misguided interventions by public health officials and policy planners. Lessons from this research can be applied in the field and observations collected from the field can provide valuable data to improve the models and validate the results. For example, our results show that a slum resident has about 50% greater total contact duration per day compared to a non-slum resident. This makes social distancing based interventions more taxing in the slum population. Public health policy makers may want to subsidize pharmaceutical resources for the slum population to make them more affordable. Similarly, we find women in slums have a higher number of contacts per day than their male counterparts whereas in non-slum regions, women have a fewer number of daily contacts than their male counterparts. This kind of information can be used to prioritize the distribution of limited resources, e.g. women could be given preference over males for vaccination in slum areas. This research provides simulation-based evidence that in general social distancing strategies are ineffective in slums because of a large number of contacts at home. Unless one applies complete isolation, which is not feasible in slums, just staying at home still keeps a large number of contacts and pathways of spread intact.

Main manuscript

Contributorship statement

AA, SE, CJK, AM, MM, SS, AV designed and conceived the study. SC carried out the experiments and simulations. SC, CJK, AM performed data analysis. CJK, BL, AM, MM, EKN, MLW helped with reviewing the results and writing the paper.

Competing Interests

There are no competing interests.

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Data Sharing Statement

Data pertaining to figures and statistical analysis are partially provided in the supplementary file, and also can be obtained by contacting the corresponding author through email.

Main manuscript

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Main manuscript

FIGURE 1: Epidemic curves for base case and vaccination case. Each time point in the curve is an average over 25 replicates. The vaccines are given randomly to 30% of the entire population and the vaccine efficacy is 30%. For Network 2, epidemic curves are shown for total population and slum and non-slum subpopulations. 'Intervene Total' refers to the epidemic curve of the entire Delhi population when the vaccine intervention is applied. 'Intervene Slum' refers to the epidemic curve for just the slum population, and 'Intervene Non-slum' refers to the epidemic curve for just the non-slum population for the intervention case. Epidemic curves for a variety of compliances and efficacies are reported in Figures S1 and S2.

FIGURE 2: Mean cumulative infection rates for different subgroups in the two networks. Two vaccination rates (v = 30%, 50%) and two vaccine efficacy rates (α = 30%, 70%) are considered. Individuals are chosen at random in the entire network for vaccination on day 0. Mean infection rates are calculated within each group. The last several lines in the plot for Network 1 are overlapping at the bottom because the mean infection rates are almost zero under those scenarios. 'Total' refers to the entire population of Delhi. 'Slum' and 'Non-slum' refer to slum and non-slum regions, respectively. 'Male' and 'Female' denote the total number of males and females in Delhi, respectively. Age groups are denoted by 'Preschool', 'School', 'Adult', and 'Senior'.

(a) Total Delhi Network 1 (b) Total Delhi Network 2

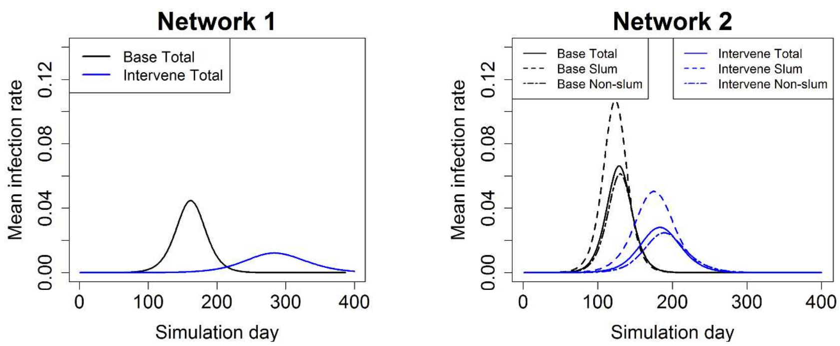
Figure 3. Mean cumulative infection rates under different interventions for Network 1 and Network 2. The larger font numbers are fractions of populations that are infected and the smaller font numbers are counts of infected individuals. Colors of the boxes correspond to the values of the large numbers (i.e., fractions of infected), and the same scheme is used for both plots for comparisons—and for all plots in this paper. Five different compliance rates are examined (10%, 30%, 50%, 70% and 90%), and 4 types of intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when the cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5) of the total population. The vaccine efficacy is set at 30%. For close-schools, two trigger points are used: when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected at random from the entire Delhi population, and the cumulative infection rates are calculated for each network.

(a) Slum (b) Non-slum

Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond to higher infection rates. The smaller font numbers are counts of infected individuals. The vaccination efficacy is fixed at 30%. Five different compliance rates (10%, 30%, 50%, 70% and 90%) and 4 types of

intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO)) are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used: when the cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population, and the mean infection rates are calculated separately for the slum and non-slum subpopulations. Although not reported here, qualitatively similar results are found for other transmission rates, as well as for higher vaccine efficacy (70%). Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals.

FIGURE 5: Mean cumulative infection rates for each category listed on the x-axis, for Network 2 and Network 1, under four different intervention scenarios. The color scheme of the boxes are based on the large values in the boxes—the cumulative infection rates. Darker colors correspond to higher infection rates. Smaller font values are the number of infected individuals. The vaccine efficacy is set at 30%. VsSs refers to the case when vaccines and social distancing are both applied to slum residents; VnSn refers to the case when vaccines and social distancing are applied to non-slum residents. Similarly, VsSn means vaccines are given to slums and stay home is applied to non-slums; and VnSs means vaccines are given to non-slums and stay home is applied to slums. Base refers to the case where no intervention is applied. The smaller-font numbers under the infection rates show the actual number of infected individuals in each category listed on the x-axis.



