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Disparities in Spread and Control of Influenza in Slums of Delhi

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6 **Disparities in Spread and Control of Influenza in Slums of Delhi**
7

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3 **ABSTRACT**
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5 **Objectives** This research studies the role of slums in the spread and control of
6 infectious diseases in the National Capital Territory of India, Delhi, using a detailed
7 social contact network of its residents.
8

9 **Methods** We use an agent-based model to study the spread of Influenza in Delhi
10 through person-to-person contact. Two different networks are used; one in which slum
11 and non-slum regions are treated the same and the other in which 298 slum zones are
12 identified. In the second network slum-specific demographics and activities are
13 assigned to the individuals whose homes reside inside these zones. The main effect of
14 integrating slums is that the network has more home-related contacts due to larger
15 family size and more outside contacts due to more daily activities outside home. Various
16 vaccination and social distancing interventions are applied to control the spread of
17 Influenza.
18

19 **Results** Simulation based results show that when slum attributes are ignored, the
20 effectiveness of vaccination can be overestimated by 30%-55%, in terms of reducing
21 the peak number of infections and the size of the epidemic, and in delaying the time to
22 peak infection. The slum population sustains greater infection rates under all
23 intervention scenarios in the network that treats slums differently. Vaccination strategy
24 performs better than social distancing strategies in slums.
25

26 **Conclusions** Unique characteristics of slums play a significant role in the spread of
27 infectious diseases. Modeling slums and estimating their impact on epidemics will help
28 policy makers and regulators more accurately prioritize allocation of scarce medical
29 resources and implement public health policies.
30

31 **Policy Implications** Currently, over a billion people reside in slums across the world
32 and this population is expected to double by 2030. This study uses Influenza as an
33 example to demonstrate the need to understand the role of slum populations in the
34 spread and containment of infectious diseases.
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36

37 **Strengths and limitations of this study**
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- 39
- 40 ➤ We show that the unique attributes of slums must be accounted for in
41 understanding the spread and control of infectious diseases.
 - 42 ➤ Policymakers should give special consideration to slums when allocating limited
43 resources.
 - 44 ➤ Intervention strategies have been applied one at a time but a combination of
45 them could be used simultaneously to more aggressively control the epidemic.
 - 46 ➤ This study does not consider age-specific susceptibility or immunity from past
47 infections; all agents are assumed to be equally susceptible.
 - 48 ➤ Co-location based contact time is used as a proxy for physical proximity and
49 short-distance airborne transmission.
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57 **INTRODUCTION**
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5 Infectious disease is one of the leading causes of human morbidity and mortality
6 worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000
7 people in the United States (US) are hospitalized with Influenza-like illnesses (ILI)
8 symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In
9 Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the
10 National Institute of Virology has shown that ILI cases are present throughout the year,
11 although they peak in rainy and winter seasons.[3] It carries a significant economic
12 burden through reduced productivity and high costs of health care.[4-7] A CDC study
13 finds that for outpatient and non-medically attended individuals, acute respiratory
14 infections cost 1%-5% of monthly per capita income in India. In contrast, cost of
15 inpatient care can be as high as 6%-34% of annual per capita income.[8] For developed
16 countries, the annual cost of Influenza is estimated to be between \$1-\$6 million per
17 100,000 people, according to the World Health Organization.[9]

20
21 In 2007, India established an Integrated Disease Surveillance Program (IDSP), which
22 included a network of 12 regional laboratories, to minimize the threat of avian influenza
23 and other highly infectious zoonotic diseases.[10] India faces some unique challenges
24 in surveillance, prevention and control because of the seasonality of Influenza at sub-
25 regional levels. This seasonal variation depends upon latitude, monsoon season,
26 humidity and climatic factors of the regions. Acute respiratory infections are estimated to
27 be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13]
28 estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in
29 year 2011, and children under age 5 had the highest incidence of them.

32
33 Given that Influenza is airborne and spreads through close proximity, population density
34 is an important factor in its spread. In India, the average population density is about
35 1000 people per square mile; in the slums, it can be 10 to 100 times higher.[14] Larger
36 household size and crowding make it easier to transmit airborne infections).[15-18] For
37 example, Baker et al.[16] find that meningococcal disease risk among children doubles
38 with the addition of 2 adolescents or adults (10 years or older) to a 6-room house. Other
39 than overcrowding, slums are characterized by their lack of medical services,[19-20]
40 which makes slum residents highly vulnerable to infectious diseases. Diseases like
41 cholera, malaria, dengue and HIV are common in slums across the world.[21-23]

44
45 This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8
46 million people live in slum areas, as an example city to study the spread and control of
47 Influenza. Delhi is an interesting case study. It ranks fourth in the world in urban
48 population, and, among the top 25 largest urban areas, it ranks tenth in population
49 density. Moreover, the results are likely to be generalizable to other slum areas within
50 and outside of India.

52
53 This paper is an extension of the work done in Chen et al.[4], which shows that slum
54 populations have a significant effect on Influenza transmission in urban areas. Ignoring
55 the influence of slum characteristics underestimates the speed of an outbreak and its
56 extent. However, Chen et al.[4] do not consider any interventions on the epidemic
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3 spread. *The focus of this research is to study the effect of different intervention*
4 *strategies on several subpopulations (slum, age and gender) in two different Delhi*
5 *networks, i.e., original (referred to as Network 1) and refined (Network 2).*
6
7

8 The original network used in Xia et al.[24] studied the spread and control of Influenza in
9 Delhi using Network 1, which did not take into account the special attributes of the slum
10 population, such as larger family sizes and different types of daily activity schedules.
11 Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for
12 slum demographics and slum activities, but did not study intervention strategies. In
13 Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.
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16 The goals of this work focus on understanding the effects of pharmaceutical and non-
17 pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI)
18 include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing
19 measures such as school closure, quarantine and staying home. These effects are
20 studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations
21 in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a
22 scenario where interventions can be applied to a limited number of individuals, we
23 explore how resources should be split between slum and non-slum subpopulations in
24 order to achieve the best outcomes with respect to total infection rate (i.e., the
25 cumulative fraction of a population infected), peak infection rate (i.e., the maximum
26 fraction of a population infected on any day), and time-to-peak infection.
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30 METHODS

31
32 We use an agent-based modeling (ABM) approach to simulate the spread and
33 containment of Influenza in social contact networks of Delhi, India. We compare two
34 networks, one considers slum-specific attributes, and the other does not. In this section,
35 we describe the networks, the disease model for each agent, the interventions, and the
36 heterogeneities of the problem that make ABM uniquely suited to study epidemics.
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40 **Social Contact Networks:** This study uses two synthetic social networks of Delhi,
41 created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found
42 in Xia et al.[24], Chen et al.[4], Barrett et al.[25], Bisset et al.[26] and references therein.
43 The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined
44 network developed in Chen et al.[4], *Network 2*.
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46

47 Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set
48 of activities of individuals, and the locations of those activities including geo-locations of
49 residential areas, shopping centers, and schools, collected through surveys by
50 MapMyIndia.com. By assigning activity locations to individuals' activities, people are
51 located at particular times at particular geographic coordinates (including office
52 buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between
53 individuals are estimated when each person is deemed to have made contact with a
54 subset of other people simultaneously present at the same location. This gives rise to a
55 synthetic social contact network where network edges represent these contacts.
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5 Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the
6 individuals whose homes reside in the slum polygons. Slum residents' attributes and
7 their daily sets of activities are collected through a ground survey in Delhi slums, by a
8 vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from
9 *MapMechanic.com*. Individuals living in the slum regions are a part of the slum
10 population. All other individuals are part of the non-slum population. Network 2 is a geo-
11 located, and contextualized social contact network of Delhi with slums integrated in it.
12

13
14 Following are the main differences between the original network (Network 1) and the
15 refined network (Network 2). The original social contact network treats the slum regions
16 like any other region in Delhi in terms of assignment of demographics and individual
17 activities, i.e. no special consideration is given to slum residents. The refined Network 2
18 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific demographics
19 and activities to the individuals whose homes reside inside these polygons. Thus, the
20 number of individuals is the same in both populations. The slum population constitutes
21 about 13% (1.8 million) of the entire Delhi population of 13.8 million people. The main
22 effect of integrating slums is that Network 2 has more home-related contacts due to
23 larger family size and more outside contacts due to more daily activities outside home.
24 Also, those individuals who reside outside of slum zones have the same activities in
25 both networks. Overall, there are over 231 million daily interactions between pairs of
26 individuals. Table S1 compares those two networks as well as data sources for slum
27 and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are in
28 the supplementary information (SI)). We refer to Chen et al.[4] for more detailed
29 information about the two networks. Several plots of properties and structural
30 characteristics of Networks 1 and 2 are given in Chen et al.[27].
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35 **Disease Model:** An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or
36 Recovered (R) model is considered within each individual. Each node in the network
37 represents an individual, and each edge represents a contact on which the disease can
38 spread. A contact represents possible transmission between two people that are co-
39 located for some duration (based on their activity schedules). This is an approximation
40 to model direct contact and short-distance airborne transmission.
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44 We start each epidemic simulation with 20 index cases, randomly chosen. (We find that
45 results are not sensitive to the number of initial infections.) The detailed description of
46 the SEIR model as well as the choices of transmissibility value, R_0 , the explicit
47 incubation and exposed periods can be found in the supplementary information. This
48 disease model has been used in other works such as Liao et al.[28], Marathe et al.[29].
49
50

51 The transmissibility value for disease transmission is that for the strong influenza model
52 in Chen et al.[4]. That work used mild, strong, and catastrophic influenza models, so we
53 chose the intermediate transmissibility. This corresponds to base attack rates (i.e.,
54 cumulative infection fractions) of 0.42 and 0.48, respectively, in Networks 1 and 2.
55 These rates are generally higher than those in some other studies that either compute
56 experimental attack rates from cases or compute them in modeling studies such as this
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4 one. Attack rates used by past researchers for different strains of influenza include Asia
5 [0.22 to 0.50],[30] Southeast Asia [0.11 to 0.31 in children [31]; 0.05 to 0.65 [32]], and
6 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];
7 0.209 for various strains [13]]. The results of Chen et al.[4] indicate that the results here,
8 for this particular transmissibility, will be qualitatively the same for other transmissibility,
9 but will scale down or up as transmissibility changes in the same direction.
10

11 **Interventions:** This work considers three vaccination scenarios, i.e., vaccinate when
12 cumulative infection rate is 0% (VAX0, i.e. vaccinate on day 1), 1% (VAX1), and 5%
13 (VAX5). Three classes of social distancing strategies are considered: (i) stay-home
14 (SHO) if infected i.e. eliminate all non-home related contacts but continue to maintain
15 contacts within the household; (ii) close-schools when cumulative infection rate has
16 reached 1% (CS1) and when it has reached 5% (CS5) i.e. eliminate school related
17 contacts; and (iii) (ISO), in which all contacts, including home contacts, of a person are
18 eliminated when a person becomes infectious. For vaccination, five different compliance
19 rates (10%, 30%, 50%, 70%, 90%) and two different vaccine efficacies (30% and 70%)
20 are considered. Interventions are applied to slum residents, non-slum residents, and the
21 entire region of Delhi. For each experiment, 25 replicates are simulated for 400 days,
22 and their mean results are reported. Table S2 summarizes all the interventions
23 considered, and Table S3 contains all variables in simulations, including intervention
24 parameters.
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29 **Heterogeneities captured:** There are several heterogeneous aspects to this problem
30 that motivate the use of an ABM approach: (i) the 298 slum zones have populations that
31 vary by more than four orders of magnitude in size; (ii) the geographic extent of slum
32 zones differ; (iii) the slum zones are located at irregular spatial intervals throughout
33 Delhi; (iv) the activity patterns of people living in slums are different from those in the
34 non-slum region; and (v) each individual interacts with specific others based on co-
35 location.
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39 The implications of these heterogeneities include the following. First, the particular
40 synthetic households that live within slums are predicated on the number of slum zones,
41 their locations, and their spatial geometries. These homes have larger family size and
42 hence more home contacts. Second, slum individuals have different activity patterns
43 which change the co-located contacts of each slum person: that is, with whom they
44 interact and for how long. For example, see the supplemental Figure S6 of Chen et
45 al.[27]. The average total contact durations by activity type and by slum/non-slum
46 residents are provided, which show that non-slum people have greater contact
47 durations for work, school, and college activities, but less for home and other types.
48 Overall, a slum person has about 50% greater total contact duration per day compared
49 to a non-slum person. Figure S7 of the same supplemental shows that in the age range
50 20 to 60 years (by year), females that live in slums have more contacts per day than
51 their male counterparts. However, females whose homes are outside of slum regions
52 have average number of daily contacts that are below their male counterparts.
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4 **RESULTS AND ANALYSIS**

5 Our results are grouped as follows. (1) Comparisons of Network 1 and Network 2 for
6 base case and intervention cases. (2) Results for both networks based on demographic
7 classes, such as slum/non-slum, gender, and age groups, for a wider range of
8 intervention strategies. (3) Effects of pharmaceutical and non-pharmaceutical
9 interventions for a wide range of parameter values. (4) Effects of different resource
10 allocation strategies.
11

12 All differences are tested with the two-sample t-test and they are all statistically
13 significant with p-values smaller than $2.2e-16$. The 95% confidence intervals are given
14 for each comparison. Here is a brief summary of selected results with examples of
15 mechanisms, to provide a high-level overview. Details of results follow this summary
16 and these details matter because there are many factors (inputs) in a simulation whose
17 interactions change results.
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20
21 (1) Ignoring the unique attributes of slums in a population overestimates the benefits of
22 the interventions. For example, in the case of vaccination intervention (efficacy 30% and
23 compliance 30%), the values for the epidemic size (i.e., cumulative percentage of
24 infected), peak infection rate, and time to peak are 33.1%, 3.0%, and 184 days,
25 respectively, in Network 2, whereas they are 23.3%, 1.34%, and 286 days in Network 1.
26 In relative terms, the epidemic size and peak infection rate are underestimated by
27 42.2% and 123.2% respectively, while the time to peak is overestimated by 35.7% in
28 Network 1 (see Figure 1 and Table S5). The larger family sizes for slum families in
29 Network 2 and the increased number of edges result in larger outbreaks and faster time
30 to peak infections.
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32

33
34 (2) Interventions are more effective in Network 1 than Network 2 for all types of
35 interventions: vaccination, closing schools, staying home, and isolation. These trends
36 also hold over wide ranges of efficacy and compliance (see Figures 3, 4, S1, S2 and
37 S7). Hence, not accounting for slums gives overly optimistic results for the effectiveness
38 of the interventions. The reduced average family size in Network 1 means fewer within-
39 home edges, which slows infection and reduces spreading. Closing schools and staying
40 home interventions do not affect home edges. However, the magnitude of this effect
41 varies with intervention conditions (e.g., compliance rate, time at which intervention is
42 applied).
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45
46 (3) Cumulative infection rates by subpopulation in Network 2 show that slums sustain
47 greater infection rates than non-slums under all intervention scenarios, sometimes by as
48 much as 44.0%. See Figure 4 and Table S9 for more details. This is due to the greater
49 household sizes in slums.
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51
52 (4) For Network 2, under a wide range of intervention compliance rates (10% to 90%),
53 the isolation strategy is up to 32% more effective in containing an outbreak than
54 vaccination (for 30% efficacy). Staying home is up to 18% more effective than
55 vaccination at 50% compliance. See Figure 3 and Table S10 for more details. Isolation,
56 although hard to implement from practical considerations, is most effective because
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3 edges to susceptible individuals are removed (isolation also provides a good
4 comparative case). Differences between staying home and vaccination depend on
5 compliance rates.
6

7
8 (5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse
9 effect in slums than in non-slum regions across compliance rates from 10% to 90%. See
10 Figure 4 and Table S7 for more details. Early interventions mean actions are taken
11 when outbreaks are smaller and are therefore more readily contained.
12

13
14 (6) A full-factorial design that splits resources between slum and non-slum regions
15 indicates that the most effective intervention is to give vaccines to slums and apply
16 social distancing to non-slums. Applying vaccine and social distancing to slum regions
17 is the next most effective intervention. See Figure 5. By applying social distancing to
18 non-slums, these individuals are kept isolated from slum individuals that are infected.
19
20

21 22 **Comparison between Networks 1 and 2: Base case versus interventions** 23

24 We start with a comparative analysis of the Influenza epidemic, with and without
25 interventions, on Network 1 and Network 2 to measure the impact of integrating slums
26 in the population on epidemic measures. Figure 1 shows the simulation time histories
27 (averaged across 25 simulations) for the base case, and when vaccination is applied
28 randomly to 30% of the population in each network with vaccine efficacy set at 30%.
29 Mean infection rate is the daily fraction of infected individuals. Simulations for other
30 vaccine efficacies and compliance rates give qualitatively similar results. Two sets of
31 those results are shown in the supplemental information, see Figures S1 and S2. Note
32 that Network 1 does not distinguish between slum and non-slum individuals, so the
33 epidemic curve is not split by subpopulation.
34
35

36
37 Results in Network 2 differ significantly from results in Network 1 for both the base case
38 and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a
39 larger epidemic size and has higher peaks compared to the corresponding epidemic
40 quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to
41 plan, there will be a false sense of security and lack of urgency to implement
42 interventions. For both the base case and the intervention case, ignoring unique
43 characteristics of the slums will result in an underestimation of the infections and the
44 speed of spread.
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46

47
48 Figure 1 goes here
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50
51 For the intervention cases, the time to peak infection decreases by 35.7%, i.e. from 286
52 days for Network 1 to 184 days for Network 2, meaning an influenza epidemic would
53 peak roughly 100 days earlier than one would expect based on the results from Network
54 1. For the base case, time to peak infection drops by 20.8%, i.e. 34 days reduction for
55 Network 2 as compared to Network 1.
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4 Percentage changes and differences must be viewed cautiously, and to illustrate this
5 point, we present data for the key parameters in Tables S4 and S5. The difference in
6 the peak infection rate (i.e., the maximum fraction of daily infected individuals during the
7 simulation) between Networks 1 and 2 for the base case is 2.2%, or 47.6% in
8 percentage change (see Table S4). For the intervention case shown in Table S5, the
9 difference between the two networks is less (1.7%), but the percentage change is more
10 (123.2%) because the magnitudes of the peak infection rates are reduced when
11 effective interventions are used. We make note of this here and mainly use the
12 percentage change values in discussing results. For more detailed comparison between
13 vaccination intervention and the base case in Network1 and Network 2, we refer to
14 Tables S6 and S7, Figures S3 and S4.
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18 **Comparison between Networks 1 and 2 based on individual demographic** 19 **information** 20

21
22 We divide the Delhi population into strata by age, gender, and geographic home
23 location (i.e., slum and non-slum), and analyze mean cumulative infection rates by
24 subpopulation for the two networks. In simulations, individuals are chosen at random in
25 the entire network for vaccination. Various vaccination scenarios are investigated.
26
27

28 Figure 2 displays the cumulative infection rate results. On the x-axis, 'Total' refers to the
29 entire population of Delhi. There are three breakdowns of the entire population. 'Slum'
30 and 'Non-slum' refer to slum and non-slum regions, respectively. 'Male' and 'Female'
31 denote the total number of males and females in Delhi, respectively. Four age groups
32 are considered: 'Preschool' (0-4), 'School' (5-18), 'Adult' (19-64), and 'Senior' (65+). The
33 black lines correspond to the mean cumulative infection rates for the base case. Other
34 curves indicate vaccination strategies under different levels of vaccination rate (v) and
35 vaccine efficacy (α). Two vaccination rates (30%, 50%) and two vaccine efficacy rates
36 (30%, 70%) are shown in the figure.
37
38

39 For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of
40 individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the
41 epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either
42 a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate
43 of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all
44 categories of individuals.
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48 In Network 1, slum and non-slums are treated the same so the infection rates are
49 identical in Figure 2. However, all scenarios in Network 2 show a higher burden of
50 disease on the slum population. This is due to the fact that slum households have larger
51 family size and more contacts on average than households in non-slum areas, see
52 Chen et al.[27]. As shown later, we find similar patterns of infection in slum and non-
53 slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.
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3 The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums
4 results in overestimation of the benefits of interventions in terms of reduction in the
5 mean infection rate and peak infection rate, as well as the time to peak. This optimism
6 holds for slum, non-slum and total population under various levels of vaccination rates
7 and efficacy rates in Network 2. See Table S8 for more detailed comparison of results
8 between slum and non-slum in Network 2.
9
10

11 Figure 2 goes here
12
13

14 **Comparison between Networks 1 and 2 across a wide range of intervention** 15 **strategies** 16

17
18 Next, we consider a variety of intervention strategies for comparative analysis. We
19 consider vaccination, school closure, stay home, and isolation strategies. For vaccines,
20 three different trigger points are considered: when cumulative infection rate reaches 0%
21 (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used:
22 when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at
23 home (SHO) strategy, all non-home activities and interactions are eliminated but all
24 contacts within the household are maintained. Under isolation (ISO) an individual has
25 no contact with other individuals (even home interactions are eliminated). The stay-at-
26 home and isolation interventions are implemented for compliant infectious individuals,
27 after they become infectious, for the entire infectious duration.
28
29
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31 Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a
32 wide range of intervention strategies. For each strategy, five different compliance rates
33 are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates
34 (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers
35 are the actual number of infected individuals. Darker colors correspond to higher
36 infection rates. Note that compliance rate is simply the vaccination rate for strategies
37 VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire
38 population. The 'Base' values do not vary with compliance because the base case has
39 no intervention. Note that all heat maps in this paper use the same color scheme so that
40 colors can be compared across figures.
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44 Since Network 1 does not distinguish between slum and non-slum populations, we only
45 compare the two networks for the whole of Delhi. The general pattern is similar for both
46 networks. However, all interventions have a larger effect on Network 1 under the same
47 compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than
48 for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0,
49 stay-home, and isolation strategies in Network 1 as compared to those for Network 2.
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52 Figure 3 goes here
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55 **Effect of vaccination versus social distancing on slum and non-slum** 56 **subpopulations** 57 58 59 60