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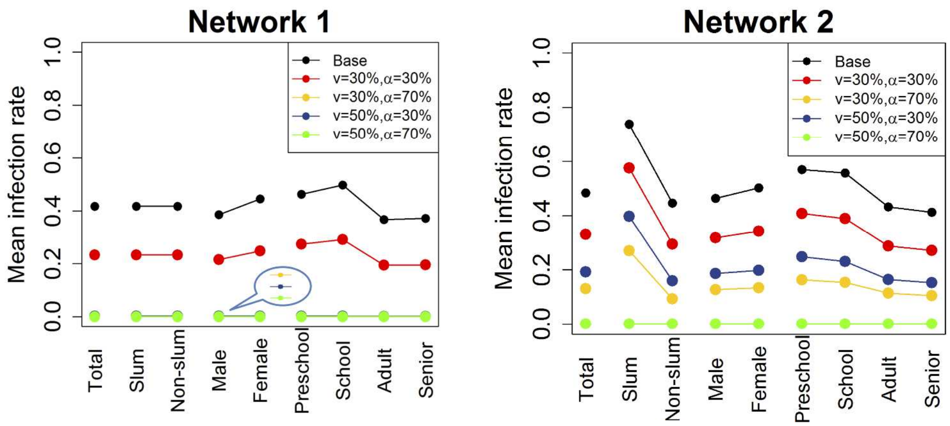

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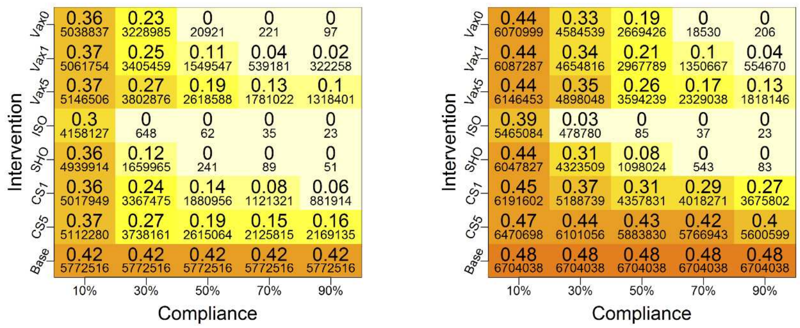

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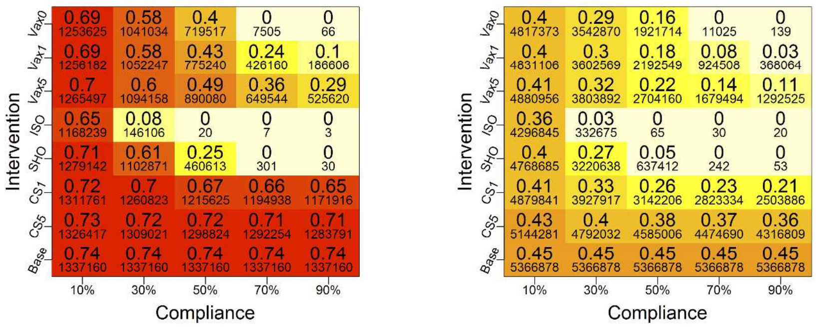

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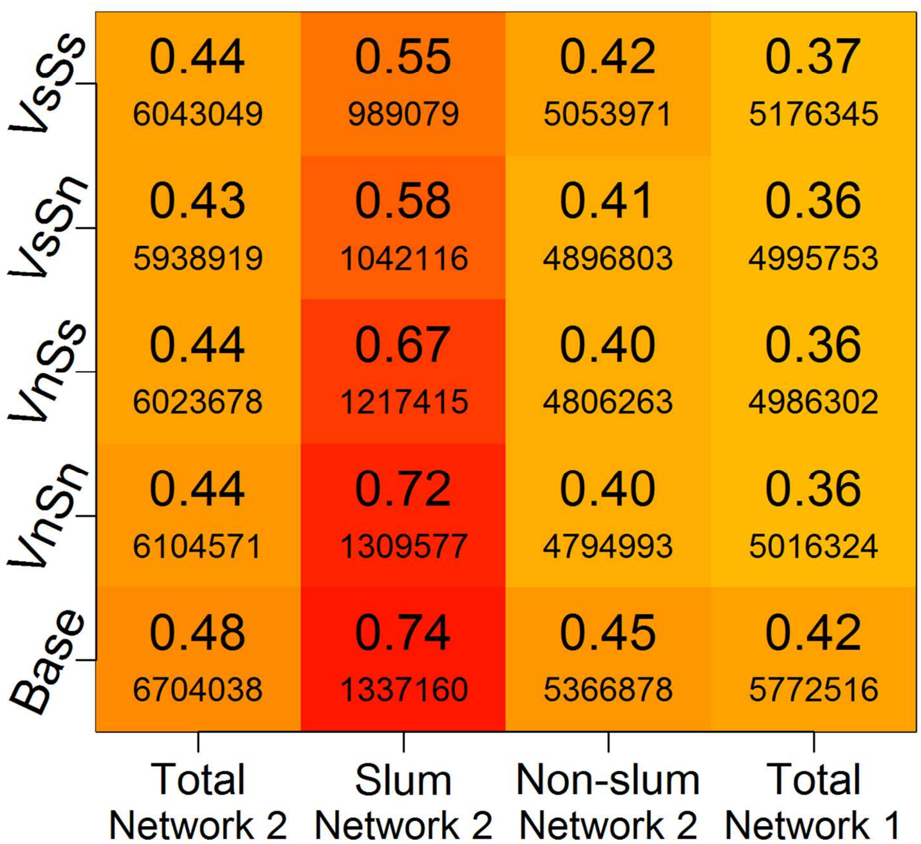

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Supplemental Information

Disparities in Spread and Control of Influenza in Slums of Delhi: Findings From An Agent-Based Modeling Study

A. Adiga, S. Chu, S. Eubank, C. J. Kuhlman, B. Lewis, A. Marathe, M. Marathe, E. K. Nordberg, S. Swarup, A. Vullikanti and M. L. Wilson

Supplemental Information

Presentation of Results.

For each set of input parameters, 25 replicates were run using agent-based simulation and the results presented are the average values over the 25 replicates. Also, 95% confidence intervals (CIs) are given when appropriate.

Comparisons Between Network 1 and Network 2.

Table S1 shows some differences between network1 and network 2 due to their different ways of modeling slum population. Note that these two networks are the same ones as those used in Chen et al.[1]. Further comparisons between the two networks are found in Chen et al.[2].

Table S1. Comparison of two networks as well as data sources for slum and non-slum Delhi, India.

	Network 1		Network 2	
	Slum	Non-slum	Slum	Non-slum
Population Size	0	13.8 million	1.8 million	12 million
Average Household Size of Slum Region	5.2		15.5	
Daily Activities	33,890,156		39,077,861	
Number of Edges	210,428,521		231,258,772	
Average Degree	30.4		33.4	
Maximum Degree	170		180	
Data Sources	MapMyIndia.com		MapMyIndia.com Indiamart.com MapMechanic.com	

Network 2 contains 298 slum zones, while network 1 models the whole population as non-slum. For network 1, the non-slum demographics and activities data is collected by survey through MapMyIndia.com. While for slum population, we collected additional data by Indiamart.com and MapMechanic.com for slum demographics and activities as well as slum polygons. More detailed demographic and activity differences can be found in the Chen et al.[1]

Terminology and Abbreviations for Interventions.

Table S2 contains abbreviations for different interventions and their meanings. Stay-at-home (SHO) and social isolation (ISO) interventions are applied to a person immediately after they become infected, while close-schools (CS) and vaccinations (VAX) may be applied after a specified fraction of the total population has been infected.

Table S2: Summary of abbreviations for interventions and their meanings.

Supplemental Information

Abbreviation	Definition
CS	Close-schools: School-related interactions are eliminated.
CSx	Close-schools is implemented after the total fraction of the population that has been infected reaches x.
ISO	Social isolation: a person who is socially isolated does not interact with any other person, even people in their home. Isolation is triggered only after a person becomes infectious.
SHO	Stay at home: All out-of-the-home activities for this person are eliminated, and this person only interacts with others at home. Stay at home is triggered only after a person becomes infectious.
VAX	Vaccination: a person who is vaccinated has a reduced probability of contracting the virus.
VAXx	Vaccination of an individual occurs after the total fraction of the population that has been infected reaches x.

Table S3 contains the variables used in simulations. The transmissibility corresponds to strong flu in Chen et al.[1] For vaccination, efficacy is either 30% or 70%. That is, for 30% efficacy, a person who gets vaccinated has reduced their susceptibility to infection by 30%.

Table S3: Summary of parameters and values used in simulations.

Category	Values
Networks of Delhi	Network 1 (does not model slums); Network 2 (models slums).
Seeding	20 people selected randomly over the entire population at time 0 as index cases.
Transmissibility	0.000027.
Intervention approaches.	Base case (no intervention); close-schools (CS); stay-home (SHO); isolation (ISO); vaccination (VAX).
Intervention/compliance rates.	10%, 30%, 50%, 70%, 90%.
Efficacy of vaccination intervention.	30%, 70%.
Intervention trigger time	Cumulative infection rate reaches 0%, 1% and 5%.
Simulation replicates	25

The Agent Epidemic States and Disease Model.

An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or Recovered (R) model is considered within each individual. An infectious person spreads the disease to each susceptible neighbor independently with a probability referred to as the transmission probability, given by

$$p = \lambda \left(1 - (1 - \tau)^{\Delta t}\right),$$

where λ is a scaling factor to lower the probability (e.g., in the case of vaccination), τ is the transmissibility and Δt is the duration of interaction in minutes. Durations of contact are labels on the network edges. A susceptible person undergoes independent trials from all of its neighbors that are infectious. The transmission probability is a function of the number and duration of contacts.[3] This is selected to simulate an Influenza model resulting in a R_0=1.26 (cumulative attack rate 42%, corresponding to a transmissibility of 0.000027 per minute of contact time) for Network 1, and R_0=1.39 (cumulative attack rate 48%) for Network 2.[4] This transmissibility value is used uniformly throughout this study and corresponds to the probability at which an infectious node infects a susceptible node per minute of contact.

At each time (day), if an infectious person infects a susceptible person, the susceptible person transitions to the exposed (or incubating) state. The exposed person has contracted Influenza but cannot yet spread it to others. The incubation period is assigned per person, according to the following distribution: 1 day (30%); 2 days (50%); 3 days (20%). At the end of the exposed or incubation period, the person switches to an infected state. The duration of infectiousness is assigned per person, according to the distribution: 3 days (30%); 4 days (40%); 5 days (20%); 6 days (10%). After the infectious period, the person recovers and stays healthy for the simulation period. This sequence of state transitions is irreversible and is the only possible disease progression.