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5 We now compare the impact of vaccination and social distancing on slum and non-slum
6 subpopulations from Network 2. Social distancing interventions are close-schools, stay-
7 home, and isolation.
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9 The mean cumulative infection rates (and actual numbers of infections underneath) for
10 each compliance level are shown in the heat maps in Figure 4 for slum and non-slum
11 populations in Network 2. The axis labels are identical to those in Figure 3, as is the
12 color scheme of the cells. The base case values are constant since there is no
13 intervention and hence no compliance. Darker colors correspond to higher infection
14 rates.
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17 Compared to the base case, all interventions reduce infection rates to some extent. As
18 the compliance rate increases, infection rates drop for all interventions. Infection rates
19 drop to zero in slum and non-slum regions at a compliance level of 70% or higher,
20 under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce
21 the infection rates significantly, and this effect increases with compliance rate.
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24 The following observations can be made from Figure 4. Social distancing i.e. SHO at
25 low and intermediate compliance and CS at all compliance levels, are less effective in
26 slum regions as compared to non-slum regions. This is because CS only eliminates
27 school interactions for those attending school, and there are fewer school edges in
28 slums compared to non-slum areas, as shown in Figure S5. The effectiveness of CS in
29 slums is mitigated by the greater average number and duration of interactions at home
30 in slums as compared to non-slums (see Figure S5 and Chen et al.[27]). Thus, if a
31 person is sick, there is a greater chance of transmitting contagion to family members,
32 who then may have activities outside of school, thus circumventing the CS intervention.
33 At high compliance, SHO is effective because all interactions outside home (including
34 school) are eliminated.[27]
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39 These observations are also supported by Figure S6, which contains numbers of edges
40 used to transmit contagion for a base-case run of Figure 1. There are several effects
41 that bear on the above observations. First, in the cases of activities "work", "other", and
42 "school", the number of edges transmitting contagion from slums to non-slums is greater
43 than the reverse: from non-slum to slum. Second, in two of these three activity
44 categories, there is more slum to non-slum transmissions than slum to slum
45 transmissions. Edges of transmission for slum dwellers is dominated by home
46 interactions. The infected homes in slums serve as launching points to drive disease to
47 non-slums through slum to non-slum interactions. (There are no "mixed" edges at
48 homes, and shopping and college activities have low levels of slum activity because of
49 socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but
50 we now return to Figure 4.
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54 Isolation works well at 30% or higher compliance rates, but it is a much harder strategy
55 to implement, especially in slums. However, it is considered here for comparative
56 analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as
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4 compliance increases. However, close-school is generally less effective because this
5 intervention removes only a fraction of interactions for a fraction of the population, i.e.
6 school aged children. Simulations were also run for 70% vaccine efficacy. Since results
7 are qualitatively similar for those parameters, these plots are provided in Figure S7.
8

9 Figure 4 goes here
10

11 **Constrained resource allocation among slum and non-slum areas**

12
13 We consider a specific scenario under Network 2. If only a limited number of vaccines
14 are available, and only a certain fraction of individuals can be kept home during an
15 epidemic, how should these interventions be applied to the slum and non-slum regions
16 so that the epidemic can be controlled effectively? Given that slum residents' attributes
17 differ from those of non-slum residents, is there a strategy that works better in slums
18 than in non-slum areas? The total population in Delhi is about 13.8 million, which
19 includes about 1.8 million slum residents. We assume that only 10% of the total
20 population can be covered by interventions, half through vaccination and the other half
21 through stay home. Enough vaccines are available to cover 5% of the total population
22 (i.e. 692,183 vaccinated, corresponding to about 38.25% of slum or 5.75% of non-slum
23 population), and 5% of the individuals can stay home (692,183 individuals; this is
24 applied to only the infected individuals). Note that an individual may receive a vaccine
25 and also stay at home if this individual, in spite of being vaccinated, gets infected.
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31 We consider 4 different ways of applying interventions to 10% of the total population: (i)
32 apply both interventions to slums, i.e. give all vaccines to slums and apply SHO only in
33 the slums (VsSs); (ii) apply all interventions to non-slum areas (VnSn); (iii) give vaccines
34 to slums and SHO to non-slums (VsSn) and (iv) give vaccines to non-slums and apply
35 SHO to slums (VnSs).
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38 For both types of intervention, the same number of individuals is chosen randomly from
39 slum or non-slum areas. 10% of the total Delhi population amounts to 76.5% of slum
40 population, 11.5% of the non-slum population, or a combination of 38.25% of the slum
41 and 5.75% of the non-slum population (i.e. half from slums and half from non-slums).
42 Figure 5 shows the mean cumulative infection rates, as well as the number of infected
43 from the entire population of Delhi, the slums, and non-slum areas under each of the
44 four scenarios.
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48 The results in Figure 5 indicate that the mean infection rates are the lowest when
49 vaccines are given to slums and social distancing is applied to non-slums, or both
50 vaccines and social distancing are applied to slums. The benefits primarily accrue to the
51 slum population because it drives down the fraction of infected slum residents from 0.74
52 to 0.55 or 0.58. Also, as described in the context of Figures 4 and S6 above, social
53 distancing of the non-slum residents helps to isolate them from the infected slum
54 residents. This effect also bears on the following.
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3 Note that vaccination is more effective in slums (top 2 rows) than in non-slums (3rd and
4 4th rows from top) in reducing infections among slums and in the overall population.
5 Although non-slums are marginally better off (compared to the base case), the overall
6 infection rate drops and the slum population is significantly better off, leading to a
7 Pareto-optimal situation. This is a counterintuitive result, since the density of population
8 is much higher in the slums, which may lead to the belief that social distancing in slums
9 will break up the dense clusters. However, a careful examination shows that keeping
10 slum residents home is not an effective social distancing strategy because their family
11 size is, on average, almost 3 times larger than the family size of non-slum
12 households.[27] The high level of mixing at home makes social distancing ineffective in
13 slums unless the infected individual is completely isolated. However, complete isolation
14 is not viable in slum areas where the entire household may live in a single room.
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19 Figure 5 goes here

20 21 22 **DISCUSSION**

23
24 With slum populations expected to grow to 2 billion by 2030,[37] it is becoming
25 increasingly urgent to understand how to control the spread of infectious diseases in
26 slum areas and measure its effect on urban populations. To our knowledge, a detailed
27 study of interventions to control Influenza epidemics in slums, using an agent-based
28 simulation model, has never been done before. Slum conditions are important for a city
29 beyond the direct effects of disease transmission. For example, civil wars may be
30 precipitated or exacerbated by disease outbreaks because they decrease social health
31 and welfare. [38]
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34
35 Even though slum regions contain only 13% of the total population of Delhi, Chen et
36 al.[4] show that omitting their attributes leads to underestimation of the overall infection
37 rate and the peak infection rate of the epidemic. This paper extends that work by
38 evaluating the differential impact of interventions on slum and non-slum regions.
39 Various vaccination and social distancing strategies are analyzed under different
40 scenarios that show that the slum population is more prone to infections under the same
41 control measures. Furthermore, taking account of slum populations significantly alters
42 the disease dynamics in the *entire* population. Differences in key measures are
43 demonstrated between the cases of accounting for slum populations and not: e.g., a
44 100% increase in the peak attack rate in some cases when slum regions' characteristics
45 are taken into account, compared to the case when they are ignored.
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49
50 Figure 4, which compares infections in slum with non-slum areas, shows that at very
51 high compliance rates, some interventions can be equally effective in both slums and
52 non-slums. However, such high compliance rates are typically not feasible due to
53 practical realities on the ground, and also because they require timely diagnosis of
54 infected cases. For SHO to be effective, the coverage rate needs to be 70% or more in
55 both slums and non-slums, and the diagnosis of the infected individuals needs to be
56 correct and immediate. In other words, effective control of a contagious epidemic in a
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3 high density place like Delhi, would require either early and drastic action (e.g. ISO) or a
4 highly compliant set of individuals, or a combination of these features.
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6
7 This work overall demonstrates the power of agent-based and population modeling to
8 evaluate complicated interaction-based epidemiological phenomena. Clearly, there are
9 limitations to this work (noted above). But these agent and population approaches
10 provide a platform for adding additional complexity. All of the figures demonstrate that
11 quantitative results depend on complicated interplay among inputs. These results are
12 important because they inform policy decisions. An equally important benefit of this type
13 of work, but not often stated, is developing intuition about epidemic dynamics (in this
14 case, with the effects of slums), to enable decision makers to reason about nuanced
15 interactions among effects to a degree that is hard to obtain with other approaches that
16 lack this level of detail.
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20 Despite this being the first work of its kind—to model the outbreak of influenza in a city-
21 level population, along with a host of intervention strategies and parameter values, that
22 includes the effects of slum populations—there are limitations of this work and areas for
23 improvement and for future work. For example: (1) Examination of different population
24 level base attack rates. (2) Different susceptibilities and infectivity for individual agents;
25 e.g., based on age. (3) Effects of asymptomatic infections (although we have addressed
26 this to some extent with compliance and efficacy of interventions). (4) Seasonal
27 effects.[39-40] (5) Effects of immunity for an individual from previous infections (in
28 previous seasons). (6) Evaluation of interaction of different strains from season to
29 season. (7) Comparison of tropical versus subtropical factors. (8) Evaluation of a
30 specific outbreak scenario. (9) Impact of sickness on absenteeism from work and its
31 economic ramifications. (10) Effects on rural versus urban populations. (11) Using
32 combinations of interventions rather than one at a time; this was only done here in
33 Figure 5. However, to disambiguate results, it is prudent to first examine individual
34 interventions. (12) To capture close-proximity airborne transmission, one could use
35 actual physical proximity. Here, we use colocation.
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40 Returning to the practical implications and recognizing this work's limitations, this
41 research demonstrates that modeling slum populations is important, not only for
42 understanding disease dynamics, but also for designing effective control measures.
43 Ignoring the influence of slum characteristics on their urban environment will
44 significantly underestimate the speed of an outbreak and its extent, and hence will lead
45 to misguided interventions by public health officials and policy planners. This research
46 also analyzes the effect of different intervention strategies on slum and non-slum
47 subpopulations. Under limited resources, policymakers should give special
48 consideration to slums in order to control the spread in not only the slum areas, but also
49 the city as a whole. Given the large family size and high population density in the slum
50 regions, it is harder to break up the social network through social distancing strategies.
51 This research provides simulation-based evidence that it may be more effective to
52 concentrate pharmaceutical resources in the slum regions to control the epidemic. The
53 social distancing strategies are ineffective in slums because of a large number of
54 contacts at home. Unless one applies complete isolation, which is not feasible in slums,
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unless isolation is orchestrated by health professional, just staying at home still keeps a large number of contacts and pathways of spread intact.

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4 **Contributorship statement**

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

13 There are no competing interests.
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15

16
17 **Funding statement**

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26 **Data Sharing Statement**

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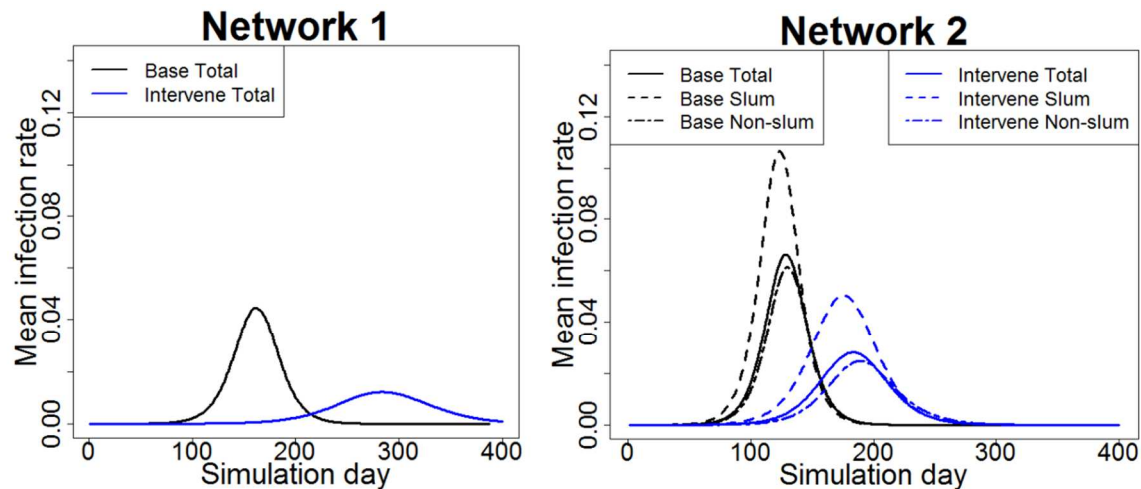


FIGURE 1: Epidemic curves for base case and vaccination case. The vaccines are given randomly to 30% of the entire population and the vaccine efficacy is 30%. For Network 2, epidemic curves are shown for total population and slum and non-slum subpopulations. ‘Intervene Total’ refers to the epidemic curve 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.

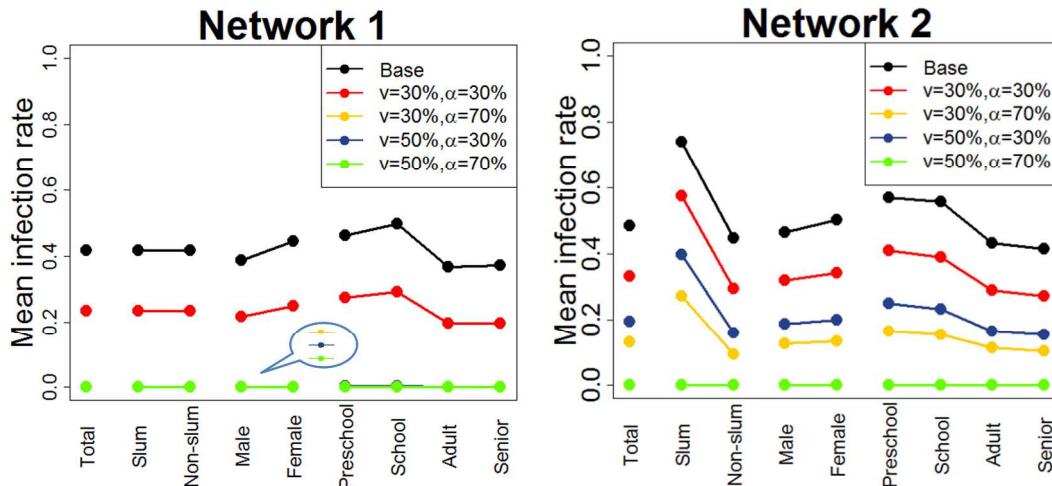
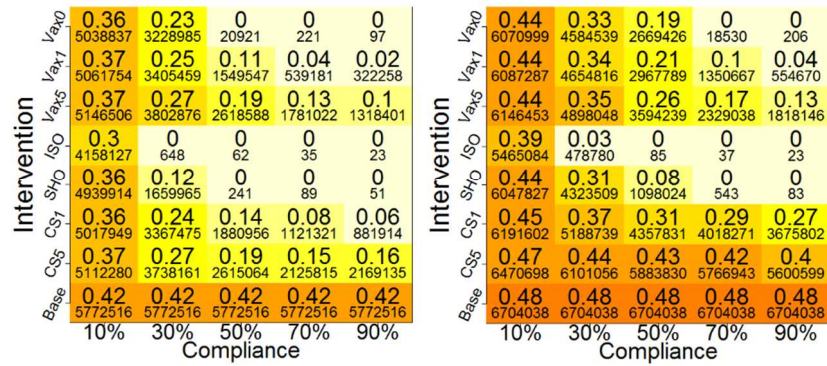


FIGURE 2: Mean cumulative infection rates for different subgroups in the two networks. Two vaccination rates ($v = 30\%$, 50%) and two vaccine efficacy rates ($\alpha = 30\%$, 70%) are considered. Individuals are chosen at random in the entire network for vaccination on day 0. Mean infection rates are 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.

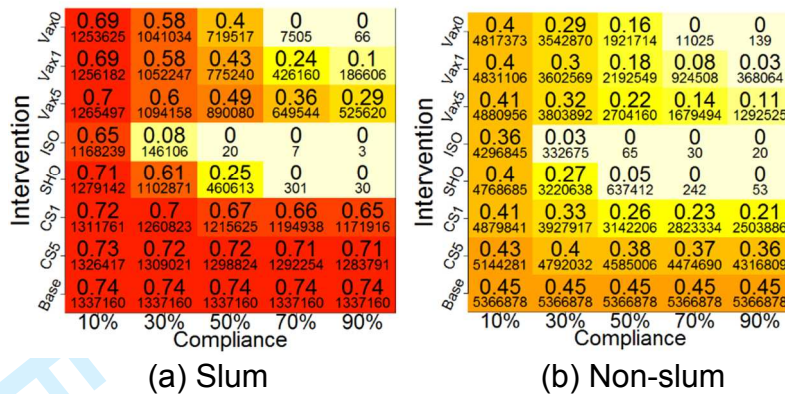


Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond 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.

Intervention	Total	Slum	Non-slum
VsSs	0.44 6043049	0.55 989079	0.42 5053971
VsSn	0.43 5938919	0.58 1042116	0.41 4896803
VnSs	0.44 6023678	0.67 1217415	0.40 4806263
VnSn	0.44 6104571	0.72 1309577	0.40 4794993
Base	0.48 6704038	0.74 1337160	0.45 5366878

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

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For peer review only

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

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	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

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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.

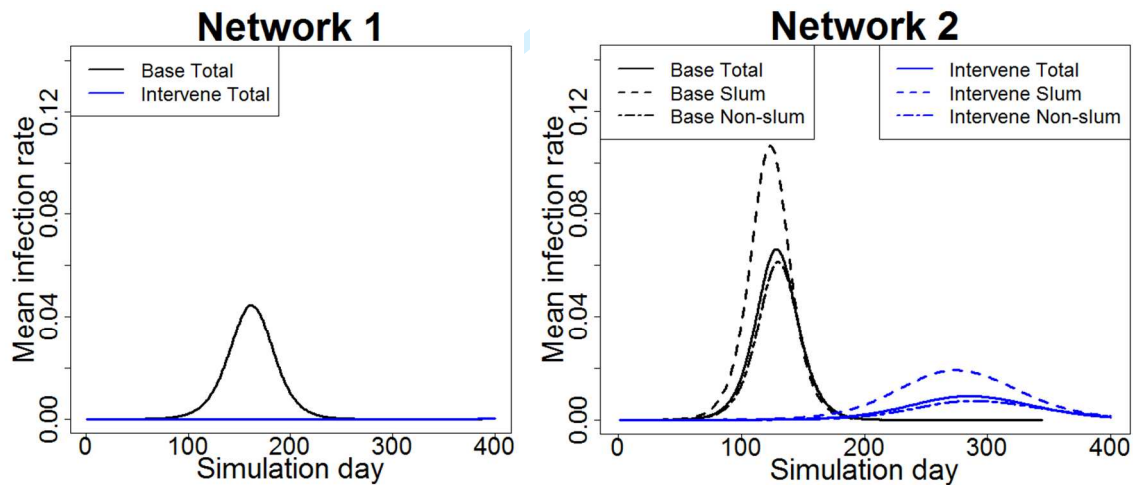


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

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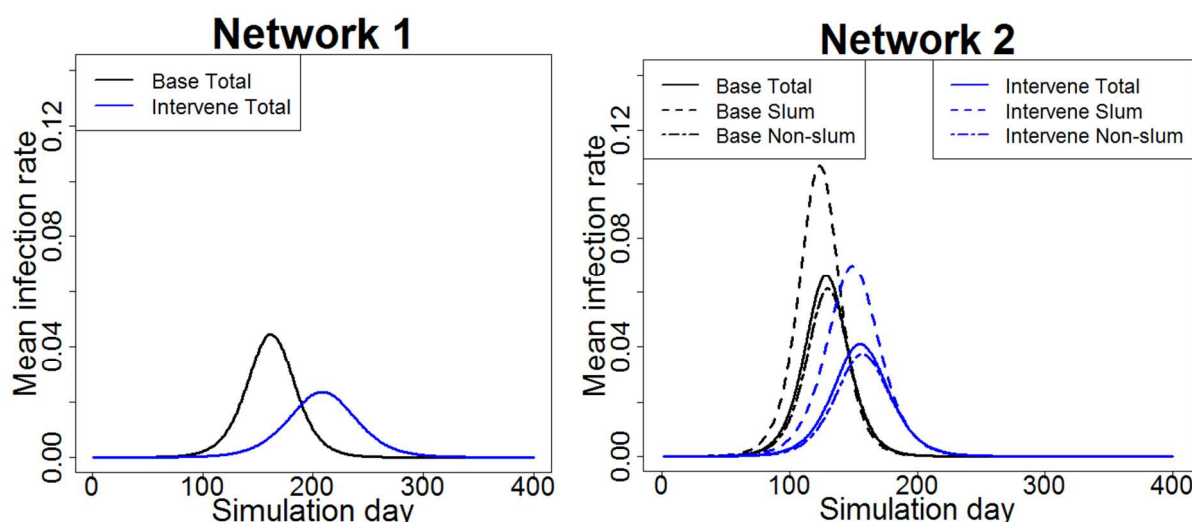


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.

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%-

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				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%)
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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.

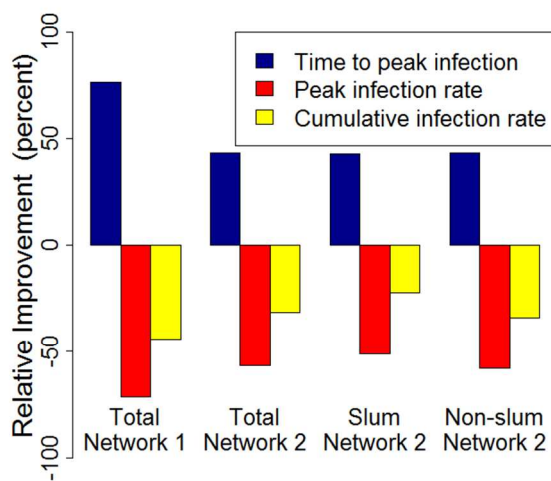


Figure S3: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 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.

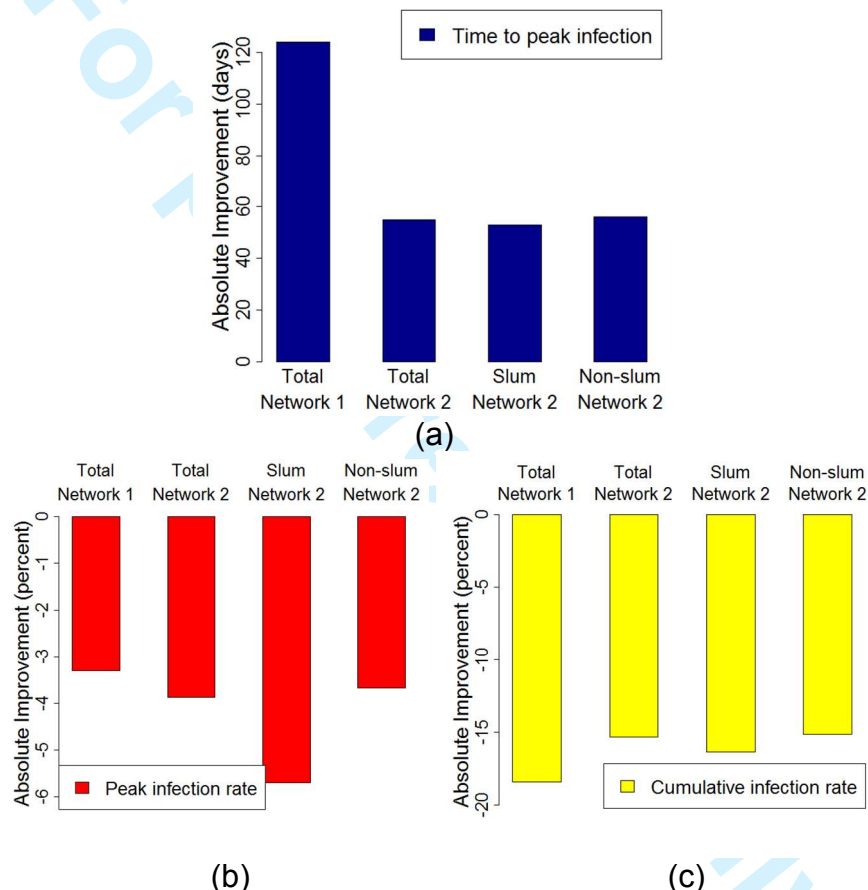


Figure S4: Comparison of absolute difference in improvement; the relative differences are shown in Figure S6. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S6 and S7.