Epidemic Curves for Other Interventions, for Varying Efficacy and Compliances.

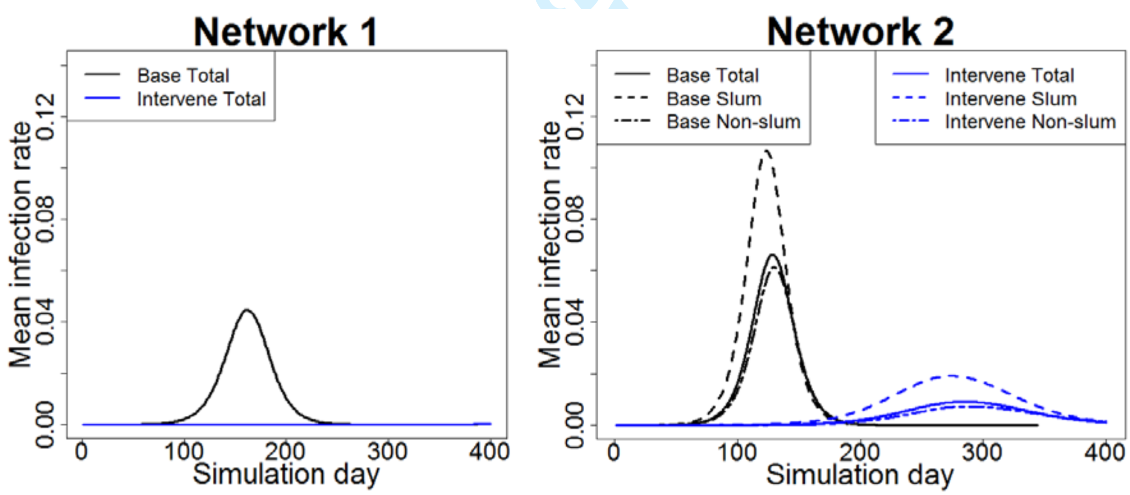


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

Supplemental Information

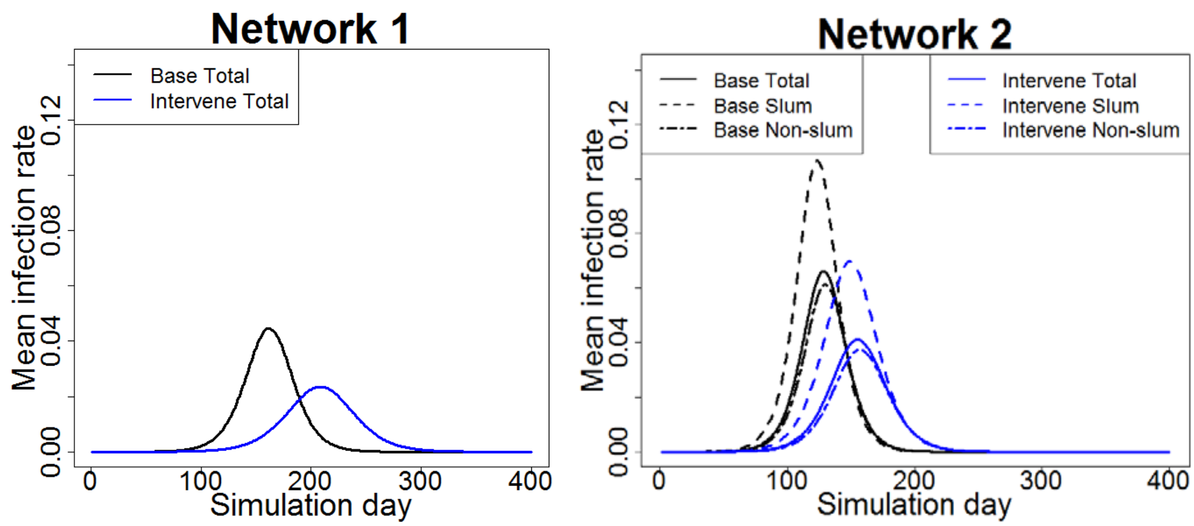
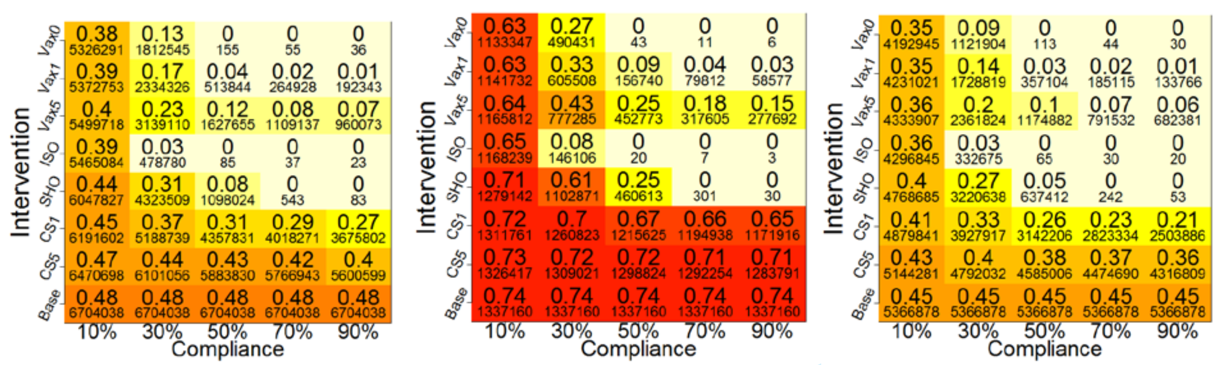


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.



(a) Total Delhi (b) Slum (c) Non-slum

Figure S3. Heat map of mean cumulative infection rates in Delhi, and slum and non-slum regions under different intervention strategies for Network 2. The vaccination efficacy is fixed at 70%. Five different compliance rates, i.e., 10%, 30%, 50%, 70% and 90% and 4 types of intervention strategies, i.e. vaccination (VAX), close-schools (CS), stay-home (SHO) and isolation (ISO), are considered. For vaccines, three different trigger points are considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used i.e. when cumulative infection rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly from the entire Delhi population and the mean cumulative infection rates are calculated separately for the total population, and slum and non-slum subpopulations. Base is the baseline case with no interventions. The smaller-font numbers under the infection rate show the actual number of infected individuals. Darker colors correspond to higher infection rates.

Supplemental Information

Tabulations of Basic Results: Comparisons between Networks 1 and 2 for Compliance of 30% and Efficacy of 30%.

Table S4 shows results when 30% of the population that is selected uniformly at random is vaccinated with a vaccine that is 30% effective. The contrast between the two populations is even greater when considering interventions. The peak infection rate of the entire population increases by 123.2% (95% CI: 122.7%-123.7%) in Network 2 compared to Network 1 for the intervention, versus 47.6% difference between the networks in Table S8. The time to peak decreases by 35.7% (95% CI: 32.9%-38.8%) in Network 2 compared to that in Network 1, for the intervention case, compared to only 20.84% percentage change between the two Networks for the base case in Table S8. The cumulative infection rate (or attack rate) is also underestimated, which is 42.2% (95% CI: 41.5%-42.8%) greater on average in Network 2 compared to Network 1 for the intervention case. Hence, the differences between key epidemic results for Networks 1 and 2 that are generated for the intervention case are even more pronounced than they are for the base case. These values are all statistically significant.

Table S4: Comparisons of key epidemic parameters for Networks 1 and 2 for a vaccination intervention before the epidemic starts (VAX0), where the vaccine efficacy is 30% and the compliance rate is 30%.

Vaccination	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	286	184	102 (95% CI: 94-111)	35.7% (95% CI: 32.9%-38.8%)
Peak Infection Rate	1.34%	2.99%	1.65% (95% CI: 1.64%-1.66%)	123.19% (95% CI: 122.69%-123.65%)
Cumulative Infection Rate	23.3%	33.1%	9.82% (95% CI: 9.67%-9.96%)	42.17% (95% CI: 41.51%-42.77%)

Table S5 shows the effect of delay in applying interventions. The numbers show the percentage difference in cumulative infection rate in slums and non-slums of Network 2 for the specified interventions and compliance rates at different trigger levels. For example, the value 30.55% at 0.1% compliance means that for intervention close-schools, where this intervention is implemented after 5% of the total population is infected, the fraction of people in slums that get infected is 30.55% greater than the fraction of non-slum residents who get infected.

Table S5. Differences of epidemic size between slum and non-slum regions for Network 2 for base case (no intervention); close-schools (CS) after 1% total outbreak fraction (CS1) and after 5% total outbreak fraction (CS5); stay at home (SHO); social isolation (ISO); vaccination (VAX) after 1% total outbreak fraction (VAX1) and after 5% total outbreak fraction (VAX5), under various compliance rates. The vaccination efficacy is 30%.

Compliance	Base	CS5	CS1	SHO	ISO	VAX5	VAX1
0.1	29.30%	30.55%	31.94%	31.06%	28.85%	29.37%	29.27%
0.3	29.30%	32.52%	37.03%	34.18%	5.31%	28.85%	28.21%

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0.5	29.30%	33.67%	41.07%	20.16%	0.00%	26.72%	24.62%
0.7	29.30%	34.23%	42.57%	0.01%	0.00%	21.94%	15.87%
0.9	29.30%	35.07%	43.95%	0.00%	0.00%	18.31%	7.25%

Table S6 examines the difference in effects of interventions on the cumulative infection rate in Network 2. These data use both the stay home (SHO) and the isolation (ISO) interventions as base cases. Each entry represents the difference between the cumulative infection rates for the specified pharmaceutical interventions and SHO or ISO. For example, 18.03% means that the cumulative infection rate for vaccinating after 5% of the population is infected, is 18.03% greater than that for the intervention of SHO; 31.92% means that the cumulative infection rate for vaccinating after 5% of the population is infected is 31.92% greater than that for the intervention of ISO. Thus, the larger the magnitude of a positive number, the greater the effectiveness of SHO or ISO compared to the specified pharmaceutical intervention.

Table S6. Differences in epidemic size between stay at home (SHO) interventions, social isolation (ISO) interventions and pharmaceutical interventions (VAX0, VAX1, VAX5), under various compliance rates. The compliance rate and efficacy for vaccination is 30% and 30%, respectively.