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Evaluation of Network 2 Home and School Contacts.

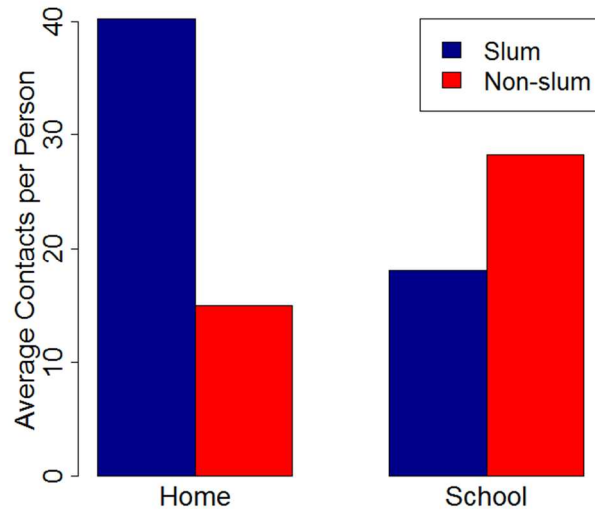


Figure S5: Comparison of average contacts per person in slum and non-slum regions for home and school activity types in Network 2.

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).

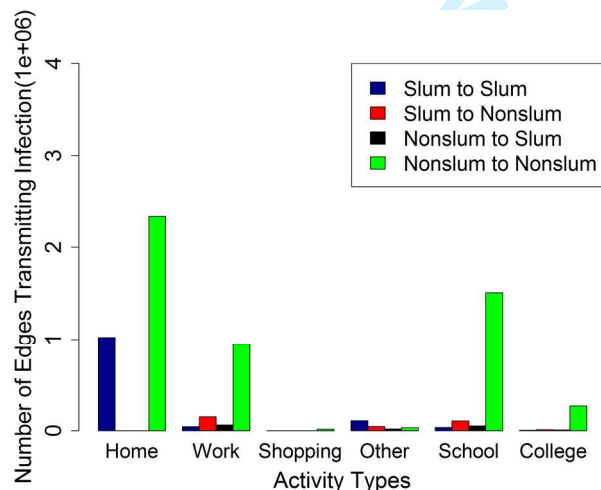


Figure S6. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater

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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%.

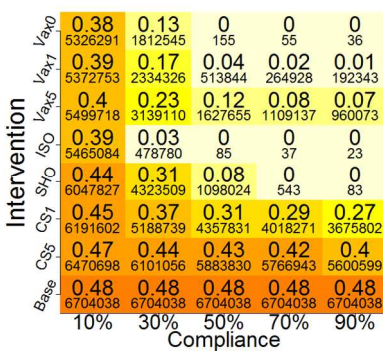
Compliance	Base	CS5	CS1	SHO	ISO	VAX5	VAX1
0.1	29.30%	30.55%	31.94%	31.06%	28.85%	29.37%	29.27%
0.3	29.30%	32.52%	37.03%	34.18%	5.31%	28.85%	28.21%
0.5	29.30%	33.67%	41.07%	20.16%	0.00%	26.72%	24.62%
0.7	29.30%	34.23%	42.57%	0.01%	0.00%	21.94%	15.87%
0.9	29.30%	35.07%	43.95%	0.00%	0.00%	18.31%	7.25%

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.

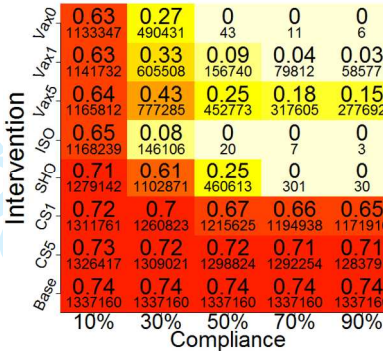
Table S10. Differences in epidemic size between stay at home (SHO) interventions, social isolation (ISO) interventions and pharmaceutical interventions (VAX0, VAX1, VAX5), under various compliance rates. The compliance rate and efficacy for vaccination is 30% and 30%, respectively.

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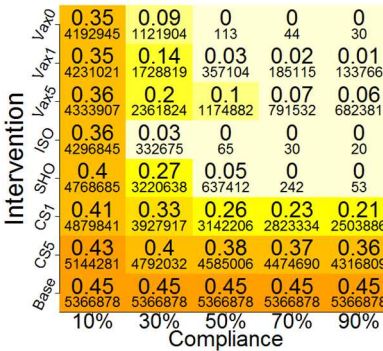
Compliance	Vax5-SHO	Vax1-SHO	Vax0-SHO	VAX5-ISO	VAX1-ISO	VAX0-ISO
0.1	0.71%	0.29%	0.17%	4.92%	4.49%	4.38%
0.3	4.15%	2.39%	1.89%	31.92%	30.17%	29.66%
0.5	18.03%	13.51%	11.35%	25.96%	21.44%	19.28%
0.7	16.82%	9.75%	0.13%	16.82%	9.76%	0.13%
0.9	13.13%	4.01%	0.00%	13.13%	4.01%	0.00%



(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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6 **Disparities in Spread and Control of Influenza in Slums of Delhi**
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4 **ABSTRACT**

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

9
10 **Methods** We use an agent-based model to study the spread of influenza in Delhi
11 through person-to-person contact. Two different networks are used; one in which slum
12 and non-slum regions are treated the same and the other in which 298 slum zones are
13 identified. In the second network, slum-specific demographics and activities are
14 assigned to the individuals whose homes reside inside these zones. The main effects of
15 integrating slums is that the network has more home-related contacts due to larger
16 family sizes and more outside contacts due to more daily activities outside home.
17 Various vaccination and social distancing interventions are applied to control the spread
18 of influenza.
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20
21 **Results** Simulation based results show that when slum attributes are ignored, the
22 effectiveness of vaccination can be overestimated by 30%-55%, in terms of reducing
23 the peak number of infections and the size of the epidemic, and in delaying the time to
24 peak infection. The slum population sustains greater infection rates under all
25 intervention scenarios in the network that treats slums differently. Vaccination strategy
26 performs better than social distancing strategies in slums.

27
28 **Conclusions** Unique characteristics of slums play a significant role in the spread of
29 infectious diseases. Modeling slums and estimating their impact on epidemics will help
30 policy makers and regulators more accurately prioritize allocation of scarce medical
31 resources and implement public health policies.

32
33 **Policy Implications** Currently, over a billion people reside in slums across the world
34 and this population is expected to double by 2030. This study uses influenza as an
35 example to demonstrate the need to understand the role of slum populations in the
36 spread and containment of infectious diseases.
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38 **Strengths and limitations of this study**

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- 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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3 **INTRODUCTION**
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5 Infectious disease is one of the leading causes of human morbidity and mortality
6 worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000
7 people in the United States (US) are hospitalized with influenza-like illness (ILI)
8 symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In
9 Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the
10 National Institute of Virology has shown that ILI cases are present throughout the year,
11 although they peak in rainy and winter seasons.[3] It carries a significant economic
12 burden through reduced productivity and high costs of health care.[4-7] A CDC study
13 finds that for outpatient and non-medically attended individuals, acute respiratory
14 infections cost 1%-5% of monthly per capita income in India. In contrast, cost of
15 inpatient care can be as high as 6%-34% of monthly per capita income.[8] For
16 developed countries, the annual cost of influenza is estimated to be between \$1-\$6
17 million per 100,000 people, according to the World Health Organization.[9]
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22 In 2007, India established an Integrated Disease Surveillance Program (IDSP), which
23 included a network of 12 regional laboratories, to minimize the threat of avian influenza
24 and other highly infectious zoonotic diseases.[10] India faces some unique challenges
25 in surveillance, prevention and control because of the seasonality of influenza at sub-
26 regional levels. This seasonal variation depends upon latitude, monsoon season,
27 humidity and climatic factors of the regions. Acute respiratory infections are estimated to
28 be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13]
29 estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in
30 year 2011, and children under age 5 had the highest incidence of them.
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34 Given that influenza is environmentally-mediated and spreads through close proximity,
35 population density is an important factor in its spread. In India, the average population
36 density is about 1000 people per square mile; in the slums, it can be 10 to 100 times
37 higher.[14] Larger household size and crowding make it easier to transmit
38 infections).[15-18] For example, Baker et al.[16] find that meningococcal disease risk
39 among children doubles with the addition of 2 adolescents or adults (10 years or older)
40 to a 6-room house. Other than overcrowding, slums are characterized by their lack of
41 medical services,[19-20] which makes slum residents highly vulnerable to infectious
42 diseases. Diseases like cholera, malaria, dengue and HIV are common in slums across
43 the world.[21-23]
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47 This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8
48 million people live in slum areas, as an example city to study the spread and control of
49 influenza. Delhi is an interesting case study. It ranks fourth in the world in urban
50 population, and, among the top 25 largest urban areas, it ranks tenth in population
51 density. Moreover, the results are likely to be generalizable to other slum areas within
52 and outside of India.
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55 This paper is an extension of the work done in Chen et al.[4], which shows that slum
56 populations have a significant effect on influenza transmission in urban areas. Ignoring
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3 the influence of slum characteristics underestimates the speed of an outbreak and its
4 extent. However, Chen et al.[4] do not consider any interventions on the epidemic
5 spread. *The focus of this research is to study the effect of different intervention*
6 *strategies on several subpopulations (slum, age and gender) in two different Delhi*
7 *networks, i.e., original (referred to as Network 1) and refined (Network 2).*
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10 The original network used in Xia et al.[24] studied the spread and control of influenza in
11 Delhi using Network 1, which did not take into account the special attributes of the slum
12 population, such as larger family sizes and different types of daily activity schedules.
13 Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for
14 slum demographics and slum activities, but did not study intervention strategies. In
15 Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.
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18 The goals of this work focus on understanding the effects of pharmaceutical and non-
19 pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI)
20 include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing
21 measures such as school closure, quarantine and staying home. These effects are
22 studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations
23 in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a
24 scenario where interventions can be applied to a limited number of individuals, we
25 explore how resources should be split between slum and non-slum subpopulations in
26 order to achieve the best outcomes with respect to total infection rate (i.e., the
27 cumulative fraction of a population infected).
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31 METHODS

32 We use an agent-based modeling (ABM) approach to simulate the spread and
33 containment of influenza in social contact networks of Delhi, India. We compare two
34 networks: one considers slum-specific attributes, and the other does not. In this
35 section, we describe the networks, the disease model for each agent, the interventions,
36 and the heterogeneities of the problem that make ABM uniquely suited to study
37 epidemics. Throughout this manuscript, each agent in the ABM is an individual human.
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42 **Social Contact Networks:** This study uses two synthetic social networks of Delhi,
43 created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found
44 in Xia et al.[24], Chen et al.[4], Barrett et al.[25], Bisset et al.[26] and references therein.
45 The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined
46 network developed in Chen et al.[4], *Network 2*.
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49 Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set
50 of activities of individuals, and the locations of those activities including geo-locations of
51 residential areas, shopping centers, and schools, collected through surveys by
52 MapMyIndia.com. By assigning activity locations to individuals' activities, people are
53 located at particular times at particular geographic coordinates (including office
54 buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between
55 individuals are estimated when each person is deemed to have made contact with a
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3 subset of other people simultaneously present at the same location. This gives rise to a
4 synthetic social contact network where network edges represent these contacts.
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7 Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the
8 individuals whose homes reside in the slum polygons. Slum residents' attributes and
9 their daily sets of activities are collected through a ground survey in Delhi slums, by a
10 vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from
11 *MapMechanic.com*. Individuals living in the slum regions are a part of the slum
12 population. All other individuals are part of the non-slum population. Network 2 is a geo-
13 located, and contextualized social contact network of Delhi with slums integrated in it.
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17 Following are the main differences between the original network (Network 1) and the
18 refined network (Network 2). The original social contact network treats the slum regions
19 like any other region in Delhi in terms of assignment of demographics and individual
20 activities, i.e. no special consideration is given to slum residents. The refined Network 2
21 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific demographics
22 and activities to the individuals whose homes reside inside these polygons. Thus, the
23 number of individuals is the same in both populations. The slum population constitutes
24 about 13% (1.8 million) of the entire Delhi population of 13.8 million people. The main
25 effects of integrating slums is that Network 2 has more home-related contacts due to
26 larger family sizes and more outside contacts due to more daily activities outside home.
27 Also, those individuals who reside outside of slum zones have the same activities in
28 both networks. Overall, there are over 231 million daily interactions between pairs of
29 individuals. Table S1 compares those two networks as well as data sources for slum
30 and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are in
31 the supplementary information (SI)). For example, the average degree increases from
32 30.4 to 33.4 from Network 1 to Network 2, and the maximum degree increases from 170
33 to 180. We refer to Chen et al.[4] for more detailed information about the two networks.
34 Several plots of properties and structural characteristics of Networks 1 and 2 are given
35 in Chen et al.[27].
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40 **Disease Model:** An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or
41 Recovered (R) model is considered within each individual. Each node in the network
42 represents an individual, and each edge represents a contact on which the disease can
43 spread. A contact represents possible transmission between two people that are co-
44 located for some duration (based on their activity schedules). This is an approximation
45 to model direct contact and short-distance environmentally-mediated transmission that
46 might include direct physical contact, fomite mediated, and airborne transmission.[28]
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49 We start each epidemic simulation with 20 index cases, randomly chosen. (We find that
50 results are not sensitive to the number of initial infections.) The detailed description of
51 the SEIR model as well as the choices of transmissibility value, R_0 , the explicit
52 incubation and exposed periods can be found in the supplementary information. This
53 disease model has been used in other works such as Liao et al.[29], Marathe et al.[30].
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4 The transmissibility value for disease transmission is that for the strong influenza model
5 in Chen et al.[4]. That work used mild, strong, and catastrophic influenza models, so we
6 chose the intermediate transmissibility. This corresponds to base attack rates (i.e.,
7 cumulative infection fractions) of 0.42 and 0.48, respectively, in Networks 1 and 2.
8 These rates are generally higher than those in some other studies that either compute
9 experimental attack rates from cases or compute them in modeling studies such as this
10 one. Attack rates used by past researchers for different strains of influenza include Asia
11 [0.22 to 0.50],[31] Southeast Asia [0.11 to 0.31 in children [32]; 0.05 to 0.65 [33]], and
12 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];
13 0.209 for various strains [13]]. The results of Chen et al.[4] indicate that the results here,
14 for this particular transmissibility, will be qualitatively the same for other
15 transmissibilities, but will scale down or up as transmissibility changes in the same
16 direction.
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20 **Interventions:** This work considers three vaccination scenarios, i.e., vaccinate when
21 cumulative infection rate is 0% (VAX0, i.e. vaccinate on day 1), 1% (VAX1), and 5%
22 (VAX5). Three classes of social distancing strategies are considered: (i) stay-home
23 (SHO) if infected, i.e. eliminate all non-home related contacts but continue to maintain
24 contacts within the household; (ii) close-schools when cumulative infection rate has
25 reached 1% (CS1) and when it has reached 5% (CS5), i.e. eliminate school related
26 contacts; and (iii) (ISO), in which all contacts, including home contacts, of a person are
27 eliminated when a person becomes infectious. For vaccination, five different compliance
28 rates (10%, 30%, 50%, 70%, 90%) and two different vaccine efficacies (30% and 70%)
29 are considered.
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33 VAX0, SHO, ISO are all fairly aggressive interventions because they are implemented
34 either before a person gets infected or immediately upon becoming infectious. These
35 are actions taken at the individual or family level. For example, vaccination before the
36 influenza season or isolating a sick child at home are family decisions. Even CS1 is an
37 aggressive intervention in the sense that this action is taken by government officials
38 based on aggregate school sickness levels—closing schools before any outbreaks is
39 typically not done. From these starting points, vaccinations when 1% or 5% of the
40 population is infected (VAX1, VAX5), and closing schools when 5% of the population is
41 infected are less aggressive treatments (CS5). The five levels of compliance are also
42 variations on aggressiveness in treatments.
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46 These conditions and parameters are consistent with results from other studies and
47 guidelines put out by international organizations. A meta-study of immunization and
48 slums [38] identifies several vaccination-related studies of slums in India. Unfortunately,
49 these studies are for other diseases such as Hepatitis B, measles, mumps, malaria, and
50 typhoid fever. Nonetheless, slum vaccination rates for children over these ailments
51 range from 25% to 69% for full immunity and from 15% to 55% for partial immunity.
52 Vaccination effectiveness for influenza-like illness (ILI) in India was determined to be
53 about 33% to 36%.[39] In 2012-2013, of 1000 pregnant women in Srinagar India, none
54 were vaccinated against influenza.[40] With regard to school closures, the World Health
55 Organization (WHO) states that school closures may be undertaken proactively (before
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3 an outbreak) or reactively (after influenza starts to spread).[41] WHO recommends that
4 school closure occur before 1% of the population becomes infected. It also
5 recommends that people (students and staff) stay home when they feel ill. In another
6 meta-study[42], it was found that school closure, effected when 0.1% of the population
7 was infected, was twice as effective in reducing the total attack rate as school closure
8 occurring after 1% of the population was infected. Moreover, the percentage of people
9 infected before school closure was triggered varied between 0.02% to 10% across
10 several studies.
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14 When a susceptible node is vaccinated, its probability of getting infected by an
15 infectious node is scaled down by the efficacy. If it becomes infectious, its probability of
16 infecting susceptible nodes is also scaled down by the efficacy. In other words, both
17 incoming and outgoing infection probabilities of vaccinated individuals are reduced by
18 the vaccine efficacy. Interventions are applied to slum residents, non-slum residents,
19 and the entire region of Delhi.
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22 For each experiment, 25 replicates are simulated for 400 days, and their mean results
23 are reported. The averages are time-point wise averages, e.g. the mean infection rate at
24 day 100 is calculated by taking the average of the 25 infection rates that occur on day
25 100 of each replicate. Table S2 summarizes all the interventions considered, and Table
26 S3 contains all variables in simulations, including intervention parameters.
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29 **Heterogeneities captured:** There are several heterogeneous aspects to this problem
30 that motivate the use of an ABM approach: (i) the 298 slum zones have populations that
31 vary by more than four orders of magnitude in size; (ii) the geographic extent of slum
32 zones differ; (iii) the slum zones are located at irregular spatial intervals throughout
33 Delhi; (iv) the activity patterns of people living in slums are different from those in the
34 non-slum region; and (v) each individual interacts with specific others based on co-
35 location.
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38 The implications of these heterogeneities include the following. First, the particular
39 synthetic households that live within slums are predicated on the number of slum zones,
40 their locations, and their spatial geometries. These homes have larger family size and
41 hence more home contacts. Second, slum individuals have different activity patterns
42 which change the co-located contacts of each slum person: that is, with whom they
43 interact and for how long. For example, see the supplemental information of Chen et
44 al.[27]. The average total contact durations by activity type and by slum/non-slum
45 residents are provided, which show that non-slum people have greater contact
46 durations for work, school, and college activities, but less for home and other types.
47 Overall, a slum person has about 50% greater total contact duration per day compared
48 to a non-slum person. The same supplemental shows that in the age range 20 to 60
49 years (by year), females that live in slums have more contacts per day than their male
50 counterparts. However, females whose homes are outside of slum regions have
51 average number of daily contacts that are below their male counterparts.
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4 **RESULTS AND ANALYSIS**

5 Our results are grouped as follows. (1) Comparison of Network 1 and Network 2 for
6 base case and intervention cases. (2) Results for both networks based on demographic
7 classes, such as slum/non-slum, gender, and age groups, for a wider range of
8 intervention strategies. (3) Comparison of Network 1 with the non-slum population of
9 Network 2. (4) Effects of pharmaceutical and non-pharmaceutical interventions for a
10 wide range of parameter values. (5) Effects of different resource allocation strategies.
11

12 All differences are tested with the two-sample t-test and they are all statistically
13 significant with p-values smaller than $2.2e-16$. The 95% confidence intervals are given
14 for each comparison. Here is a brief summary of selected results with examples of
15 mechanisms, to provide a high-level overview. Details of results follow this summary
16 and these details matter because there are many factors (inputs) in a simulation whose
17 interactions change results.
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20
21 (1) Ignoring the unique attributes of slums in a population overestimates the benefits of
22 the interventions. For example, in the case of vaccination intervention (efficacy 30% and
23 compliance 30%), the values for the epidemic size (i.e., cumulative percentage of
24 infected), peak infection rate (i.e., maximum percentage of a population infected on any
25 day), and time to peak are 33.1%, 3.0%, and 184 days, respectively, in Network 2,
26 whereas they are 23.3%, 1.34%, and 286 days in Network 1. In relative terms, the
27 epidemic size and peak infection rate are underestimated by 42.2% and 123.2%
28 respectively, while the time to peak is overestimated by 35.7% in Network 1 (see
29 Figures 1, 2 and Table S4). The larger family sizes for slum families in Network 2 and
30 the increased number of edges result in larger outbreaks and faster time to peak
31 infections.
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35 (2) Interventions are more effective in Network 1 than Network 2 for all types of
36 interventions: vaccination, closing schools, staying home, and isolation. These trends
37 also hold over wide ranges of efficacy and compliance (see Figures 3, 4, S1, S2 and
38 S3). Hence, not accounting for slums gives overly optimistic results for the effectiveness
39 of the interventions. The reduced average family size in Network 1 means fewer within-
40 home edges, which slows infection and reduces spreading. Closing schools and staying
41 home interventions do not affect home edges. However, the magnitude of this effect
42 varies with intervention conditions (e.g., compliance rate, time at which intervention is
43 applied).
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47 (3) Cumulative infection rates by subpopulation in Network 2 show that slums sustain
48 greater infection rates than non-slums under all intervention scenarios, sometimes by as
49 much as 44.0%. See Figure 4 and Table S5 for more details. This is due to the greater
50 household sizes in slums.
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53 (4) For Network 2, under a wide range of intervention compliance rates (10% to 90%),
54 the isolation strategy is up to 32% more effective in containing an outbreak than
55 vaccination (for 30% efficacy). Staying home is up to 18% more effective than
56 vaccination at 50% compliance. See Figure 3 and Table S6 for more details. Isolation,
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3 although hard to implement from practical considerations, is most effective because
4 edges to susceptible individuals are removed (isolation also provides a good
5 comparative case). Differences between staying home and vaccination depend on
6 compliance rates.
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9 (5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse
10 effect in slums than in non-slum regions across compliance rates from 10% to 90%. See
11 Figure 4 and Table S7 for more details. Early interventions mean actions are taken
12 when outbreaks are smaller and are therefore more readily contained.
13

14
15 (6) Comparison of Network 1 (Figure 3a) with the non-slum population (Figure 4b) of
16 Network 2 shows that just the presence of slum specific activities and interactions with
17 non-slum population makes social-distancing based interventions less effective in the
18 non-slum regions of Network 2.
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21 (7) A full-factorial design that splits resources between slum and non-slum regions
22 indicates that the most effective intervention is to give vaccines to slums and apply
23 social distancing to non-slums. Applying vaccine and social distancing to slum regions
24 is the next most effective intervention. See Figure 5. By applying social distancing to
25 non-slums, these individuals are kept isolated from slum individuals that are infected.
26 The greatest benefits accrue to the slum populations.
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29 30 31 **Comparison between Networks 1 and 2: Base case versus interventions**

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33 We start with a comparative analysis of the influenza epidemic, with and without
34 interventions, on Network 1 and Network 2 to measure the impact of integrating slums
35 in the population on epidemic measures. Figure 1 shows the average simulation time
36 histories for the base case, and when vaccination is applied randomly to 30% of the
37 population in each network with vaccine efficacy set at 30%. Mean infection rate is the
38 daily fraction of infected individuals. It is the time-point wise average over 25
39 simulations. For example, the mean infection rate at day 100 is calculated by taking the
40 average of all 25 infection rates. Simulations for other vaccine efficacies and
41 compliance rates give qualitatively similar results. Two sets of those results are shown
42 in the supplemental information, see Figures S1 and S2. Note that Network 1 does not
43 distinguish between slum and non-slum individuals, so the epidemic curve is not split by
44 subpopulation.
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48 Results in Network 2 differ significantly from results in Network 1 for both the base case
49 and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a
50 larger epidemic size and has higher peaks compared to the corresponding epidemic
51 quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to
52 plan, there will be a false sense of security and lack of urgency to implement
53 interventions. For both the base case and the intervention case, ignoring unique
54 characteristics of the slums will result in an underestimation of the infections and the
55 speed of spread.
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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.

30 **Comparison between Networks 1 and 2 based on individual demographic** 31 **information**

32 We divide the Delhi population into strata by age, gender, and geographic home
33 location (i.e., slum and non-slum), and analyze mean cumulative infection rates by
34 subpopulation for the two networks. In simulations, individuals are chosen at random in
35 the entire network for vaccination. Various vaccination scenarios are investigated.
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39 Figure 2 displays the cumulative infection rate results. On the x-axis, 'Total' refers to the
40 entire population of Delhi. There are three breakdowns of the entire population. 'Slum'
41 and 'Non-slum' refer to slum and non-slum regions, respectively. 'Male' and 'Female'
42 denote the total number of males and females in Delhi, respectively. Four age groups
43 are considered: 'Preschool' (0-4), 'School' (5-18), 'Adult' (19-64), and 'Senior' (65+). The
44 black lines correspond to the mean cumulative infection rates for the base case. Other
45 curves indicate vaccination strategies under different levels of vaccination rate (v) and
46 vaccine efficacy (α). Two vaccination rates (30%, 50%) and two vaccine efficacy rates
47 (30%, 70%) are shown in the figure.
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51 For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of
52 individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the
53 epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either
54 a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate
55 of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all
56 categories of individuals.
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5 In Network 1, slum and non-slums are treated the same so the infection rates are
6 identical in Figure 2. However, all scenarios in Network 2 show a higher burden of
7 disease on the slum population. This is due to the fact that slum households have larger
8 family size and more contacts on average than households in non-slum areas, see
9 Chen et al.[27] As shown later, we find similar patterns of infection in slum and non-
10 slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.
11

12 The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums
13 results in overestimation of the benefits of interventions in terms of reduction in the
14 mean cumulative infection rate and peak infection rate, as well as the time to peak. This
15 optimism holds for slum, non-slum and total population under various levels of
16 vaccination rates and efficacy rates in Network 2. See Table S10 for more detailed
17 comparison of results between slum and non-slum in Network 2.
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21 Figure 2 goes here
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24 **Comparison between Networks 1 and 2 across a wide range of intervention** 25 **strategies** 26

27 Next, we consider a variety of intervention strategies for comparative analysis. We
28 consider vaccination, school closure, stay home, and isolation strategies. For vaccines,
29 three different trigger points are considered: when cumulative infection rate reaches 0%
30 (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used:
31 when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at
32 home (SHO) strategy, all non-home activities and interactions are eliminated but all
33 contacts within the household are maintained. Under isolation (ISO) an individual has
34 no contact with other individuals (even home interactions are eliminated). The stay-at-
35 home and isolation interventions are implemented for compliant infectious individuals,
36 after they become infectious, for the entire infectious duration.
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40 Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a
41 wide range of intervention strategies. For each strategy, five different compliance rates
42 are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates
43 (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers
44 are the actual number of infected individuals. Darker colors correspond to higher
45 infection rates. Note that compliance rate is simply the vaccination rate for strategies
46 VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire
47 population. The 'Base' values do not vary with compliance because the base case has
48 no intervention. Note that all heat maps in this paper use the same color scheme so that
49 colors can be compared across figures.
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53 Since Network 1 does not distinguish between slum and non-slum populations, we only
54 compare the two networks for the whole of Delhi. The general pattern is similar for both
55 networks. However, all interventions have a larger effect on Network 1 under the same
56 compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than
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3 for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0,
4 stay-home, and isolation strategies in Network 1 as compared to those for Network 2.
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7 Figure 3 goes here
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10 At a high level, among all intervention strategies, early vaccination (VAX0 and VAX1),
11 social isolation (ISO), and stay home (SHO) are more effective than the other
12 strategies, and this is more readily observed at higher compliance rates. For these
13 more effective strategies, the interventions per person are implemented right after (or
14 very shortly after) the person is infected. For example, SHO is implemented
15 immediately after a person becomes infectious. Thus, a person that becomes infectious
16 can infect their family members, but if these other members become infectious, then
17 they, too, will be confined to home. Thus, home-bound people can infect their family
18 members, but no one beyond their family (for 100% compliance). As compliance rate
19 increases, this effect approaches, roughly, a “family-based” isolation intervention
20 (similar to ISO), consistent with the results in Figure 3 and in subsequent results.
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26 **Effect of vaccination versus social distancing on slum and non-slum** 27 **subpopulations** 28

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30 We now compare the impact of vaccination and social distancing on slum and non-slum
31 subpopulations from Network 2. Social distancing interventions are close-schools, stay-
32 home, and isolation.
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35 The mean cumulative infection rates (and actual numbers of infections underneath) for
36 each compliance level are shown in the heat maps in Figure 4 for slum and non-slum
37 populations in Network 2. The axis labels are identical to those in Figure 3, as is the
38 color scheme of the cells. The base case values are constant since there is no
39 intervention and hence no compliance. Darker colors correspond to higher infection
40 rates.
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43 Compared to the base case, all interventions reduce infection rates to some extent. As
44 the compliance rate increases, infection rates drop for all interventions. Infection rates
45 drop to zero in slum and non-slum regions at a compliance level of 70% or higher,
46 under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce
47 the infection rates significantly, and this effect increases with compliance rate.
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49
50 The following observations can be made from Figure 4. Social distancing, i.e. SHO, at
51 low and intermediate compliance and CS at all compliance levels, are less effective in
52 slum regions as compared to non-slum regions. This is because CS only eliminates
53 school interactions for those attending school, and there are fewer school edges in
54 slums compared to non-slum areas, as shown in Figure S6. The effectiveness of CS in
55 slums is mitigated by the greater average number and duration of interactions at home
56 in slums as compared to non-slums (see Figure S6 and Chen et al.[27]). Thus, if a
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3 person is sick, there is a greater chance of transmitting contagion to family members,
4 who then may have activities outside of school, thus circumventing the CS intervention.
5 At high compliance, SHO is effective because all interactions outside home (including
6 school) are eliminated.[27]
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9 These observations are also supported by Figure S7, which contains numbers of edges
10 used to transmit contagion for a base-case run of Figure 1. There are several effects
11 that bear on the above observations. First, in the cases of activities “work”, “other”, and
12 “school”, the number of edges transmitting contagion from slums to non-slums is greater
13 than the reverse: from non-slum to slum. Second, in two of these three activity
14 categories, there is more slum to non-slum transmissions than slum to slum
15 transmissions. Edges of transmission for slum dwellers is dominated by home
16 interactions. The infected homes in slums serve as launching points to drive disease to
17 non-slums through slum to non-slum interactions. (There are no “mixed” edges at
18 homes, and shopping and college activities have low levels of slum activity because of
19 socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but
20 we now return to Figure 4.
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24 Isolation works well at 30% or higher compliance rates, but it is a much harder strategy
25 to implement, especially in slums. However, it is considered here for comparative
26 analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as
27 compliance increases. However, close-school is generally less effective because this
28 intervention removes only a fraction of interactions for a fraction of the population, i.e.
29 school aged children. Simulations were also run for 70% vaccine efficacy. Since results
30 are qualitatively similar for those parameters, these plots are provided in Figure S3.
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34 Figure 4 goes here
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37 **Comparison between Network 1 and non-slum areas of Network 2**

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

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5 We consider a specific scenario under Network 2. If only a limited number of vaccines
6 are available, and only a certain fraction of individuals can be kept home during an
7 epidemic, how should these interventions be applied to the slum and non-slum regions
8 so that the epidemic can be controlled effectively? Given that slum residents' attributes
9 differ from those of non-slum residents, is there a strategy that works better in slums
10 than in non-slum areas? The total population in Delhi is about 13.8 million, which
11 includes about 1.8 million slum residents. We assume that only 10% of the total
12 population can be covered by interventions, half through vaccination and the other half
13 through stay home. Enough vaccines are available to cover 5% of the total population
14 (i.e. 692,183 vaccinated, corresponding to about 38.25% of slum or 5.75% of non-slum
15 population), and 5% of the individuals can stay home (692,183 individuals; this is
16 applied to only the infected individuals). Note that an individual may receive a vaccine
17 and also stay at home if this individual, in spite of being vaccinated, gets infected.
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21 We consider 4 different ways of applying interventions to 10% of the total population: (i)
22 apply both interventions to slums, i.e. give all vaccines to slums and apply SHO only in
23 the slums (VsSs); (ii) apply all interventions to non-slum areas (VnSn); (iii) give vaccines
24 to slums and SHO to non-slums (VsSn) and (iv) give vaccines to non-slums and apply
25 SHO to slums (VnSs).
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28 For both types of intervention, the same number of individuals is chosen randomly from
29 slum or non-slum areas. 10% of the total Delhi population amounts to 76.5% of slum
30 population, 11.5% of the non-slum population, or a combination of 38.25% of the slum
31 and 5.75% of the non-slum population (i.e. half from slums and half from non-slums).
32 Figure 5 shows the mean cumulative infection rates, as well as the number of infected
33 from the entire population of Delhi, the slums, and non-slum areas under each of the
34 four scenarios. The first 3 columns refer to Network 2 and the last column shows results
35 for Network 1. Since Network 1 does not distinguish between slum and non-slum areas,
36 the infection rates in each subpopulation remain the same as for the total population.
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39 Comparison of the last two columns in Figure 5 indicates that the non-slum population
40 in Network 2 faces 3-5% additional disease risk compared to Network 1 in all cases.
41 This is primarily driven by the increased interactions within slum populations and
42 between slum and non-slum populations in Network 2.
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45 In Figure 5, all four intervention strategies produce essentially the same total attack
46 rates (around 43% to 44%), a drop of 4% to 5% over the base case. The dominant
47 effect on Network 2, is the benefits that primarily accrue to the slum population for the
48 VsSs and VsSn strategies because they drive down the fraction of infected slum
49 residents from 0.74 to 0.55 or 0.58. Also, as described in the context of Figures 4 and
50 S6 above, social distancing of the non-slum residents helps to isolate them from the
51 infected slum residents. Results such as these may be helpful to policy makers in
52 breaking the poverty trap in economically poor regions.[43]
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3 Also, the strategy of vaccinating non-slums and social distancing slums (VnSs) is not as
4 effective as the interventions in rows 1 and 2 of Figure 5. This is a counterintuitive
5 result, since the density of population is much higher in the slums, which may lead to
6 the belief that social distancing in slums will break up the dense clusters. However, a
7 careful examination shows that keeping slum residents home is not an effective social
8 distancing strategy because their family size is, on average, almost 3 times the family
9 size of non-slum households.[27] The high level of mixing at home makes social
10 distancing ineffective in slums unless the infected individual is completely isolated.
11 However, complete isolation is not viable in slum areas where the entire household may
12 live in a single room.
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19 Figure 5 goes here
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21 DISCUSSION 22

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24 With slum populations expected to grow to 2 billion by 2030,[44] it is becoming
25 increasingly urgent to understand how to control the spread of infectious diseases in
26 slum areas and measure its effect on urban populations. To our knowledge, a detailed
27 study of interventions to control influenza epidemics in slums, using an agent-based
28 simulation model, has never been done before. Slum conditions are important for a city
29 beyond the direct effects of disease transmission. For example, civil wars may be
30 precipitated or exacerbated by disease outbreaks because they decrease social health
31 and welfare.[45]
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35 Even though slum regions contain only 13% of the total population of Delhi, Chen et
36 al.[4] show that omitting their attributes leads to underestimation of the overall infection
37 rate and the peak infection rate of the epidemic. This paper extends that work by
38 evaluating the differential impact of interventions on slum and non-slum regions.
39 Various vaccination and social distancing strategies are analyzed under different
40 scenarios that show that the slum population is more prone to infections under the same
41 control measures. Furthermore, taking account of slum populations significantly alters
42 the disease dynamics in the *entire* population. Differences in key measures are
43 demonstrated between the cases of accounting for slum populations and not: e.g., a
44 100% increase in the peak attack rate in some cases when slum regions' characteristics
45 are taken into account, compared to the case when they are ignored.
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49 Figure 4, which compares infections in slum with non-slum areas, shows that at very
50 high compliance rates, some interventions can be equally effective in both slums and
51 non-slums. However, such high compliance rates are typically not feasible due to
52 practical realities on the ground, and also because they require timely diagnosis of
53 infected cases. For SHO to be effective, the coverage rate needs to be 70% or more in
54 both slums and non-slums, and the diagnosis of the infected individuals needs to be
55 correct and immediate. In other words, effective control of a contagious epidemic in a
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4 high-density place like Delhi, would require either early and drastic action (e.g. ISO) or a
5 highly compliant set of individuals, or a combination of these features.
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7 This work overall demonstrates the power of agent-based and population modeling to
8 evaluate complicated interaction-based epidemiological phenomena. Clearly, there are
9 limitations to this work (several are itemized below). But these agent and population
10 approaches provide a platform for adding additional complexity. All of the figures
11 demonstrate that quantitative results depend on complicated interplay among inputs.
12 These results are important because they inform policy decisions. An equally important
13 benefit of this type of work, but not often stated, is developing intuition about epidemic
14 dynamics (in this case, with the effects of slums), to enable decision makers to reason
15 about nuanced interactions among effects to a degree that is hard to obtain with other
16 approaches that lack this level of detail.
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20 Despite the detailed modeling effort, there are limitations of this work and areas for
21 improvement in the future. For example: (1) Examination of different population level
22 base attack rates derived from different transmission probabilities. (2) Different
23 susceptibilities and infectivity for individual agents; e.g., based on age. (3) Effects of
24 asymptomatic infections (although we have addressed this to some extent with
25 compliance and efficacy of interventions). (4) Seasonal effects.[46-47] (5) Effects of
26 immunity for an individual from previous infections (in previous seasons). (6) Evaluation
27 of interaction of different strains from season to season. (7) Comparison of tropical
28 versus subtropical factors. (8) Evaluation of a specific outbreak scenario. (9) Impact of
29 sickness on absenteeism from work and its economic ramifications. (10) Effects on rural
30 versus urban populations. (11) Using combinations of interventions rather than one at a
31 time; this was only done here in Figure 5. However, to disambiguate results, it is
32 prudent to first examine individual interventions. (12) Effect of changing disease
33 transmission rate for different activity types. (13) Effect of changing contact times at
34 different locations. (14) To capture close-proximity transmission, one could use actual
35 physical proximity. Here, we use colocation. Finally, just as changes in modeling details
36 can change model results, so, too, changes in the conditions in actual outbreaks can
37 change results; some of these factors are listed above. It is essentially impossible to
38 capture all of these effects—many of which are unknown—down to the level of
39 individual humans.
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45 Public health implications: This research demonstrates that modeling slum populations
46 is important, not only for understanding disease dynamics, but also for designing
47 effective control measures. Ignoring the influence of slum characteristics on their urban
48 environment will significantly underestimate the speed of an outbreak and its extent,
49 and hence will lead to misguided interventions by public health officials and policy
50 planners. Lessons from this research can be applied in the field and observations
51 collected from the field can provide valuable data to improve the models and validate
52 the results. For example, our results show that a slum resident has about 50% greater
53 total contact duration per day compared to a non-slum resident. This makes social
54 distancing based interventions more taxing in the slum population. Public health policy
55 makers may want to subsidize pharmaceutical resources for the slum population to
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3 make them more affordable. Similarly, we find women in slums have a higher number of
4 contacts per day than their male counterparts whereas in non-slum regions, women
5 have a fewer number of daily contacts than their male counterparts. This kind of
6 information can be used to prioritize the distribution of limited resources, e.g. women
7 could be given preference over males for vaccination in slum areas. This research
8 provides simulation-based evidence that in general social distancing strategies are
9 ineffective in slums because of a large number of contacts at home. Unless one applies
10 complete isolation, which is not feasible in slums, just staying at home still keeps a large
11 number of contacts and pathways of spread intact.
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4 **Contributorship statement**

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

13 There are no competing interests.
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26 **Data Sharing Statement**

27 Data pertaining to figures and statistical analysis are partially provided in the
28 supplementary file, and also can be obtained by contacting the corresponding author
29 through email.
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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 ($\alpha = 30\%$, 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

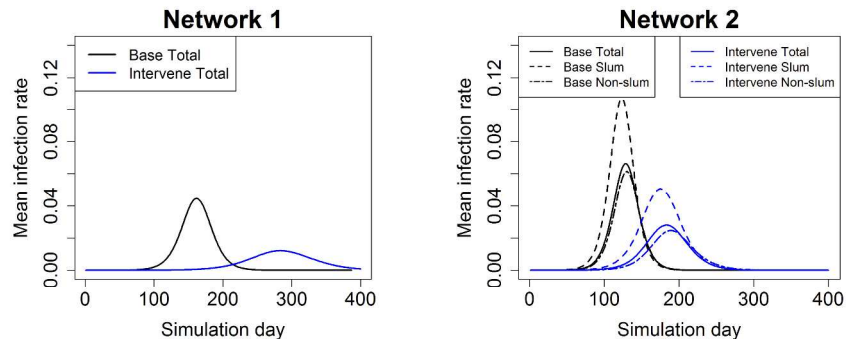
Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond 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

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3 intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and
4 isolation (ISO)) are considered. For vaccines, three different trigger points are
5 considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5%
6 (VAX5). For close-schools, two trigger points are used: when the cumulative infection
7 rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly
8 from the entire Delhi population, and the mean infection rates are calculated separately
9 for the slum and non-slum subpopulations. Although not reported here, qualitatively
10 similar results are found for other transmission rates, as well as for higher vaccine
11 efficacy (70%). Base is the baseline case with no interventions. The smaller-font
12 numbers under the infection rate show the actual number of infected individuals.
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16 **FIGURE 5:** Mean cumulative infection rates for each category listed on the x-axis, for
17 Network 2 and Network 1, under four different intervention scenarios. The color scheme
18 of the boxes are based on the large values in the boxes—the cumulative infection rates.
19 Darker colors correspond to higher infection rates. Smaller font values are the number
20 of infected individuals. The vaccine efficacy is set at 30%. VsSs refers to the case when
21 vaccines and social distancing are both applied to slum residents; VnSn refers to the
22 case when vaccines and social distancing are applied to non-slum residents. Similarly,
23 VsSn means vaccines are given to slums and stay home is applied to non-slums; and
24 VnSs means vaccines are given to non-slums and stay home is applied to slums. Base
25 refers to the case where no intervention is applied. The smaller-font numbers under the
26 infection rates show the actual number of infected individuals in each category listed on
27 the x-axis.
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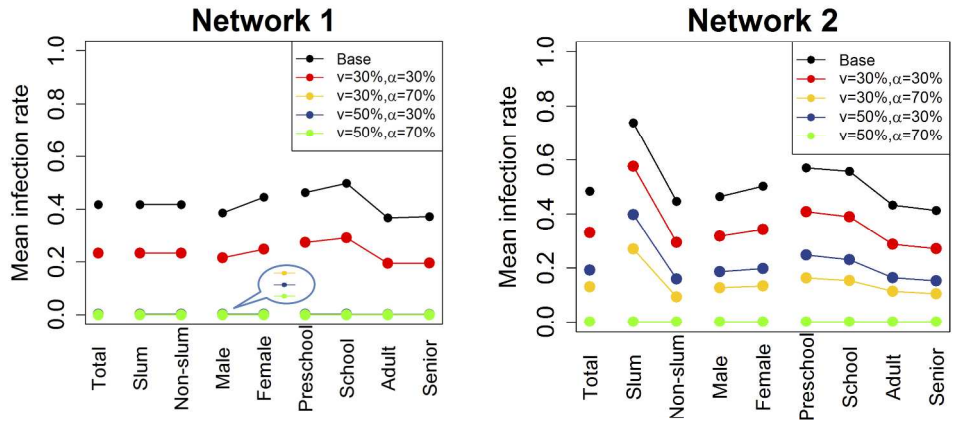
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Intervention	Base	C ₁	C ₂	S ₁	S ₂	I ₁	I ₂	V ₁	V ₂
V ₁	0.36	0.23	0	0	0	0	0	0	0
V ₂	5038837	3228985	20921	221	97				
I ₁	0.37	0.25	0.11	0.04	0.02				
I ₂	5061754	3405459	1549547	539181	322258				
S ₁	0.37	0.27	0.19	0.13	0.1				
S ₂	5146506	3802876	2618588	1781022	1318401				
C ₁	0.3	0	0	0	0				
C ₂	4158127	648	62	35	23				
S ₁	0.36	0.12	0	0	0				
S ₂	4939914	1659965	241	89	51				
I ₁	0.36	0.24	0.14	0.08	0.06				
I ₂	5017949	3367475	1880956	1121321	881914				
C ₁	0.37	0.27	0.19	0.15	0.16				
C ₂	5112280	3738161	2615064	2125815	2169135				
Base	0.42	0.42	0.42	0.42	0.42				
	5772516	5772516	5772516	5772516	5772516				

Intervention	Base	C ₁	C ₂	S ₁	S ₂	I ₁	I ₂	V ₁	V ₂
V ₁	0.44	0.33	0.19	0	0				
V ₂	6070999	4584539	2669426	18530	206				
I ₁	0.44	0.34	0.21	0.1	0.04				
I ₂	6087287	4654816	2967789	1350667	554670				
S ₁	0.44	0.35	0.26	0.17	0.13				
S ₂	6146453	4898048	3594239	2329038	1818146				
C ₁	0.39	0.03	0	0	0				
C ₂	5465084	478780	85	37	23				
S ₁	0.44	0.31	0.08	0	0				
S ₂	6047827	4323509	1098024	543	83				
I ₁	0.45	0.37	0.31	0.29	0.27				
I ₂	6191602	5188739	4357831	4018271	3675802				
C ₁	0.47	0.44	0.43	0.42	0.4				
C ₂	6470698	6101056	5883830	5766943	5600599				
Base	0.48	0.48	0.48	0.48	0.48				
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		0.69	0.58	0.4	0	0
	<i>V_{air0}</i>	1263625	1041034	719517	7505	66
	<i>V_{air1}</i>	0.69	0.58	0.43	0.24	0.1
	<i>V_{air5}</i>	1296162	1052247	775240	426160	166606
	<i>V_{air10}</i>	0.7	0.6	0.49	0.36	0.29
	<i>V_{air15}</i>	1265497	1094158	890080	649544	525620
	<i>ISO</i>	0.65	0.08	0	0	0
	<i>ISO</i>	1168239	146106	20	7	3
	<i>SHO</i>	0.71	0.61	0.25	0	0
	<i>SHO</i>	1279142	1102671	460613	301	30
	<i>CS₁</i>	0.72	0.7	0.67	0.66	0.65
	<i>CS₁</i>	1311761	1260823	1215625	1194938	1171916
	<i>CS₅</i>	0.73	0.72	0.72	0.71	0.71
	<i>CS₅</i>	1326417	1309021	1298824	1292254	1283791
	<i>Base</i>	0.74	0.74	0.74	0.74	0.74
	<i>Base</i>	1337160	1337160	1337160	1337160	1337160
		10%	30%	50%	70%	90%
		Compliance				

		0.4	0.29	0.16	0	0
	<i>V_{air0}</i>	4817373	3542870	1921714	11025	139
	<i>V_{air1}</i>	0.4	0.3	0.18	0.08	0.03
	<i>V_{air5}</i>	4831106	3602969	2192949	924508	368084
	<i>V_{air10}</i>	0.41	0.32	0.22	0.14	0.11
	<i>V_{air15}</i>	4880956	3803892	2704160	1679494	1292525
	<i>ISO</i>	0.36	0.03	0	0	0
	<i>ISO</i>	4298845	332675	65	30	20
	<i>SHO</i>	0.4	0.27	0.05	0	0
	<i>SHO</i>	4768685	3220638	637412	242	53
	<i>CS₁</i>	0.41	0.33	0.26	0.23	0.21
	<i>CS₁</i>	4879841	3927917	3142206	2823334	2503886
	<i>CS₅</i>	0.43	0.4	0.38	0.37	0.36
	<i>CS₅</i>	5144281	4792032	4585006	4474690	4316809
	<i>Base</i>	0.45	0.45	0.45	0.45	0.45
	<i>Base</i>	5366878	5366878	5366878	5366878	5366878
		10%	30%	50%	70%	90%
		Compliance				

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V_{sSs}	0.44 6043049	0.55 989079	0.42 5053971	0.37 5176345
V_{sSn}	0.43 5938919	0.58 1042116	0.41 4896803	0.36 4995753
V_{nSs}	0.44 6023678	0.67 1217415	0.40 4806263	0.36 4986302
V_{nSn}	0.44 6104571	0.72 1309577	0.40 4794993	0.36 5016324
Base	0.48 6704038	0.74 1337160	0.45 5366878	0.42 5772516
	Total Network 2	Slum Network 2	Non-slum Network 2	Total Network 1

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Supplemental Information

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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

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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

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

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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.