Compliance	Vax5-SHO	Vax1-SHO	Vax0-SHO	VAX5-ISO	VAX1-ISO	VAX0-ISO
0.1	0.71%	0.29%	0.17%	4.92%	4.49%	4.38%
0.3	4.15%	2.39%	1.89%	31.92%	30.17%	29.66%
0.5	18.03%	13.51%	11.35%	25.96%	21.44%	19.28%
0.7	16.82%	9.75%	0.13%	16.82%	9.76%	0.13%
0.9	13.13%	4.01%	0.00%	13.13%	4.01%	0.00%

Effect of intervention on Network 2, With and Without Interventions.

The comparison between vaccination intervention and the base case in Network 2 is detailed in Table S7 below.

In Network 2, for the total population, vaccination delays the time to peak infection by 43.27% (95% CI: 40.14%-46.41%) relatively, from 128 to 184 days on average, while the peak infection rate is reduced by about 3.88% from 2.99% to 6.87% on average (56.47% relatively with 95% CI: 56.35%-56.56%). The total infection rate is reduced by 15.31% from 33.12% to 48.43% (31.62% relatively with 95% CI: 31.57%-31.67%).

In slum regions in Network 2, vaccination delays the time to peak infection by 43.09% (95% CI: 39.78%-46.4%) relatively, from 123 to 176 days on average, while the peak infection rate is reduced by about 5.70% from 5.42% to 11.12% on average (51.26% relatively with 95% CI: 50.88%-51.64%). The total infection rate in slums is reduced by 16.35% from 57.53% to 73.88% (22.13% relatively with 95% CI: 22.07% to 22.19%).

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In non-slum regions in Network 2, the time to peak is delayed by 43.44% (95% CI: 40.32%-46.56%) relatively, from 130 to 186 days on average, while the peak infection rate is reduced by about 3.68% from 2.69% to 6.36% on average (57.79% relatively with 95% CI: 57.64%-57.94%). The total infection rate in non-slums is reduced by 15.16% from 44.60% to 29.45% (33.98% relatively with 95% CI: 33.93% -34.03%).

Table S7: Comparisons between the base and vaccination cases for Network 2. The three parameters (time to peak, peak infection rate and cumulative infection rate) are broken out, and for each, values for the total population, and slum and non-slum subpopulations are given. The vaccination rate is 30% and efficacy is 30% for those receiving the vaccine.

Network 2, Time to Peak	Base	Vaccination	Compare-absolute	Compare-Relative
Total	128	184	55 (95% CI: 51-59)	43.27% (95% CI: 40.14%-46.41%)
Slum	123	176	53 (95% CI: 49-57)	43.09% (95% CI: 39.78%-46.4%)
Non-Slum	130	186	56 (95% CI: 52-60)	43.44% (95% CI: 40.32% - 46.56%)

Network 2, Peak Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	6.87%	2.99%	-3.88% (95% CI: -3.870% -3.884%)	-56.46% (95% CI: -56.35% -56.56%)
Slum	11.12%	5.42%	-5.70% (95% CI: -5.66% -5.74%)	-51.26% (95% CI: -50.88% -51.64%)
Non-Slum	6.36%	2.69%	-3.68% (95% CI: -3.67% -3.69%)	-57.79% (95% CI: -57.64% -57.94%)

Network 2, Cumulative Infection Rate	Base	Vaccination	Compare-absolute	Compare-Relative
Total	48.43%	33.12%	-15.31% (95% CI: -15.29% -15.34%)	-31.62% (95% CI: -31.57% -31.67%)
Slum	73.88%	57.53%	-16.35% (95% CI: -16.30% -16.39%)	-22.13% (95% CI: -22.07% -22.19%)
Non-Slum	44.60%	29.45%	-15.16% 95% CI: (-15.14% -15.18%)	-33.98% (95% CI: -33.93% -34.03%)

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Table S8 summarizes differences in key epidemic parameters for Networks 1 and 2 for the base case with no interventions. The peak infection rate is the maximum fraction of individuals who are infected on any day, the time to peak is the day on which the peak infection rate occurs, and cumulative infection rate is the cumulative fraction of individuals who get infected in the epidemic. Under the base case, the peak infection rate in Network 2 is 47.6% (95% CI: 47.4%-47.8%) greater compared to that in Network 1 (47.6%=(6.87%-4.65%)/4.65%). The time to peak infection for Network 2 is decreased by 20.8% (95% CI: 19.2%-22.7%) compared to that in Network 1. The cumulative infection rate (or attack rate) is also underestimated under Network 1 by 16.1% (95% CI: 16.1%-16.2%) compared to Network 2. These results, presented in the main paper, are tabulated here in Table S8 for convenience and comparison.

Table S8: Comparisons of key epidemic parameters for Networks 1 and 2 for the base case.

Base	Network 1	Network 2	Compare-absolute	Compare-relative
Time to Peak	162	128	34 (95% CI: 31-37)	20.84% (95% CI: 19.19%-22.71%)
Peak Infection Rate	4.65%	6.87%	2.215% (95% CI: 2.206%-2.224%)	47.6% (95% CI: 47.4%-47.8%)
Cumulative Infection Rate	41.70%	48.43%	6.73% (95% CI: 6.71%-6.75%)	16.1% (95% CI: 16.1%-16.2%)

Effect of intervention on Network 1, With and Without Interventions.

In Network 1, vaccination delays the time to peak infection by 76.41%, from 162 to 286 days on average, with 95% CI: 71.53%-81.28%. The peak infection rate is reduced by 3.3121 percentage points, from 1.34% to 4.65%, which is a relative percentage difference (RPD) of -71.20%, with 95% CI: -71.02% to -71.38%. These and cumulative infection rate data are given in Table S9.