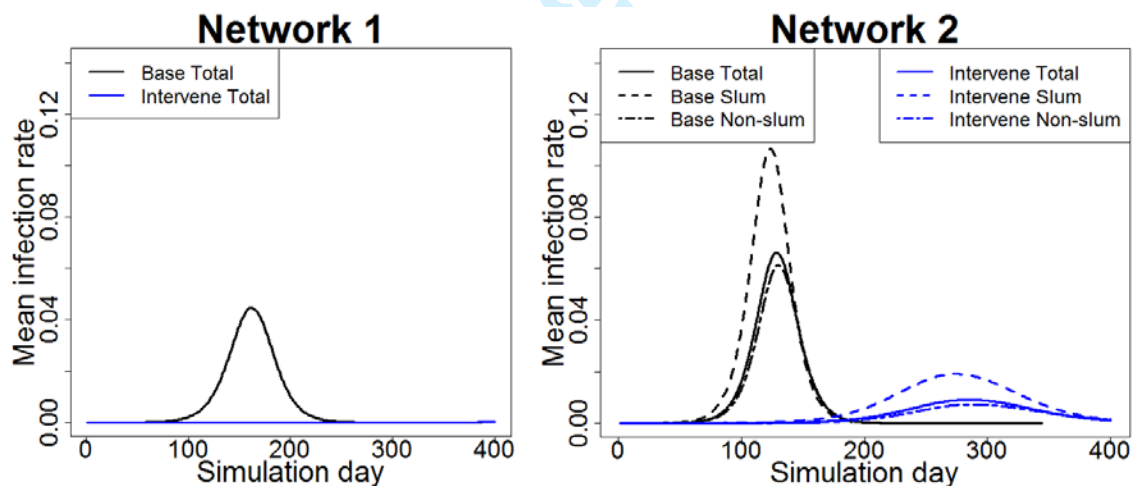


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

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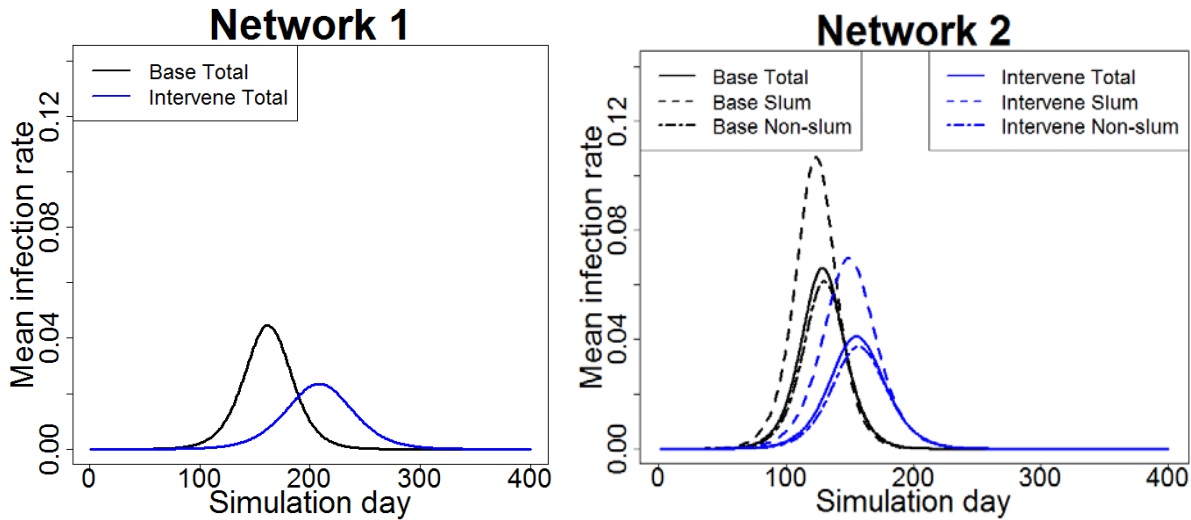


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.

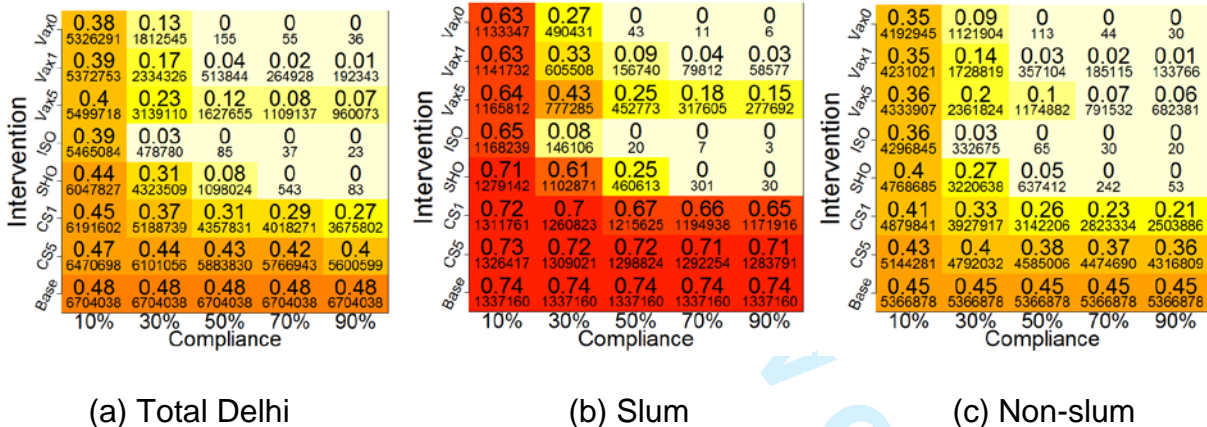


Figure S3. Heat map of mean cumulative infection rates in Delhi, and slum and non-slum regions under different intervention strategies for Network 2. The vaccination efficacy is fixed at 70%. Five different compliance rates, i.e., 10%, 30%, 50%, 70% and 90% and 4 types of intervention strategies, i.e. 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.

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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%,

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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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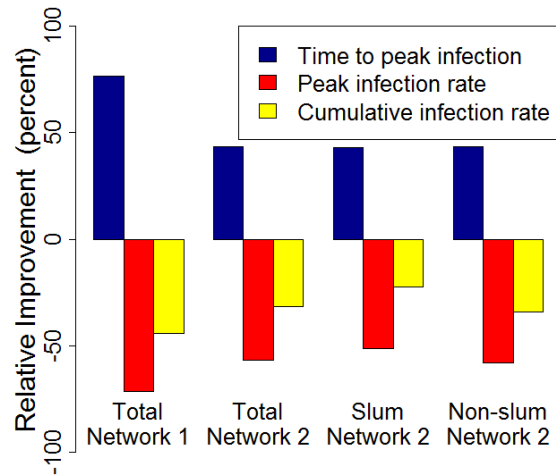


Figure S4: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 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 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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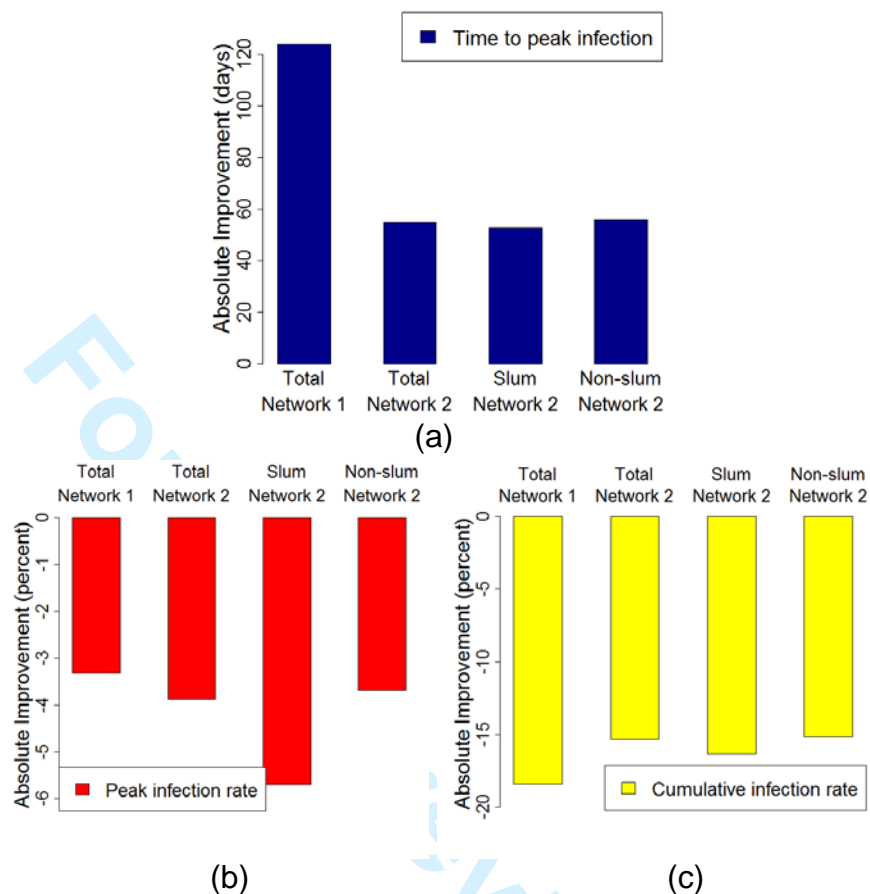
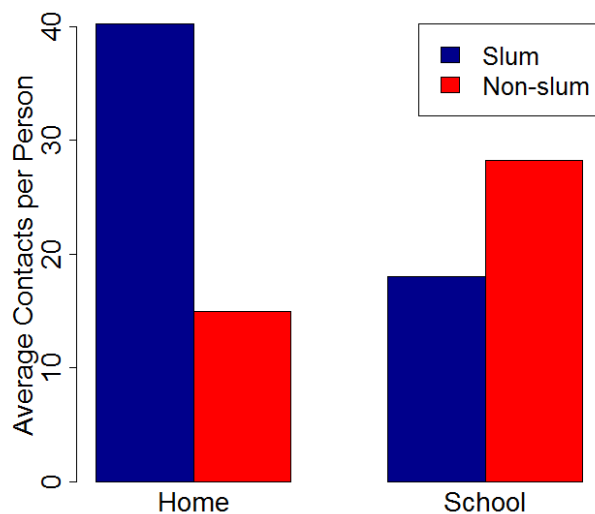


Figure S5: Comparison of absolute difference in improvement; the relative differences are shown in Figure S7. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S7 and S9.

Evaluation of Network 2 Home and School Contacts.



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).

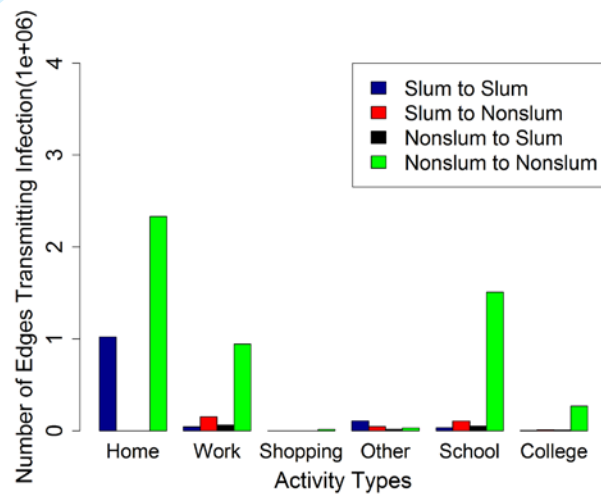


Figure S7. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater than nonslum-to-slum ones because once infection 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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Disparities in Spread and Control of Influenza in Slums of Delhi: Findings From An Agent-Based Modeling Study

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6 **Disparities in Spread and Control of Influenza in Slums of Delhi:**
7 **Findings From An Agent-Based Modeling Study**
8

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1 Main manuscript
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4 **ABSTRACT**

5
6 **Objectives** This research studies the role of slums in the spread and control of
7 infectious diseases in the National Capital Territory of India, Delhi, using a detailed
8 social contact network of its residents.

9
10 **Methods** We use an agent-based model to study the spread of influenza in Delhi
11 through person-to-person contact. Two different networks are used; one in which slum
12 and non-slum regions are treated the same and the other in which 298 slum zones are
13 identified. In the second network, slum-specific demographics and activities are
14 assigned to the individuals whose homes reside inside these zones. The main effects of
15 integrating slums is that the network has more home-related contacts due to larger
16 family sizes and more outside contacts due to more daily activities outside home.
17 Various vaccination and social distancing interventions are applied to control the spread
18 of influenza.
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20
21 **Results** Simulation based results show that when slum attributes are ignored, the
22 effectiveness of vaccination can be overestimated by 30%-55%, in terms of reducing
23 the peak number of infections and the size of the epidemic, and in delaying the time to
24 peak infection. The slum population sustains greater infection rates under all
25 intervention scenarios in the network that treats slums differently. Vaccination strategy
26 performs better than social distancing strategies in slums.

27
28 **Conclusions** Unique characteristics of slums play a significant role in the spread of
29 infectious diseases. Modeling slums and estimating their impact on epidemics will help
30 policy makers and regulators more accurately prioritize allocation of scarce medical
31 resources and implement public health policies.

32
33 **Policy Implications** Currently, over a billion people reside in slums across the world
34 and this population is expected to double by 2030. This study uses influenza as an
35 example to demonstrate the need to understand the role of slum populations in the
36 spread and containment of infectious diseases.
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38 **Strengths and limitations of this study**

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- 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.

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5 INTRODUCTION 6

7 Infectious disease is one of the leading causes of human morbidity and mortality
8 worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000
9 people in the United States (US) are hospitalized with influenza-like illness (ILI)
10 symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In
11 Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the
12 National Institute of Virology has shown that ILI cases are present throughout the year,
13 although they peak in rainy and winter seasons.[3] It carries a significant economic
14 burden through reduced productivity and high costs of health care.[4-7] A CDC study
15 finds that for outpatient and non-medically attended individuals, acute respiratory
16 infections cost 1%-5% of monthly per capita income in India. In contrast, cost of
17 inpatient care can be as high as 6%-34% of monthly per capita income.[8] For
18 developed countries, the annual cost of influenza is estimated to be between \$1-\$6
19 million per 100,000 people, according to the World Health Organization.[9]
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23 In 2007, India established an Integrated Disease Surveillance Program (IDSP), which
24 included a network of 12 regional laboratories, to minimize the threat of avian influenza
25 and other highly infectious zoonotic diseases.[10] India faces some unique challenges
26 in surveillance, prevention and control because of the seasonality of influenza at sub-
27 regional levels. This seasonal variation depends upon latitude, monsoon season,
28 humidity and climatic factors of the regions. Acute respiratory infections are estimated to
29 be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13]
30 estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in
31 year 2011, and children under age 5 had the highest incidence of them.
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35 Given that influenza is environmentally-mediated and spreads through close proximity,
36 population density is an important factor in its spread. In India, the average population
37 density is about 1000 people per square mile; in the slums, it can be 10 to 100 times
38 higher.[14] Larger household size and crowding make it easier to transmit
39 infections).[15-18] For example, Baker et al.[16] find that meningococcal disease risk
40 among children doubles with the addition of 2 adolescents or adults (10 years or older)
41 to a 6-room house. Other than overcrowding, slums are characterized by their lack of
42 medical services,[19-20] which makes slum residents highly vulnerable to infectious
43 diseases. Diseases like cholera, malaria, dengue and HIV are common in slums across
44 the world.[21-23]
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48 This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8
49 million people live in slum areas, as an example city to study the spread and control of
50 influenza. Delhi is an interesting case study. It ranks fourth in the world in urban
51 population, and, among the top 25 largest urban areas, it ranks tenth in population
52 density. Moreover, the results are likely to be generalizable to other slum areas within
53 and outside of India.
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3 This paper is an extension of the work done in Chen et al.[4], which shows that slum
4 populations have a significant effect on influenza transmission in urban areas. Ignoring
5 the influence of slum characteristics underestimates the speed of an outbreak and its
6 extent. However, Chen et al.[4] do not consider any interventions on the epidemic
7 spread. *The focus of this research is to study the effect of different intervention
8 strategies on several subpopulations (slum, age and gender) in two different Delhi
9 networks, i.e., original (referred to as Network 1) and refined (Network 2).*
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12 The original network used in Xia et al.[24] studied the spread and control of influenza in
13 Delhi using Network 1, which did not take into account the special attributes of the slum
14 population, such as larger family sizes and different types of daily activity schedules.
15 Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for
16 slum demographics and slum activities, but did not study intervention strategies. In
17 Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.
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20 The goals of this work focus on understanding the effects of pharmaceutical and non-
21 pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI)
22 include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing
23 measures such as school closure, quarantine and staying home. These effects are
24 studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations
25 in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a
26 scenario where interventions can be applied to a limited number of individuals, we
27 explore how resources should be split between slum and non-slum subpopulations in
28 order to achieve the best outcomes with respect to total infection rate (i.e., the
29 cumulative fraction of a population infected).
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34 METHODS

35 We use an agent-based modeling (ABM) approach to simulate the spread and
36 containment of influenza in social contact networks of Delhi, India. We compare two
37 networks: one considers slum-specific attributes, and the other does not. In this
38 section, we describe the networks, the disease model for each agent, the interventions,
39 and the heterogeneities of the problem that make ABM uniquely suited to study
40 epidemics. Throughout this manuscript, each agent in the ABM is an individual human.
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45 **Social Contact Networks:** This study uses two synthetic social networks of Delhi,
46 created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found
47 in Xia et al.[24], Chen et al.[4], Barrett et al.[25], Bisset et al.[26] and references therein.
48 The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined
49 network developed in Chen et al.[4], *Network 2*.
50

51 Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set
52 of activities of individuals, and the locations of those activities including geo-locations of
53 residential areas, shopping centers, and schools, collected through surveys by
54 MapMyIndia.com. By assigning activity locations to individuals' activities, people are
55 located at particular times at particular geographic coordinates (including office
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3 buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between
4 individuals are estimated when each person is deemed to have made contact with a
5 subset of other people simultaneously present at the same location. This gives rise to a
6 synthetic social contact network where network edges represent these contacts.
7

8
9 Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the
10 individuals whose homes reside in the slum polygons. Slum residents' attributes and
11 their daily sets of activities are collected through a ground survey in Delhi slums, by a
12 vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from
13 *MapMechanic.com*. Individuals living in the slum regions are a part of the slum
14 population. All other individuals are part of the non-slum population. Network 2 is a geo-
15 located, and contextualized social contact network of Delhi with slums integrated in it.
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19 Following are the main differences between the original network (Network 1) and the
20 refined network (Network 2). The original social contact network treats the slum regions
21 like any other region in Delhi in terms of assignment of demographics and individual
22 activities, i.e. no special consideration is given to slum residents. The refined Network 2
23 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific demographics
24 and activities to the individuals whose homes reside inside these polygons. Thus, the
25 number of individuals is the same in both populations. The slum population constitutes
26 about 13% (1.8 million) of the entire Delhi population of 13.8 million people. The main
27 effects of integrating slums is that Network 2 has more home-related contacts due to
28 larger family sizes and more outside contacts due to more daily activities outside home.
29 Also, those individuals who reside outside of slum zones have the same activities in
30 both networks. Overall, there are over 231 million daily interactions between pairs of
31 individuals. Table S1 compares those two networks as well as data sources for slum
32 and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are in
33 the supplementary information (SI)). For example, the average degree increases from
34 30.4 to 33.4 from Network 1 to Network 2, and the maximum degree increases from 170
35 to 180. We refer to Chen et al.[4] for more detailed information about the two networks.
36 Several plots of properties and structural characteristics of Networks 1 and 2 are given
37 in Chen et al.[27].
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42 **Disease Model:** An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or
43 Recovered (R) model is considered within each individual. Each node in the network
44 represents an individual, and each edge represents a contact on which the disease can
45 spread. A contact represents possible transmission between two people that are co-
46 located for some duration (based on their activity schedules). This is an approximation
47 to model direct contact and short-distance environmentally-mediated transmission that
48 might include direct physical contact, fomite mediated, and airborne transmission.[28]
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52 We start each epidemic simulation with 20 index cases, randomly chosen. (We find that
53 results are not sensitive to the number of initial infections.) The detailed description of
54 the SEIR model as well as the choices of transmissibility value, R_0 , the explicit
55 incubation and exposed periods can be found in the supplementary information. This
56 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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3 Organization (WHO) states that school closures may be undertaken proactively (before
4 an outbreak) or reactively (after influenza starts to spread).[41] WHO recommends that
5 school closure occur before 1% of the population becomes infected. It also
6 recommends that people (students and staff) stay home when they feel ill. In another
7 meta-study[42], it was found that school closure, effected when 0.1% of the population
8 was infected, was twice as effective in reducing the total attack rate as school closure
9 occurring after 1% of the population was infected. Moreover, the percentage of people
10 infected before school closure was triggered varied between 0.02% to 10% across
11 several studies.
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15 When a susceptible node is vaccinated, its probability of getting infected by an
16 infectious node is scaled down by the efficacy. If it becomes infectious, its probability of
17 infecting susceptible nodes is also scaled down by the efficacy. In other words, both
18 incoming and outgoing infection probabilities of vaccinated individuals are reduced by
19 the vaccine efficacy. Interventions are applied to slum residents, non-slum residents,
20 and the entire region of Delhi.
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24 For each experiment, 25 replicates are simulated for 400 days, and their mean results
25 are reported. The averages are time-point wise averages, e.g. the mean infection rate at
26 day 100 is calculated by taking the average of the 25 infection rates that occur on day
27 100 of each replicate. Table S2 summarizes all the interventions considered, and Table
28 S3 contains all variables in simulations, including intervention parameters.
29

30
31 **Heterogeneities captured:** There are several heterogeneous aspects to this problem
32 that motivate the use of an ABM approach: (i) the 298 slum zones have populations that
33 vary by more than four orders of magnitude in size; (ii) the geographic extent of slum
34 zones differ; (iii) the slum zones are located at irregular spatial intervals throughout
35 Delhi; (iv) the activity patterns of people living in slums are different from those in the
36 non-slum region; and (v) each individual interacts with specific others based on co-
37 location.
38

39
40 The implications of these heterogeneities include the following. First, the particular
41 synthetic households that live within slums are predicated on the number of slum zones,
42 their locations, and their spatial geometries. These homes have larger family size and
43 hence more home contacts. Second, slum individuals have different activity patterns
44 which change the co-located contacts of each slum person: that is, with whom they
45 interact and for how long. For example, see the supplemental information of Chen et
46 al.[27]. The average total contact durations by activity type and by slum/non-slum
47 residents are provided, which show that non-slum people have greater contact
48 durations for work, school, and college activities, but less for home and other types.
49 Overall, a slum person has about 50% greater total contact duration per day compared
50 to a non-slum person. The same supplemental shows that in the age range 20 to 60
51 years (by year), females that live in slums have more contacts per day than their male
52 counterparts. However, females whose homes are outside of slum regions have
53 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

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3 vaccination at 50% compliance. See Figure 3 and Table S6 for more details. Isolation,
4 although hard to implement from practical considerations, is most effective because
5 edges to susceptible individuals are removed (isolation also provides a good
6 comparative case). Differences between staying home and vaccination depend on
7 compliance rates.
8

9
10 (5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse
11 effect in slums than in non-slum regions across compliance rates from 10% to 90%. See
12 Figure 4 and Table S7 for more details. Early interventions mean actions are taken
13 when outbreaks are smaller and are therefore more readily contained.
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16 (6) Comparison of Network 1 (Figure 3a) with the non-slum population (Figure 4b) of
17 Network 2 shows that just the presence of slum specific activities and interactions with
18 non-slum population makes social-distancing based interventions less effective in the
19 non-slum regions of Network 2.
20

21
22 (7) A full-factorial design that splits resources between slum and non-slum regions
23 indicates that the most effective intervention is to give vaccines to slums and apply
24 social distancing to non-slums. Applying vaccine and social distancing to slum regions
25 is the next most effective intervention. See Figure 5. By applying social distancing to
26 non-slums, these individuals are kept isolated from slum individuals that are infected.
27 The greatest benefits accrue to the slum populations.
28
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30 31 32 **Comparison between Networks 1 and 2: Base case versus interventions**

33
34 We start with a comparative analysis of the influenza epidemic, with and without
35 interventions, on Network 1 and Network 2 to measure the impact of integrating slums
36 in the population on epidemic measures. Figure 1 shows the average simulation time
37 histories for the base case, and when vaccination is applied randomly to 30% of the
38 population in each network with vaccine efficacy set at 30%. Mean infection rate is the
39 daily fraction of infected individuals. It is the time-point wise average over 25
40 simulations. For example, the mean infection rate at day 100 is calculated by taking the
41 average of all 25 infection rates. Simulations for other vaccine efficacies and
42 compliance rates give qualitatively similar results. Two sets of those results are shown
43 in the supplemental information, see Figures S1 and S2. Note that Network 1 does not
44 distinguish between slum and non-slum individuals, so the epidemic curve is not split by
45 subpopulation.
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48
49 Results in Network 2 differ significantly from results in Network 1 for both the base case
50 and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a
51 larger epidemic size and has higher peaks compared to the corresponding epidemic
52 quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to
53 plan, there will be a false sense of security and lack of urgency to implement
54 interventions. For both the base case and the intervention case, ignoring unique
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3 characteristics of the slums will result in an underestimation of the infections and the
4 speed of spread.
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7 Figure 1 goes here
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9
10 For the intervention cases, the time to peak infection decreases by 35.7%, i.e. from 286
11 days for Network 1 to 184 days for Network 2, meaning an influenza epidemic would
12 peak roughly 100 days earlier than one would expect based on the results from Network
13 1. For the base case, time to peak infection drops by 20.8%, i.e. 34 days reduction for
14 Network 2 as compared to Network 1.
15

16
17 Percentage changes and differences must be viewed cautiously, and to illustrate this
18 point, we present data for the key parameters in Tables S4 and S8. The difference in
19 the peak infection rate (i.e., the maximum fraction of daily infected individuals during the
20 simulation) between Networks 1 and 2 for the base case is 2.2%, or 47.6% in
21 percentage change (see Table S8). For the intervention case shown in Table S4, the
22 difference between the two networks is less (1.7%), but the percentage change is more
23 (123.2%) because the magnitudes of the peak infection rates are reduced when
24 effective interventions are used. We make note of this here and mainly use the
25 percentage change values in discussing results. For more detailed comparison between
26 vaccination intervention and the base case in Network 1 and Network 2, we refer to
27 Tables S7 and S9 and Figures S4 and S5.
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32 **Comparison between Networks 1 and 2 based on individual demographic** 33 **information** 34

35
36 We divide the Delhi population into strata by age, gender, and geographic home
37 location (i.e., slum and non-slum), and analyze mean cumulative infection rates by
38 subpopulation for the two networks. In simulations, individuals are chosen at random in
39 the entire network for vaccination. Various vaccination scenarios are investigated.
40

41
42 Figure 2 displays the cumulative infection rate results. On the x-axis, 'Total' refers to the
43 entire population of Delhi. There are three breakdowns of the entire population. 'Slum'
44 and 'Non-slum' refer to slum and non-slum regions, respectively. 'Male' and 'Female'
45 denote the total number of males and females in Delhi, respectively. Four age groups
46 are considered: 'Preschool' (0-4), 'School' (5-18), 'Adult' (19-64), and 'Senior' (65+). The
47 black lines correspond to the mean cumulative infection rates for the base case. Other
48 curves indicate vaccination strategies under different levels of vaccination rate (v) and
49 vaccine efficacy (α). Two vaccination rates (30%, 50%) and two vaccine efficacy rates
50 (30%, 70%) are shown in the figure.
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53
54 For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of
55 individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the
56 epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either
57 a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate
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3 of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all
4 categories of individuals.
5

6
7 In Network 1, slum and non-slums are treated the same so the infection rates are
8 identical in Figure 2. However, all scenarios in Network 2 show a higher burden of
9 disease on the slum population. This is due to the fact that slum households have larger
10 family size and more contacts on average than households in non-slum areas, see
11 Chen et al.[27] As shown later, we find similar patterns of infection in slum and non-
12 slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.
13

14
15 The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums
16 results in overestimation of the benefits of interventions in terms of reduction in the
17 mean cumulative infection rate and peak infection rate, as well as the time to peak. This
18 optimism holds for slum, non-slum and total population under various levels of
19 vaccination rates and efficacy rates in Network 2. See Table S10 for more detailed
20 comparison of results between slum and non-slum in Network 2.
21
22

23 Figure 2 goes here
24

25 26 **Comparison between Networks 1 and 2 across a wide range of intervention** 27 **strategies** 28

29
30 Next, we consider a variety of intervention strategies for comparative analysis. We
31 consider vaccination, school closure, stay home, and isolation strategies. For vaccines,
32 three different trigger points are considered: when cumulative infection rate reaches 0%
33 (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used:
34 when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at
35 home (SHO) strategy, all non-home activities and interactions are eliminated but all
36 contacts within the household are maintained. Under isolation (ISO) an individual has
37 no contact with other individuals (even home interactions are eliminated). The stay-at-
38 home and isolation interventions are implemented for compliant infectious individuals,
39 after they become infectious, for the entire infectious duration.
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42
43 Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a
44 wide range of intervention strategies. For each strategy, five different compliance rates
45 are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates
46 (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers
47 are the actual number of infected individuals. Darker colors correspond to higher
48 infection rates. Note that compliance rate is simply the vaccination rate for strategies
49 VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire
50 population. The 'Base' values do not vary with compliance because the base case has
51 no intervention. Note that all heat maps in this paper use the same color scheme so that
52 colors can be compared across figures.
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56 Since Network 1 does not distinguish between slum and non-slum populations, we only
57 compare the two networks for the whole of Delhi. The general pattern is similar for both
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4 networks. However, all interventions have a larger effect on Network 1 under the same
5 compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than
6 for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0,
7 stay-home, and isolation strategies in Network 1 as compared to those for Network 2.
8

9 Figure 3 goes here
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11
12 At a high level, among all intervention strategies, early vaccination (VAX0 and VAX1),
13 social isolation (ISO), and stay home (SHO) are more effective than the other
14 strategies, and this is more readily observed at higher compliance rates. For these
15 more effective strategies, the interventions per person are implemented right after (or
16 very shortly after) the person is infected. For example, SHO is implemented
17 immediately after a person becomes infectious. Thus, a person that becomes infectious
18 can infect their family members, but if these other members become infectious, then
19 they, too, will be confined to home. Thus, home-bound people can infect their family
20 members, but no one beyond their family (for 100% compliance). As compliance rate
21 increases, this effect approaches, roughly, a “family-based” isolation intervention
22 (similar to ISO), consistent with the results in Figure 3 and in subsequent results.
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29 **Effect of vaccination versus social distancing on slum and non-slum** 30 **subpopulations** 31

32 We now compare the impact of vaccination and social distancing on slum and non-slum
33 subpopulations from Network 2. Social distancing interventions are close-schools, stay-
34 home, and isolation.
35

36
37 The mean cumulative infection rates (and actual numbers of infections underneath) for
38 each compliance level are shown in the heat maps in Figure 4 for slum and non-slum
39 populations in Network 2. The axis labels are identical to those in Figure 3, as is the
40 color scheme of the cells. The base case values are constant since there is no
41 intervention and hence no compliance. Darker colors correspond to higher infection
42 rates.
43
44

45 Compared to the base case, all interventions reduce infection rates to some extent. As
46 the compliance rate increases, infection rates drop for all interventions. Infection rates
47 drop to zero in slum and non-slum regions at a compliance level of 70% or higher,
48 under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce
49 the infection rates significantly, and this effect increases with compliance rate.
50
51

52 The following observations can be made from Figure 4. Social distancing, i.e. SHO, at
53 low and intermediate compliance and CS at all compliance levels, are less effective in
54 slum regions as compared to non-slum regions. This is because CS only eliminates
55 school interactions for those attending school, and there are fewer school edges in
56 slums compared to non-slum areas, as shown in Figure S6. The effectiveness of CS in
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3 slums is mitigated by the greater average number and duration of interactions at home
4 in slums as compared to non-slums (see Figure S6 and Chen et al.[27]). Thus, if a
5 person is sick, there is a greater chance of transmitting contagion to family members,
6 who then may have activities outside of school, thus circumventing the CS intervention.
7 At high compliance, SHO is effective because all interactions outside home (including
8 school) are eliminated.[27]
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12 These observations are also supported by Figure S7, which contains numbers of edges
13 used to transmit contagion for a base-case run of Figure 1. There are several effects
14 that bear on the above observations. First, in the cases of activities “work”, “other”, and
15 “school”, the number of edges transmitting contagion from slums to non-slums is greater
16 than the reverse: from non-slum to slum. Second, in two of these three activity
17 categories, there is more slum to non-slum transmissions than slum to slum
18 transmissions. Edges of transmission for slum dwellers is dominated by home
19 interactions. The infected homes in slums serve as launching points to drive disease to
20 non-slums through slum to non-slum interactions. (There are no “mixed” edges at
21 homes, and shopping and college activities have low levels of slum activity because of
22 socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but
23 we now return to Figure 4.
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27 Isolation works well at 30% or higher compliance rates, but it is a much harder strategy
28 to implement, especially in slums. However, it is considered here for comparative
29 analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as
30 compliance increases. However, close-school is generally less effective because this
31 intervention removes only a fraction of interactions for a fraction of the population, i.e.
32 school aged children. Simulations were also run for 70% vaccine efficacy. Since results
33 are qualitatively similar for those parameters, these plots are provided in Figure S3.
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37 Figure 4 goes here
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39 **Comparison between Network 1 and non-slum areas of Network 2**

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41 Note that Network 1 treats all parts of the region as non-slum, i.e. all individuals follow
42 non-slum activities and demographics. In order to capture the additional disease risk to
43 the non-slum population that arises from the interactions with the slum population, we
44 compare Network 1 in Figure 3a with the non-slum population of Network 2 in Figure 4b.
45 In base case, the additional disease risk to the non-slum population goes up from 42%
46 to 45%. However, the beneficial effects of social distancing strategies drop by a large
47 amount, e.g. close school strategies are 5-20% less effective in the non-slum areas of
48 Network 2. This effect changes non-linearly with the compliance rate. As compliance
49 rate goes up, the difference between performance of Network 1 and non-slum parts of
50 Network 2 goes up in CS1 and CS5. This implies that in Network 2, non-slum population
51 requires much higher levels of compliance to achieve the same results as in Network 1.
52 This difference is less stark for vaccination based interventions, i.e. VAX0, VAX1 and
53 VAX5. This is expected since the effect of vaccination is less dependent on interactions;
54 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]

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5 Also, the strategy of vaccinating non-slums and social distancing slums (VnSs) is not as
6 effective as the interventions in rows 1 and 2 of Figure 5. This is a counterintuitive
7 result, since the density of population is much higher in the slums, which may lead to
8 the belief that social distancing in slums will break up the dense clusters. However, a
9 careful examination shows that keeping slum residents home is not an effective social
10 distancing strategy because their family size is, on average, almost 3 times the family
11 size of non-slum households.[27] The high level of mixing at home makes social
12 distancing ineffective in slums unless the infected individual is completely isolated.
13 However, complete isolation is not viable in slum areas where the entire household may
14 live in a single room.
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20 Figure 5 goes here
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23 DISCUSSION 24

25 With slum populations expected to grow to 2 billion by 2030,[44] it is becoming
26 increasingly urgent to understand how to control the spread of infectious diseases in
27 slum areas and measure its effect on urban populations. To our knowledge, a detailed
28 study of interventions to control influenza epidemics in slums, using an agent-based
29 simulation model, has never been done before. Slum conditions are important for a city
30 beyond the direct effects of disease transmission. For example, civil wars may be
31 precipitated or exacerbated by disease outbreaks because they decrease social health
32 and welfare.[45]
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36 Even though slum regions contain only 13% of the total population of Delhi, Chen et
37 al.[4] show that omitting their attributes leads to underestimation of the overall infection
38 rate and the peak infection rate of the epidemic. This paper extends that work by
39 evaluating the differential impact of interventions on slum and non-slum regions.
40 Various vaccination and social distancing strategies are analyzed under different
41 scenarios that show that the slum population is more prone to infections under the same
42 control measures. Furthermore, taking account of slum populations significantly alters
43 the disease dynamics in the *entire* population. Differences in key measures are
44 demonstrated between the cases of accounting for slum populations and not: e.g., a
45 100% increase in the peak attack rate in some cases when slum regions' characteristics
46 are taken into account, compared to the case when they are ignored.
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50 Figure 4, which compares infections in slum with non-slum areas, shows that at very
51 high compliance rates, some interventions can be equally effective in both slums and
52 non-slums. However, such high compliance rates are typically not feasible due to
53 practical realities on the ground, and also because they require timely diagnosis of
54 infected cases. For SHO to be effective, the coverage rate needs to be 70% or more in
55 both slums and non-slums, and the diagnosis of the infected individuals needs to be
56 correct and immediate. In other words, effective control of a contagious epidemic in a
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3 high-density place like Delhi, would require either early and drastic action (e.g. ISO) or a
4 highly compliant set of individuals, or a combination of these features.
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7 This work overall demonstrates the power of agent-based and population modeling to
8 evaluate complicated interaction-based epidemiological phenomena. Clearly, there are
9 limitations to this work (several are itemized below). But these agent and population
10 approaches provide a platform for adding additional complexity. All of the figures
11 demonstrate that quantitative results depend on complicated interplay among inputs.
12 These results are important because they inform policy decisions. An equally important
13 benefit of this type of work, but not often stated, is developing intuition about epidemic
14 dynamics (in this case, with the effects of slums), to enable decision makers to reason
15 about nuanced interactions among effects to a degree that is hard to obtain with other
16 approaches that lack this level of detail. However, we believe that other modeling
17 approaches may also be valuable in understanding epidemic dynamics in slum
18 populations.
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22 Despite the detailed modeling effort, there are limitations of this work and areas for
23 improvement in the future. For example: (1) Examination of different population level
24 base attack rates derived from different transmission probabilities. (2) Different
25 susceptibilities and infectivity for individual agents; e.g., based on age. (3) Effects of
26 asymptomatic infections (although we have addressed this to some extent with
27 compliance and efficacy of interventions). (4) Seasonal effects.[46-47] (5) Effects of
28 immunity for an individual from previous infections (in previous seasons). (6) Evaluation
29 of interaction of different strains from season to season. (7) Comparison of tropical
30 versus subtropical factors. (8) Evaluation of a specific outbreak scenario. (9) Impact of
31 sickness on absenteeism from work and its economic ramifications. (10) Effects on rural
32 versus urban populations. (11) Using combinations of interventions rather than one at a
33 time; this was only done here in Figure 5. However, to disambiguate results, it is
34 prudent to first examine individual interventions. (12) Effect of changing disease
35 transmission rate for different activity types. (13) Effect of changing contact times at
36 different locations. (14) To capture close-proximity transmission, one could use actual
37 physical proximity. Here, we use colocation. Finally, just as changes in modeling details
38 can change model results, so, too, changes in the conditions in actual outbreaks can
39 change results; some of these factors are listed above. It is essentially impossible to
40 capture all of these effects—many of which are unknown—down to the level of
41 individual humans.
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47 Public health implications: This research demonstrates that modeling slum populations
48 is important, not only for understanding disease dynamics, but also for designing
49 effective control measures. Ignoring the influence of slum characteristics on their urban
50 environment will significantly underestimate the speed of an outbreak and its extent,
51 and hence will lead to misguided interventions by public health officials and policy
52 planners. Lessons from this research can be applied in the field and observations
53 collected from the field can provide valuable data to improve the models and validate
54 the results. For example, our results show that a slum resident has about 50% greater
55 total contact duration per day compared to a non-slum resident. This makes social
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3 distancing based interventions more taxing in the slum population. Public health policy
4 makers may want to subsidize pharmaceutical resources for the slum population to
5 make them more affordable. Similarly, we find women in slums have a higher number of
6 contacts per day than their male counterparts whereas in non-slum regions, women
7 have a fewer number of daily contacts than their male counterparts. This kind of
8 information can be used to prioritize the distribution of limited resources, e.g. women
9 could be given preference over males for vaccination in slum areas. This research
10 provides simulation-based evidence that in general social distancing strategies are
11 ineffective in slums because of a large number of contacts at home. Unless one applies
12 complete isolation, which is not feasible in slums, just staying at home still keeps a large
13 number of contacts and pathways of spread intact.
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4 **Contributorship statement**

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

13 There are no competing interests.
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18 **Funding statement**

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24 Disease Agent Study (MIDAS) (grant no. 2U01GM070694-11 and 3U01FM070694-
25 09S1).
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30 **Data Sharing Statement**

31 Data pertaining to figures and statistical analysis are partially provided in the
32 supplementary file, and also can be obtained by contacting the corresponding author
33 through email.
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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 ($\alpha = 30\%$, 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

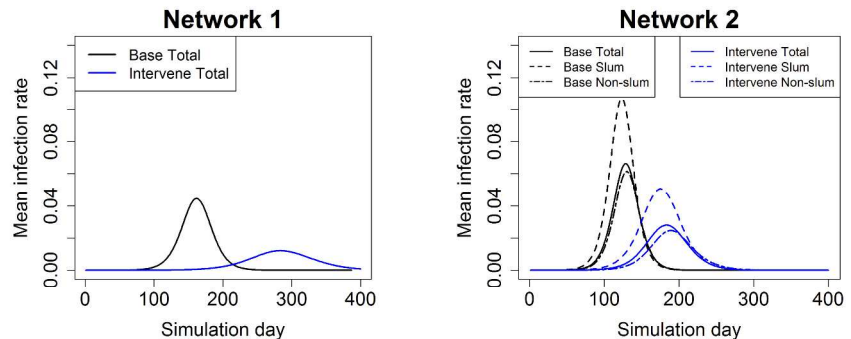
Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond 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

Main manuscript

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3 intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and
4 isolation (ISO)) are considered. For vaccines, three different trigger points are
5 considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5%
6 (VAX5). For close-schools, two trigger points are used: when the cumulative infection
7 rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly
8 from the entire Delhi population, and the mean infection rates are calculated separately
9 for the slum and non-slum subpopulations. Although not reported here, qualitatively
10 similar results are found for other transmission rates, as well as for higher vaccine
11 efficacy (70%). Base is the baseline case with no interventions. The smaller-font
12 numbers under the infection rate show the actual number of infected individuals.
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16 **FIGURE 5:** Mean cumulative infection rates for each category listed on the x-axis, for
17 Network 2 and Network 1, under four different intervention scenarios. The color scheme
18 of the boxes are based on the large values in the boxes—the cumulative infection rates.
19 Darker colors correspond to higher infection rates. Smaller font values are the number
20 of infected individuals. The vaccine efficacy is set at 30%. VsSs refers to the case when
21 vaccines and social distancing are both applied to slum residents; VnSn refers to the
22 case when vaccines and social distancing are applied to non-slum residents. Similarly,
23 VsSn means vaccines are given to slums and stay home is applied to non-slums; and
24 VnSs means vaccines are given to non-slums and stay home is applied to slums. Base
25 refers to the case where no intervention is applied. The smaller-font numbers under the
26 infection rates show the actual number of infected individuals in each category listed on
27 the x-axis.
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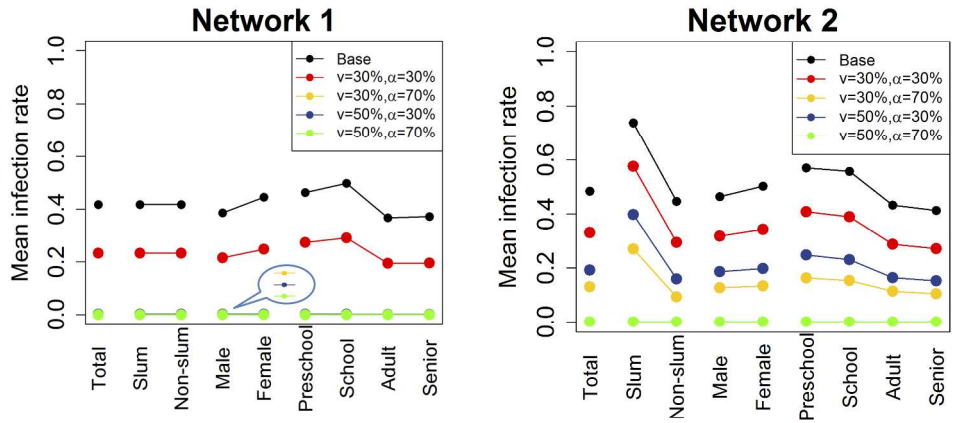
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Intervention	Base	C ₁	C ₂	S ₁	S ₂	I ₁	I ₂	V ₁	V ₂
V ₁	0.36	0.23	0	0	0	0	0	0	0
V ₂	5038837	3228985	20921	221	97				
I ₁	0.37	0.25	0.11	0.04	0.02				
I ₂	5061754	3405459	1549547	539181	322258				
S ₁	0.37	0.27	0.19	0.13	0.1				
S ₂	5146506	3802876	2618588	1781022	1318401				
C ₁	0.3	0	0	0	0				
C ₂	4158127	648	62	35	23				
S ₁	0.36	0.12	0	0	0				
S ₂	4939914	1659965	241	89	51				
I ₁	0.36	0.24	0.14	0.08	0.06				
I ₂	5017949	3367475	1880956	1121321	881914				
C ₁	0.37	0.27	0.19	0.15	0.16				
C ₂	5112280	3738161	2615064	2125815	2169135				
Base	0.42	0.42	0.42	0.42	0.42				
	5772516	5772516	5772516	5772516	5772516				