Table S9: Comparisons of a vaccination intervention (30% vaccination rate, 30% efficacy of a vaccination) with the base case in Network 1 Delhi.

Network 1,Total	Base	Vaccination	Compare-absolute	Compare-relative
Time to Peak	162	286	124 (95% CI: 116-132)	76.41% (95% CI: 71.53%-81.28%)
Peak Infection Rate	4.65%	1.34%	3.31% (95% CI: 3.30%-3.32%)	71.20% (95% CI: 71.02%-71.38)
Cumulative Infection Rate	41.7%	23.3%	18.40% (95% CI: 18.25%-18.55%)	44.13% (95% CI: 43.77%-44.48%)

Tables S7 and S9 show that, generally, Network 1 is more responsive to intervention than Network 2. In Network 1, the percentage changes in time-to-peak, peak infection rate, and cumulative infection rate, due to intervention, are 76.4%, -71.2%, and -44.1%,

respectively. For Network 2, these values are 43.3%, -56.5%, and -31.6%, respectively. The reason for lower impact in Network 2 is the greater connectivity of households in slums, which helps drive the contagion.

Effect of interventions on slum and non-slum subpopulations of Network 2, compared to the base case.

The data used in comparing key outbreak parameters in slum and non-slum regions are taken from Table S7, and the corresponding epidemic curves are in Figure 1. The percentage change in peak infection rate due to intervention in slum (-51.3%) and non-slum (-57.8%) regions in Network 2, are comparable, although the magnitudes of the peak infections in slums are about twice those in the non-slum regions. For the cumulative infection rates, the relative drop from the intervention is greater for the non-slum (-34.0% vs. -22.1%) population than it is for the slum population, but the absolute drop is about the same (-16.3% vs. -15.1%).

Table S10: Comparison of results between slum and non-slum in Network 2. The input data is the same as in Table S7.

Network 2, **Base**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	123	130	7(95% CI: 4-9)	5.26% (95% CI: 3.37%-7.16%)
Peak Infection Rate	1.12%	6.36%	4.76% (95% CI: 4.72%-4.80%)	42.79% (95% CI: 42.46%-43.14%)
Cumulative infection rate	73.88%	44.60%	29.25% (95% CI: 29.25% - 29.31%)	39.63% (95% CI: 39.59%-39.67%)

Network 2, **Vaccination**	Slum	Nonslum	Compare-absolute	Compare-relative
Time to Peak	176	186	10(95% CI: 5-15)	5.23% (95% CI: 2.58%-8.46%)
Peak Infection Rate	5.42%	2.69%	2.74% (95% CI: 2.71% - 2.76%)	50.46% (95% CI: 50.06%-50.86%)
Cumulative infection rate	57.53%	29.45%	28.08% (95% CI: 28.04%-28.12%)	48.82% (95% CI: 48.74%-48.89%)

Figure S4 contains the percentage changes between the base case and intervention case for Networks 1 and 2 for the three parameters in the legend, and further breaks down Network 2 into slum and non-slum subpopulations. This plot provides a summary of differences between the base and intervention cases. For all four conditions considered, the intervention reduces the severity of an epidemic. It delays the time when the infection peaks, and reduces the peak infection and the cumulative infection rates. Note that the intervention has a larger effect on the epidemics when applied to Network 1, as consistent with Figure 1.

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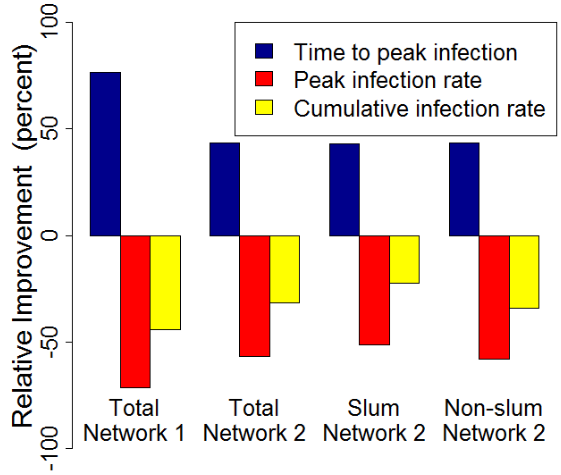

Figure S4: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 than Network 2, while, for Network 2, it is slightly more effective for the non-slum population than slum. Details of the data associated with this plot are provided in Tables S7 and S9.

Figure S5 provides the same data in as in Figure S7, but now the data are provided as absolute differences, rather than as percentage changes. (There are three separate plots owing to the different ranges in absolute differences. Qualitatively, the time to peak infection (blue bars) does not change between the two networks and the two subpopulations of Network 2 (Figure S4 versus Figure S5(a)). However, the red bars in Figure S4 are qualitatively different from those in Figure S5(b), when considering absolute changes. That is, the magnitude of the percentage change in peak infection rate between the base and intervention cases is greatest in Network 1 (Figure S4, red bars), while in Figure S5(b), it is least on an absolute change basis. Similarly, the slum population in Network 2 shows the least percentage change in Figure S4, but the greatest absolute change in Figure S5(b). Rankings of the subpopulations in Network 2 is also reversed for cumulative infection rate: the percentage change is greatest in the non-slum region, while it is greatest for the slum regions in absolute terms.

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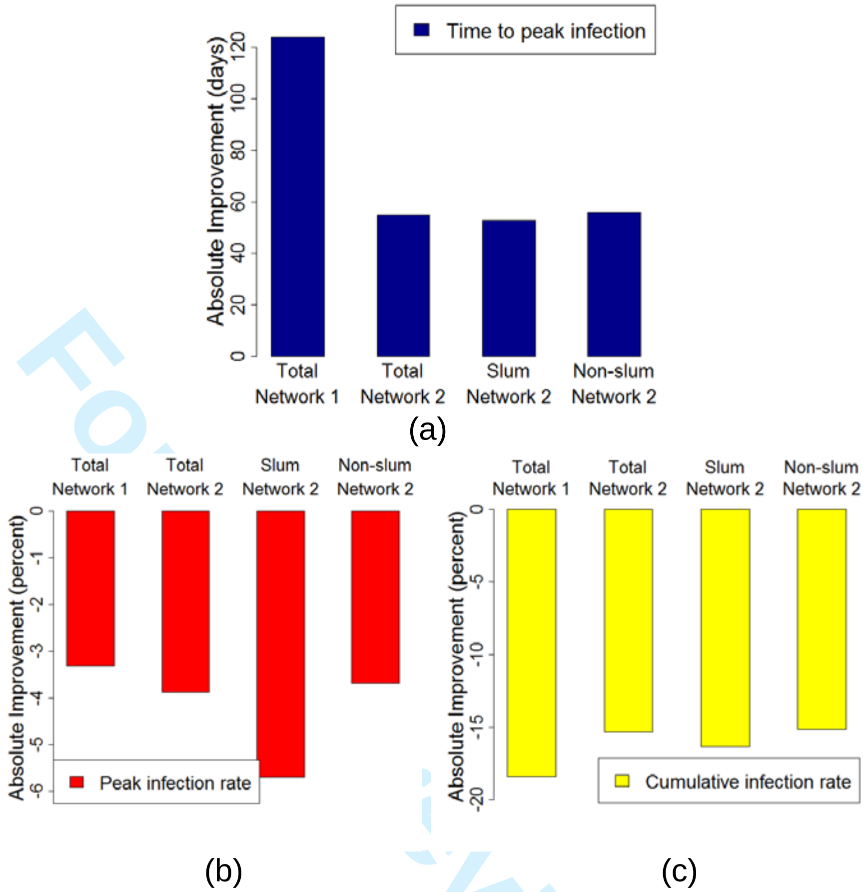

Figure S5: Comparison of absolute difference in improvement; the relative differences are shown in Figure S7. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S7 and S9.

Evaluation of Network 2 Home and School Contacts.

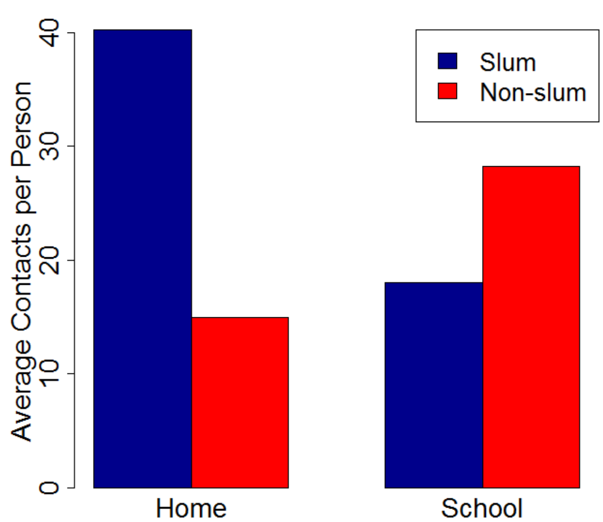

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Figure S6: Comparison of average contacts per person in slum and non-slum regions for home and school activity types in Network 2.

Evaluation of Network 2 Edges Transmitting Infection.

Figure S7 provides counts of edges used to transmit infection for a base case simulation in Network 2 of Figure 1 of the main text. Edges are broken down by activity types of people who are interacting during transmission. Data are also broken down by the classifications of individuals interacting (e.g., slum and nonslum, see legend).

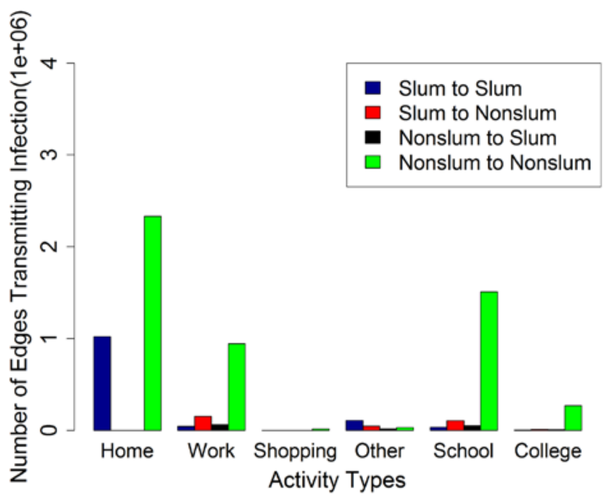

Figure S7. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater than nonslum-to-slum ones because once infection gets into a slum household, it may spread within the household more (because there are more people and connections). Thus, a slum household carries more infection to its interactions with nonslum people. The "Other" activity category, like home activity, shows more edges carrying infection for slum-to-slum interactions than slum-to-nonslum, which is consistent with Figures S4 and S6 of Chen et al.[2], where further network characteristics are given.

Supplemental Information

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