Intervention	Base	C ₁	C ₂	S ₁	S ₂	I ₁	I ₂	V ₁	V ₂
V ₁	0.44	0.33	0.19	0	0				
V ₂	6070999	4584539	2669426	18530	206				
I ₁	0.44	0.34	0.21	0.1	0.04				
I ₂	6087287	4654816	2967789	1350667	554670				
S ₁	0.44	0.35	0.26	0.17	0.13				
S ₂	6146453	4898048	3594239	2329038	1818146				
C ₁	0.39	0.03	0	0	0				
C ₂	5465084	478780	85	37	23				
S ₁	0.44	0.31	0.08	0	0				
S ₂	6047827	4323509	1098024	543	83				
I ₁	0.45	0.37	0.31	0.29	0.27				
I ₂	6191602	5188739	4357831	4018271	3675802				
C ₁	0.47	0.44	0.43	0.42	0.4				
C ₂	6470698	6101056	5883830	5766943	5600599				
Base	0.48	0.48	0.48	0.48	0.48				
	6704038	6704038	6704038	6704038	6704038				

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		0.69	0.58	0.4	0	0
	V ₁₀₀	1263625	1041034	719517	7505	66
	V ₉₀	0.69	0.58	0.43	0.24	0.1
	V ₈₀	1296162	1052247	775240	426160	166606
	V ₇₀	0.7	0.6	0.49	0.36	0.29
	V ₆₀	1265497	1094158	890080	649544	525620
	ISO	0.65	0.08	0	0	0
	ISO	1168239	146106	20	7	3
	SHO	0.71	0.61	0.25	0	0
	SHO	1279142	1102671	460613	301	30
	CS ₁	0.72	0.7	0.67	0.66	0.65
	CS ₁	1311761	1260823	1215625	1194938	1171916
	CS ₂	0.73	0.72	0.72	0.71	0.71
	CS ₂	1326417	1309021	1298824	1292254	1283791
	Base	0.74	0.74	0.74	0.74	0.74
	Base	1337160	1337160	1337160	1337160	1337160
		10%	30%	50%	70%	90%

Compliance

		0.4	0.29	0.16	0	0
	V ₁₀₀	4817373	3542870	1921714	11025	139
	V ₉₀	0.4	0.3	0.18	0.08	0.03
	V ₈₀	4831106	3602969	2192949	924508	368084
	V ₇₀	0.41	0.32	0.22	0.14	0.11
	V ₆₀	4880956	3803892	2704160	1679494	1292525
	ISO	0.36	0.03	0	0	0
	ISO	4298845	332875	65	30	20
	SHO	0.4	0.27	0.05	0	0
	SHO	4768685	3220638	637412	242	53
	CS ₁	0.41	0.33	0.26	0.23	0.21
	CS ₁	4879841	3927917	3142206	2823334	2503886
	CS ₂	0.43	0.4	0.38	0.37	0.36
	CS ₂	5144281	4792032	4585006	4474690	4316809
	Base	0.45	0.45	0.45	0.45	0.45
	Base	5366878	5366878	5366878	5366878	5366878
		10%	30%	50%	70%	90%

Compliance

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V_{sSs}	0.44 6043049	0.55 989079	0.42 5053971	0.37 5176345
V_{sSn}	0.43 5938919	0.58 1042116	0.41 4896803	0.36 4995753
V_{nSs}	0.44 6023678	0.67 1217415	0.40 4806263	0.36 4986302
V_{nSn}	0.44 6104571	0.72 1309577	0.40 4794993	0.36 5016324
Base	0.48 6704038	0.74 1337160	0.45 5366878	0.42 5772516
	Total Network 2	Slum Network 2	Non-slum Network 2	Total Network 1

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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

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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

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

Supplemental Information

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.

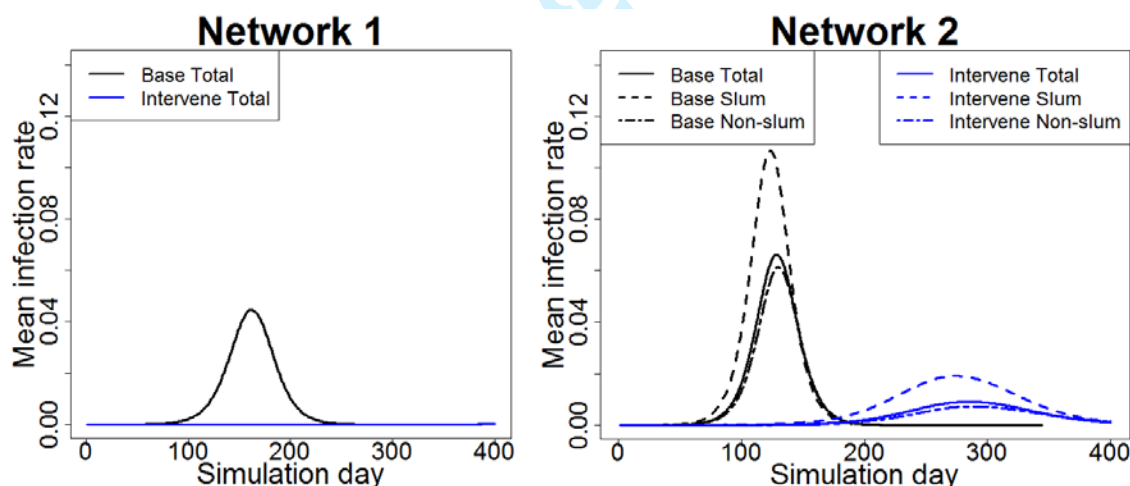


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

Supplemental Information

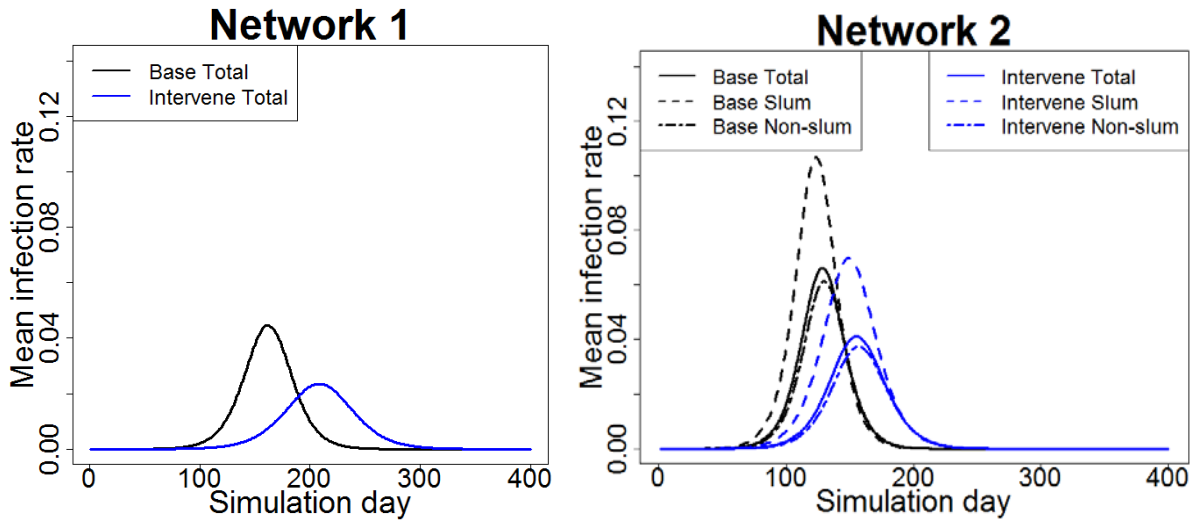


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.

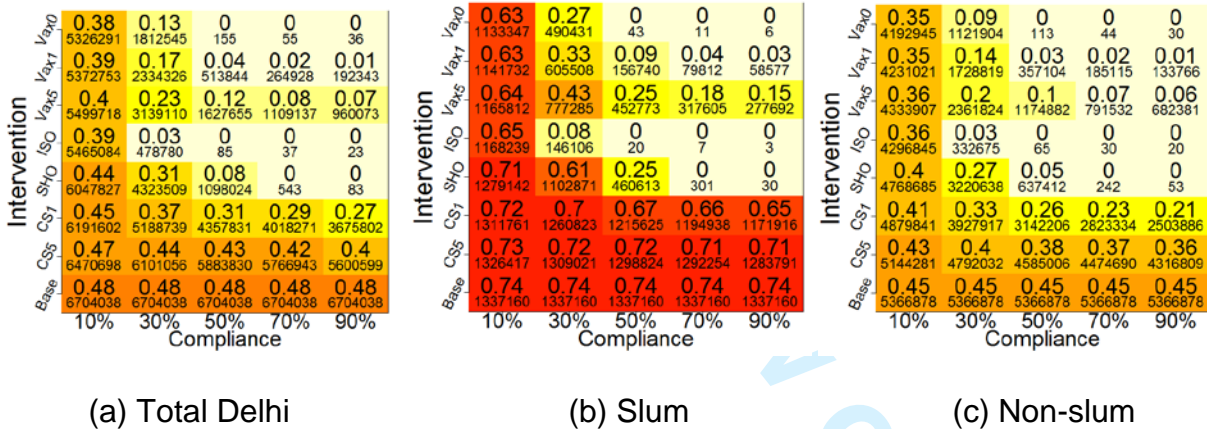


Figure S3. Heat map of mean cumulative infection rates in Delhi, and slum and non-slum regions under different intervention strategies for Network 2. The vaccination efficacy is fixed at 70%. Five different compliance rates, i.e., 10%, 30%, 50%, 70% and 90% and 4 types of intervention strategies, i.e. 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%

Supplemental Information

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%,

Supplemental Information

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

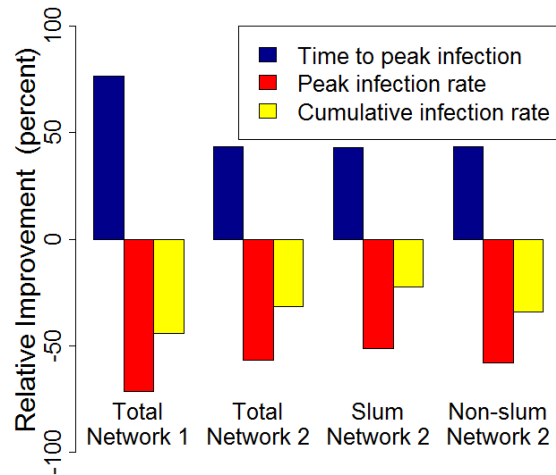


Figure S4: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 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

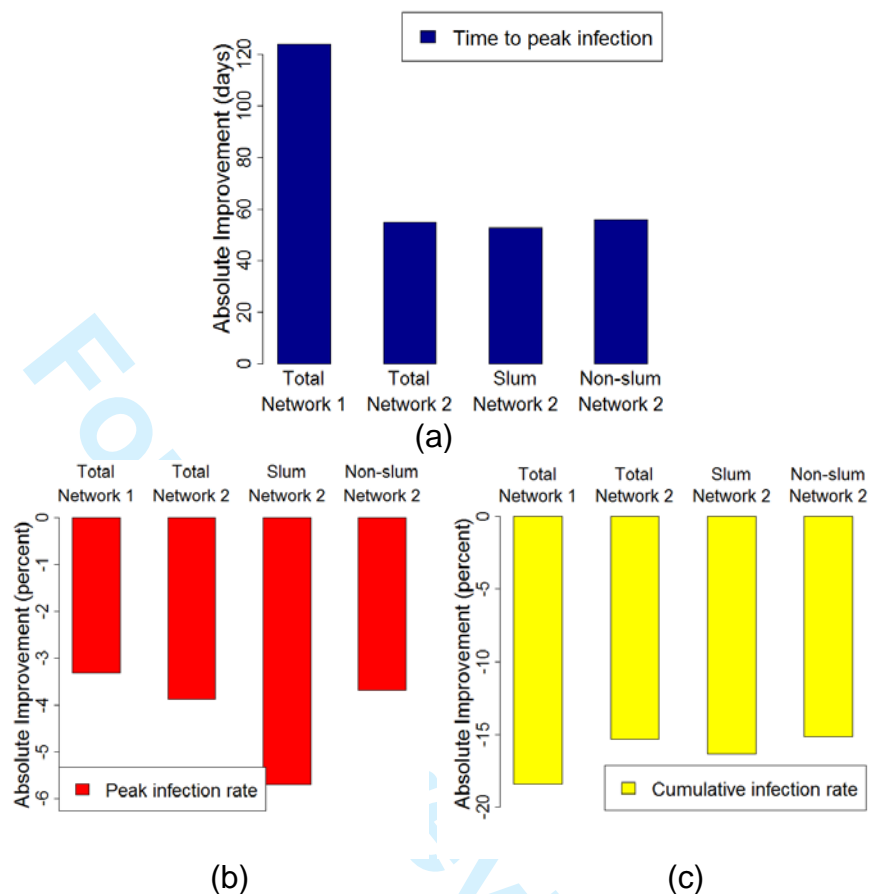
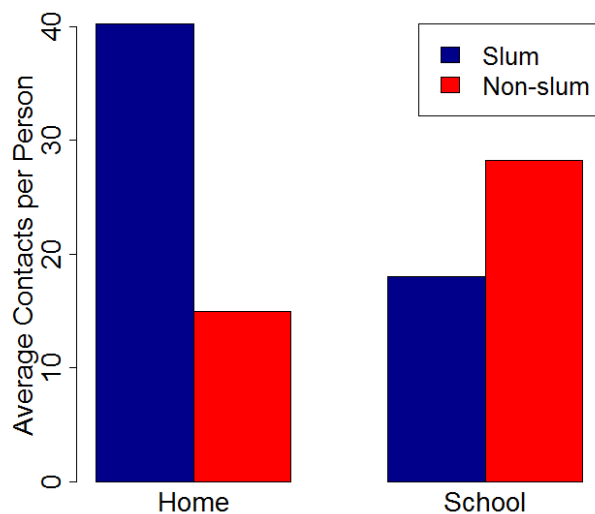


Figure S5: Comparison of absolute difference in improvement; the relative differences are shown in Figure S7. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S7 and S9.

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).

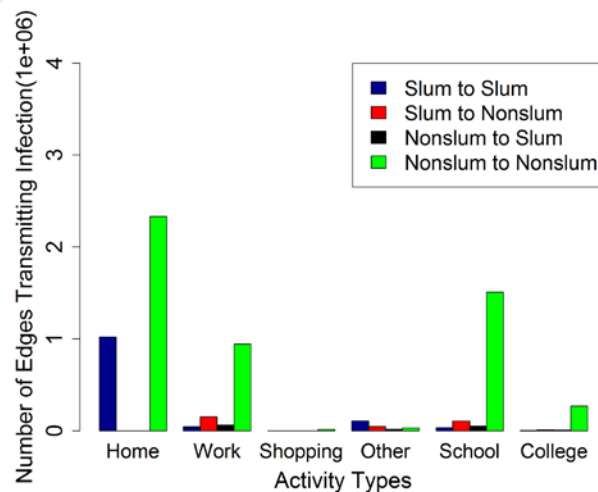


Figure S7. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater than nonslum-to-slum ones because once infection 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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Disparities in Spread and Control of Influenza in Slums of Delhi: Findings From An Agent-Based Modeling Study

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6 **Disparities in Spread and Control of Influenza in Slums of Delhi:**
7 **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

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3 Infectious disease is one of the leading causes of human morbidity and mortality
4 worldwide. Reports from Centers for Disease Control (CDC) show that over 200,000
5 people in the United States (US) are hospitalized with influenza-like illness (ILI)
6 symptoms each year, and the mortality on average is over 36,000 annually.[1-2] In
7 Delhi, India, a joint study by CDC, All India Institute of Medical Sciences, and the
8 National Institute of Virology has shown that ILI cases are present throughout the year,
9 although they peak in rainy and winter seasons.[3] It carries a significant economic
10 burden through reduced productivity and high costs of health care.[4-7] A CDC study
11 finds that for outpatient and non-medically attended individuals, acute respiratory
12 infections cost 1%-5% of monthly per capita income in India. In contrast, cost of
13 inpatient care can be as high as 6%-34% of monthly per capita income.[8] For
14 developed countries, the annual cost of influenza is estimated to be between \$1-\$6
15 million per 100,000 people, according to the World Health Organization.[9]
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20 In 2007, India established an Integrated Disease Surveillance Program (IDSP), which
21 included a network of 12 regional laboratories, to minimize the threat of avian influenza
22 and other highly infectious zoonotic diseases.[10] India faces some unique challenges
23 in surveillance, prevention and control because of the seasonality of influenza at sub-
24 regional levels. This seasonal variation depends upon latitude, monsoon season,
25 humidity and climatic factors of the regions. Acute respiratory infections are estimated to
26 be 43 million per year, of which 4-12% are due to influenza.[11-12] Chadha et al.[13]
27 estimated hospitalizations due to respiratory illnesses to be 160 per 10,000 persons in
28 year 2011, and children under age 5 had the highest incidence of them.
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32 Given that influenza is environmentally-mediated and spreads through close proximity,
33 population density is an important factor in its spread. In India, the average population
34 density is about 1000 people per square mile; in the slums, it can be 10 to 100 times
35 higher.[14] Larger household size and crowding make it easier to transmit
36 infections).[15-18] For example, Baker et al.[16] find that meningococcal disease risk
37 among children doubles with the addition of 2 adolescents or adults (10 years or older)
38 to a 6-room house. Other than overcrowding, slums are characterized by their lack of
39 medical services,[19-20] which makes slum residents highly vulnerable to infectious
40 diseases. Diseases like cholera, malaria, dengue and HIV are common in slums across
41 the world.[21-23]
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45 This research uses Delhi, the National Capital Territory of India, where 13% of its 13.8
46 million people live in slum areas, as an example city to study the spread and control of
47 influenza. Delhi is an interesting case study. It ranks fourth in the world in urban
48 population, and, among the top 25 largest urban areas, it ranks tenth in population
49 density. Although Delhi is our target population, the results are likely to be useful in
50 studying other slum areas within and outside of India because of the wide range of
51 intervention types and parameter values examined.
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54 This paper is an extension of the work done in Chen et al.[4], which shows that slum
55 populations have a significant effect on influenza transmission in urban areas. Ignoring
56 the influence of slum characteristics underestimates the speed of an outbreak and its
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4 extent. However, Chen et al.[4] do not consider any interventions on the epidemic
5 spread. *The focus of this research is to study the effect of different intervention*
6 *strategies on several subpopulations (slum, age and gender) in two different Delhi*
7 *networks, i.e., original (referred to as Network 1) and refined (Network 2).*
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9 The original network used in Xia et al.[24] studied the spread and control of influenza in
10 Delhi using Network 1, which did not take into account the special attributes of the slum
11 population, such as larger family sizes and different types of daily activity schedules.
12 Chen et al.[4] used Network 2, the refined social network of Delhi, which accounted for
13 slum demographics and slum activities, but did not study intervention strategies. In
14 Network 2, there are 298 slum regions in Delhi, containing about 1.8 million people.
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17 The goals of this work focus on understanding the effects of pharmaceutical and non-
18 pharmaceutical interventions on epidemic outcomes. Pharmaceutical interventions (PI)
19 include vaccinations, and non-pharmaceutical interventions (NPI) are social distancing
20 measures such as school closure, quarantine and staying home. These effects are
21 studied comparatively: (i) in Network 1 versus Network 2, overall and for subpopulations
22 in each; and (ii) in the slum and non-slum regions of Network 2. Additionally, in a
23 scenario where interventions can be applied to a limited number of individuals, we
24 explore how resources should be split between slum and non-slum subpopulations in
25 order to achieve the best outcomes with respect to total infection rate (i.e., the
26 cumulative fraction of a population infected).
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30 METHODS 31

32 We use an agent-based modeling (ABM) approach to simulate the spread and
33 containment of influenza in social contact networks of Delhi, India. We compare two
34 networks: one considers slum-specific attributes, and the other does not. In this section,
35 we describe the networks, the disease model for each agent, the interventions, and the
36 heterogeneities of the problem that make ABM uniquely suited to study epidemics.
37 Throughout this manuscript, each agent in the ABM is an individual human.
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41 **Social Contact Networks:** This study uses two synthetic social networks of Delhi,
42 created in Xia et al.[24] and in Chen et al.[4]. Details on their construction can be found
43 in Xia et al.[24], Chen et al.[4], Barrett et al.[25], Bisset et al.[26] and references therein.
44 The synthetic social network by Xia et al.[24] is called *Network 1*, and the more refined
45 network developed in Chen et al.[4], *Network 2*.
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48 It is important to note that while the social contact networks are inputs in
49 epidemiological simulations, these networks are not specified directly. Rather, these
50 networks are the outputs of population generation methods that are overviewed below
51 and cited immediately above, and include activity surveys and demographic data, both
52 inside and outside of slums. Thus, the topologies of the networks arise from the
53 population generation process, and its inputs.
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3 Network 1 was developed in part from Land Scan and Census data for Delhi, a daily set
4 of activities of individuals, and the locations of those activities including geo-locations of
5 residential areas, shopping centers, and schools, collected through surveys by
6 MapMyIndia.com. By assigning activity locations to individuals' activities, people are
7 located at particular times at particular geographic coordinates (including office
8 buildings, schools, etc.) and within particular rooms of buildings. Next, contacts between
9 individuals are estimated when each person is deemed to have made contact with a
10 subset of other people simultaneously present at the same location. This gives rise to a
11 synthetic social contact network where network edges represent these contacts.
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15 Network 2 models the slum regions in Delhi and assigns slum-specific attributes to the
16 individuals whose homes reside in the slum polygons. Slum residents' attributes and
17 their daily sets of activities are collected through a ground survey in Delhi slums, by a
18 vendor, Indiamart (www.Indiamart.com/trips). The slum polygons are obtained from
19 *MapMechanic.com*. Individuals living in the slum regions are a part of the slum
20 population. All other individuals are part of the non-slum population. Network 2 is a geo-
21 located, and contextualized social contact network of Delhi with slums integrated in it.
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25 Following are the main differences between the original network (Network 1) and the
26 refined network (Network 2). The original social contact Network 1 treats the slum
27 regions like any other region in Delhi in terms of assignment of demographics and
28 individual activities, i.e. no special consideration is given to slum residents. The refined
29 Network 2 identifies 298 slum polygons (zones) in Delhi and assigns slum-specific
30 demographics and activities to the individuals whose homes reside inside these
31 polygons. Thus, the number of individuals is the same in both populations. The slum
32 population constitutes about 13% (1.8 million) of the entire Delhi population of 13.8
33 million people. The main effects of integrating slums is that Network 2 has more home-
34 related contacts due to larger family sizes and more outside contacts due to more daily
35 activities outside home. Also, those individuals who reside outside of slum zones have
36 the same activities in both networks (but their contacts may change if their interactions
37 include slum residents). Overall, there are over 231 million daily interactions between
38 pairs of individuals. Table S1 compares those two networks as well as data sources for
39 slum and non-slum Delhi, India. (Table and figure numbers that are prefixed with 'S' are
40 in the supplementary information (SI)). For example, the average degree increases from
41 30.4 to 33.4 from Network 1 to Network 2, and the maximum degree increases from 170
42 to 180. We refer to Chen et al.[4] for more detailed information about the two networks.
43 Several plots of properties and structural characteristics of Networks 1 and 2 are given
44 in Chen et al.[27].
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49 **Disease Model:** An SEIR, Susceptible (S), Exposed (E), Infectious (I) and Removed or
50 Recovered (R) model is considered within each individual. Each node in the network
51 represents an individual, and each edge represents a contact on which the disease can
52 spread. A contact represents possible transmission between two people that are co-
53 located for some duration (based on their activity schedules). This is an approximation
54 to model direct contact and short-distance environmentally-mediated transmission that
55 might include direct physical contact, fomite mediated, and airborne transmission.[28]
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5 We start each epidemic simulation with 20 index cases, randomly chosen. (We find that
6 results are not sensitive to the number of initial infections.) The detailed description of
7 the SEIR model as well as the choices of transmissibility value, R_0 , the explicit
8 incubation and exposed periods can be found in the supplementary information. This
9 disease model has been used in other works such as Liao et al.[29], Marathe et al.[30].
10

11 The transmissibility value for disease transmission is that for the strong influenza model
12 in Chen et al.[4]. That work used mild, strong, and catastrophic influenza models, so we
13 chose the intermediate transmissibility. This corresponds to base attack rates (i.e.,
14 cumulative infection fractions) of 0.42 and 0.48, respectively, in Networks 1 and 2.
15 These rates are generally higher than those in some other studies that either compute
16 experimental attack rates from cases or compute them in modeling studies such as this
17 one. Attack rates used by past researchers for different strains of influenza include Asia
18 [0.22 to 0.50],[31] Southeast Asia [0.11 to 0.31 in children [32]; 0.05 to 0.65 [33]], and
19 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];
20 0.209 for various strains [13]]. The results of Chen et al.[4] indicate that the results here,
21 for this particular transmissibility, will be qualitatively the same for other
22 transmissibilities, but will scale down or up as transmissibility changes in the same
23 direction.
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28 **Interventions:** This work considers three vaccination scenarios, i.e., vaccinate when
29 cumulative infection rate is 0% (VAX0, i.e. vaccinate on day 1), 1% (VAX1), and 5%
30 (VAX5). Three classes of social distancing strategies are considered: (i) stay-home
31 (SHO) if infected, i.e. eliminate all non-home related contacts but continue to maintain
32 contacts within the household; (ii) close-schools when cumulative infection rate has
33 reached 1% (CS1) and when it has reached 5% (CS5), i.e. eliminate school related
34 contacts; and (iii) (ISO), in which all contacts, including home contacts, of a person are
35 eliminated when a person becomes infectious. For vaccination, five different compliance
36 rates (10%, 30%, 50%, 70%, 90%) and two different vaccine efficacies (30% and 70%)
37 are considered.
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40

41 VAX0, SHO, ISO are all fairly aggressive interventions because they are implemented
42 either before a person gets infected or immediately upon becoming infectious. These
43 are actions taken at the individual or family level. For example, vaccination before the
44 influenza season or isolating a sick child at home are family decisions. Even CS1 is an
45 aggressive intervention in the sense that this action is taken by government officials
46 based on aggregate school sickness levels—closing schools before any outbreaks is
47 typically not done. From these starting points, vaccinations when 1% or 5% of the
48 population is infected (VAX1, VAX5), and closing schools when 5% of the population is
49 infected (CS5) are less aggressive treatments. The five levels of compliance are also
50 variations on aggressiveness in treatments.
51
52
53

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

18
19 When a susceptible node is vaccinated, its probability of getting infected by an
20 infectious node is scaled down by the efficacy. If it becomes infectious, its probability of
21 infecting susceptible nodes is also scaled down by the efficacy. In other words, both
22 incoming and outgoing infection probabilities of vaccinated individuals are reduced by
23 the vaccine efficacy. Interventions are applied to slum residents, non-slum residents,
24 and the entire region of Delhi.

25
26 For each experiment, 25 replicates are simulated for 400 days, and their mean results
27 are reported. The averages are time-point wise averages, e.g. the mean infection rate at
28 day 100 is calculated by taking the average of the 25 infection rates that occur on day
29 100 of each replicate. Table S2 summarizes all the interventions considered, and Table
30 S3 contains all variables in simulations, including intervention parameters.

31
32 **Heterogeneities captured:** There are several heterogeneous aspects to this problem
33 that motivate the use of an ABM approach: (i) the 298 slum zones have populations that
34 vary by more than four orders of magnitude in size; (ii) the geographic extent of slum
35 zones differ; (iii) the slum zones are located at irregular spatial intervals throughout
36 Delhi; (iv) the activity patterns of people living in slums are different from those in the
37 non-slum region; and (v) each individual interacts with specific others based on co-
38 location.

39
40 The implications of these heterogeneities include the following. First, the particular
41 synthetic households that live within slums are predicated on the number of slum zones,
42 their locations, and their spatial geometries. These homes have larger family size and
43 hence more home contacts. Second, slum individuals have different activity patterns
44 which change the co-located contacts of each slum person: that is, with whom they
45 interact and for how long. For example, see the supplemental information of Chen et
46 al.^[27]. The average total contact durations by activity type and by slum/non-slum
47 residents are provided, which show that non-slum people have greater contact
48 durations for work, school, and college activities, but less for home and other types.

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4 Overall, a slum person has about 50% greater total contact duration per day compared
5 to a non-slum person. The same supplemental shows that in the age range 20 to 60
6 years (by year), females that live in slums have more contacts per day than their male
7 counterparts. However, females whose homes are outside of slum regions have
8 average number of daily contacts that are below their male counterparts.
9

10 11 **RESULTS AND ANALYSIS**

12 Our results are grouped as follows. (1) Comparison of Network 1 and Network 2 for
13 base case and intervention cases. (2) Results for both networks based on demographic
14 classes, such as slum/non-slum, gender, and age groups, for a wider range of
15 intervention strategies. (3) Comparison of Network 1 with the non-slum population of
16 Network 2. (4) Effects of pharmaceutical and non-pharmaceutical interventions for a
17 wide range of parameter values. (5) Effects of different resource allocation strategies.
18
19

20 All differences are tested with the two-sample t-test and they are all statistically
21 significant with p-values smaller than $2.2e-16$. The 95% confidence intervals are given
22 for each comparison. Here is a brief summary of selected results with examples of
23 mechanisms, to provide a high-level overview. Details of results follow this summary
24 and these details matter because there are many factors (inputs) in a simulation whose
25 interactions change results.
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29 (1) Ignoring the unique attributes of slums in a population overestimates the benefits of
30 the interventions. For example, in the case of vaccination intervention (efficacy 30% and
31 compliance 30%), the values for the epidemic size (i.e., cumulative percentage of
32 infected), peak infection rate (i.e., maximum percentage of a population infected on any
33 day), and time to peak are 33.1%, 3.0%, and 184 days, respectively, in Network 2,
34 whereas they are 23.3%, 1.34%, and 286 days in Network 1. In relative terms, the
35 epidemic size and peak infection rate are underestimated by 42.2% and 123.2%
36 respectively, while the time to peak is overestimated by 35.7% in Network 1 (see
37 Figures 1, 2 and Table S4). The larger family sizes for slum families in Network 2 and
38 the increased number of edges result in larger outbreaks and faster time to peak
39 infections.
40
41
42

43 (2) Interventions are more effective in Network 1 than Network 2 for all types of
44 interventions: vaccination, closing schools, staying home, and isolation. These trends
45 also hold over wide ranges of efficacy and compliance (see Figures 3, 4, S1, S2 and
46 S3). Hence, not accounting for slums gives overly optimistic results for the effectiveness
47 of the interventions. The reduced average family size in Network 1 means fewer within-
48 home edges, which slows infection and reduces spreading. Closing schools and staying
49 home interventions do not affect home edges. However, the magnitude of this effect
50 varies with intervention conditions (e.g., compliance rate, time at which intervention is
51 applied).
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55 (3) Cumulative infection rates by subpopulation in Network 2 show that slums sustain
56 greater infection rates than non-slums under all intervention scenarios, sometimes by as
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3 much as 44.0%. See Figure 4 and Table S5 for more details. This is due to the greater
4 household sizes in slums.
5

6
7 (4) For Network 2, under a wide range of intervention compliance rates (10% to 90%),
8 the isolation strategy is up to 32% more effective in containing an outbreak than
9 vaccination (for 30% efficacy). Staying home is up to 18% more effective than
10 vaccination at 50% compliance. See Figure 3 and Table S6 for more details. Isolation,
11 although hard to implement from practical considerations, is most effective because
12 edges to susceptible individuals are removed (isolation also provides a good
13 comparative case). Differences between staying home and vaccination depend on
14 compliance rates.
15

16
17 (5) For Network 2, delay in triggering interventions has 7.3% to 44.0% more adverse
18 effect in slums than in non-slum regions across compliance rates from 10% to 90%. See
19 Figure 4 and Table S7 for more details. Early interventions mean actions are taken
20 when outbreaks are smaller and are therefore more readily contained.
21

22
23 (6) Comparison of Network 1 (Figure 3a) with the non-slum population (Figure 4b) of
24 Network 2 shows that just the presence of slum specific activities and interactions with
25 non-slum population makes social-distancing based interventions less effective in the
26 non-slum regions of Network 2.
27

28
29 (7) A full-factorial design that splits resources between slum and non-slum regions
30 indicates that the most effective intervention is to give vaccines to slums and apply
31 social distancing to non-slums. Applying vaccine and social distancing to slum regions
32 is the next most effective intervention. See Figure 5. By applying social distancing to
33 non-slums, these individuals are kept isolated from slum individuals that are infected.
34 The greatest benefits accrue to the slum populations.
35
36

37 38 39 **Comparison between Networks 1 and 2: Base case versus interventions**

40
41 We start with a comparative analysis of the influenza epidemic, with and without
42 interventions, on Network 1 and Network 2, to measure the impact of integrating slums
43 in the population on epidemic measures. Figure 1 shows the average simulation time
44 histories for the base case, and when vaccination is applied randomly to 30% of the
45 population in each network with vaccine efficacy set at 30%. Mean infection rate is the
46 daily fraction of infected individuals. It is the time-point wise average over 25
47 simulations. For example, the mean infection rate at day 100 is calculated by taking the
48 average of all 25 infection rates. Simulations for other vaccine efficacies and
49 compliance rates give qualitatively similar results. Two sets of those results are shown
50 in the supplemental information, see Figures S1 and S2. Note that Network 1 does not
51 distinguish between slum and non-slum individuals, so the epidemic curve is not split by
52 subpopulation.
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4 Results in Network 2 differ significantly from results in Network 1 for both the base case
5 and intervention case. In Network 2, the epidemic starts earlier, peaks earlier, has a
6 larger epidemic size and has higher peaks compared to the corresponding epidemic
7 quantities in Network 1. Thus, if policy planners ignore slums and use Network 1 to
8 plan, there will be a false sense of security and lack of urgency to implement
9 interventions. For both the base case and the intervention case, ignoring unique
10 characteristics of the slums will result in an underestimation of the infections and the
11 speed of spread.
12

13
14 Figure 1 goes here
15

16
17 For the intervention cases, the time to peak infection decreases by 35.7%, i.e. from 286
18 days for Network 1 to 184 days for Network 2, meaning an influenza epidemic would
19 peak roughly 100 days earlier than one would expect based on the results from Network
20 1. For the base case, time to peak infection drops by 20.8%, i.e. 34 days reduction for
21 Network 2 as compared to Network 1.
22

23
24 Percentage changes and differences must be viewed cautiously, and to illustrate this
25 point, we present data for the key parameters in Tables S4 and S8. The difference in
26 the peak infection rate (i.e., the maximum fraction of daily infected individuals during the
27 simulation) between Networks 1 and 2 for the base case is 2.2%, or 47.6% in
28 percentage change (see Table S8). For the intervention case shown in Table S4, the
29 difference between the two networks is less (1.7%), but the percentage change is more
30 (123.2%) because the magnitudes of the peak infection rates are reduced when
31 effective interventions are used. We make note of this here and mainly use the
32 percentage change values in discussing results. For more detailed comparison between
33 vaccination intervention and the base case in Network 1 and Network 2, we refer to
34 Tables S7 and S9 and Figures S4 and S5.
35
36
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38

39 **Comparison between Networks 1 and 2 based on individual demographic** 40 **information** 41

42
43 We divide the Delhi population into strata by age, gender, and geographic home
44 location (i.e., slum and non-slum), and analyze mean cumulative infection rates by
45 subpopulation for the two networks. In simulations, individuals are chosen at random in
46 the entire network for vaccination. Various vaccination scenarios are investigated.
47
48

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

6
7 For Network 1, vaccination rate of 50% or higher stops the epidemic for all categories of
8 individuals, regardless of vaccine efficacy. An efficacy of 70% also contains the
9 epidemic, given a vaccination rate of at least 30%. In comparison, for Network 2, either
10 a vaccination rate of 70% is required (not shown in plot for clarity) or a vaccination rate
11 of 50% combined with a vaccine efficacy of 70% is required to stop the epidemic for all
12 categories of individuals.
13

14
15 In Network 1, slum and non-slums are treated the same so the infection rates are
16 identical in Figure 2. However, all scenarios in Network 2 show a higher burden of
17 disease on the slum population. This is due to the fact that slum households have larger
18 family size and more contacts on average than households in non-slum areas, see
19 Chen et al.[27] As shown later, we find similar patterns of infection in slum and non-
20 slum subpopulations for other interventions such as 'close-schools' and 'stay-home'.
21
22

23
24 The results in both Figure 1 and Figure 2 indicate that ignoring the effect of slums
25 results in overestimation of the benefits of interventions in terms of reduction in the
26 mean cumulative infection rate and peak infection rate, as well as the time to peak. This
27 optimism holds for slum, non-slum and total population under various levels of
28 vaccination rates and efficacy rates in Network 2. See Table S10 for more detailed
29 comparison of results between slum and non-slum in Network 2.
30

31
32 Figure 2 goes here
33

34 35 **Comparison between Networks 1 and 2 across a wide range of intervention** 36 **strategies** 37

38
39 Next, we consider a variety of intervention strategies for comparative analysis. We
40 consider vaccination, school closure, stay home, and isolation strategies. For vaccines,
41 three different trigger points are considered: when cumulative infection rate reaches 0%
42 (VAX0), 1% (VAX1) and 5% (VAX5). For close-schools, two trigger points are used:
43 when the cumulative infection rate reaches 1% (CS1), and 5% (CS5). Under the stay at
44 home (SHO) strategy, all non-home activities and interactions are eliminated but all
45 contacts within the household are maintained. Under isolation (ISO) an individual has
46 no contact with other individuals (even home interactions are eliminated). The stay-at-
47 home and isolation interventions are implemented for compliant infectious individuals,
48 after they become infectious, for the entire infectious duration.
49
50

51
52 Figure 3 displays average cumulative infection rates in Network 1 and Network 2 for a
53 wide range of intervention strategies. For each strategy, five different compliance rates
54 are considered, i.e., 10%, 30%, 50%, 70% and 90%. The cumulative infection rates
55 (i.e., fractions) are displayed as larger numbers in boxes, while smaller-font numbers
56 are the actual number of infected individuals. Darker colors correspond to higher
57 infection rates. Note that compliance rate is simply the vaccination rate for strategies
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3 VAX0, VAX1 and VAX5. Compliant individuals are selected at random from the entire
4 population. The 'Base' values do not vary with compliance because the base case has
5 no intervention. Note that all heat maps in this paper use the same color scheme so that
6 colors can be compared across figures.
7

8
9 Since Network 1 does not distinguish between slum and non-slum populations, we only
10 compare the two networks for the whole of Delhi. The general pattern is similar for both
11 networks. However, all interventions have a larger effect on Network 1 under the same
12 compliance rate (that is, corresponding numbers are uniformly lower for Network 1 than
13 for Network 2). The infection rates drop to zero at a smaller compliance rate for VAX0,
14 stay-home, and isolation strategies in Network 1 as compared to those for Network 2.
15
16

17 Figure 3 goes here
18
19

20
21 At a high level, among all intervention strategies, early vaccination (VAX0 and VAX1),
22 social isolation (ISO), and stay home (SHO) are more effective than the other
23 strategies, and this is more readily observed at higher compliance rates. For these
24 more effective strategies, the interventions per person are implemented right after (or
25 very shortly after) the person is infected. For example, SHO is implemented
26 immediately after a person becomes infectious. Thus, a person that becomes infectious
27 can infect their family members, but if these other members become infectious, then
28 they, too, will be confined to home. Thus, home-bound people can infect their family
29 members, but no one beyond their family (for 100% compliance). As compliance rate
30 increases, this effect approaches, roughly, a "family-based" isolation intervention
31 (similar to ISO), consistent with the results in Figure 3 and in subsequent results.
32
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37 **Effect of vaccination versus social distancing on slum and non-slum** 38 **subpopulations** 39

40 We now compare the impact of vaccination and social distancing on slum and non-slum
41 subpopulations from Network 2. Social distancing interventions are close-schools, stay-
42 home, and isolation.
43
44

45 The mean cumulative infection rates (and actual numbers of infections underneath) for
46 each compliance level are shown in the heat maps in Figure 4 for slum and non-slum
47 populations in Network 2. The axis labels are identical to those in Figure 3, as is the
48 color scheme of the cells. The base case values are constant since there is no
49 intervention and hence no compliance. Darker colors correspond to higher infection
50 rates.
51
52

53 Compared to the base case, all interventions reduce infection rates to some extent. As
54 the compliance rate increases, infection rates drop for all interventions. Infection rates
55 drop to zero in slum and non-slum regions at a compliance level of 70% or higher,
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3 under SHO, ISO, and VAX0 strategies. Early interventions or lower trigger levels reduce
4 the infection rates significantly, and this effect increases with compliance rate.
5

6
7 The following observations can be made from Figure 4. Social distancing, i.e. SHO, at
8 low and intermediate compliance and CS at all compliance levels, are less effective in
9 slum regions as compared to non-slum regions. This is because CS only eliminates
10 school interactions for those attending school, and there are fewer school edges in
11 slums compared to non-slum areas, as shown in Figure S6. The effectiveness of CS in
12 slums is mitigated by the greater average number and duration of interactions at home
13 in slums as compared to non-slums (see Figure S6 and Chen et al.[27]). Thus, if a
14 person is sick, there is a greater chance of transmitting contagion to family members,
15 who then may have activities outside of school, thus circumventing the CS intervention.
16 At high compliance, SHO is effective because all interactions outside home (including
17 school) are eliminated.[27]
18
19

20
21 These observations are also supported by Figure S7, which contains numbers of edges
22 used to transmit contagion for a base-case run of Figure 1. There are several effects
23 that bear on the above observations. First, in the cases of activities “work”, “other”, and
24 “school”, the number of edges transmitting contagion from slums to non-slums is greater
25 than the reverse: from non-slum to slum. Second, in two of these three activity
26 categories, there is more slum to non-slum transmissions than slum to slum
27 transmissions. Edges of transmission for slum dwellers is dominated by home
28 interactions. The infected homes in slums serve as launching points to drive disease to
29 non-slums through slum to non-slum interactions. (There are no “mixed” edges at
30 homes, and shopping and college activities have low levels of slum activity because of
31 socio-economic factors.) We will see the effects of these mechanisms in Figure 5, but
32 we now return to Figure 4.
33
34
35

36 Isolation works well at 30% or higher compliance rates, but it is a much harder strategy
37 to implement, especially in slums. However, it is considered here for comparative
38 analysis. Vaccination also produces marked decreases in cumulative outbreak sizes as
39 compliance increases. However, close-school is generally less effective because this
40 intervention removes only a fraction of interactions for a fraction of the population, i.e.
41 school aged children. Simulations were also run for 70% vaccine efficacy. Since results
42 are qualitatively similar for those parameters, these plots are provided in Figure S3.
43
44
45

46 Figure 4 goes here

47 48 49 **Comparison between Network 1 and non-slum areas of Network 2**

50
51 Note that Network 1 treats all parts of the region as non-slum, i.e. all individuals follow
52 non-slum activities and demographics. In order to capture the additional disease risk to
53 the non-slum population that arises from the interactions with the slum population, we
54 compare Network 1 in Figure 3a with the non-slum population of Network 2 in Figure 4b.
55 In base case, the additional disease risk to the non-slum population goes up from 42%
56 to 45%. However, the beneficial effects of social distancing strategies drop by a large
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3 amount, e.g. close school strategies are 5-20% less effective in the non-slum areas of
4 Network 2. This effect changes non-linearly with the compliance rate. As compliance
5 rate goes up, the difference between performance of Network 1 and non-slum parts of
6 Network 2 goes up in CS1 and CS5. This implies that in Network 2, non-slum population
7 requires much higher levels of compliance to achieve the same results as in Network 1.
8 This difference is less stark for vaccination based interventions, i.e. VAX0, VAX1 and
9 VAX5. This is expected since the effect of vaccination is less dependent on interactions;
10 it is only through herd immunity that interactions come into play.
11
12

13 **Constrained resource allocation among slum and non-slum areas**

14
15 We consider a specific scenario under Network 2. If only a limited number of vaccines
16 are available, and only a certain fraction of individuals can be kept home during an
17 epidemic, how should these interventions be applied to the slum and non-slum regions
18 so that the epidemic can be controlled effectively? Given that slum residents' attributes
19 differ from those of non-slum residents, is there a strategy that works better in slums
20 than in non-slum areas? The total population in Delhi is about 13.8 million, which
21 includes about 1.8 million slum residents. We assume that only 10% of the total
22 population can be covered by interventions, half through vaccination and the other half
23 through stay home. Enough vaccines are available to cover 5% of the total population
24 (i.e. 692,183 vaccinated, corresponding to about 38.25% of slum or 5.75% of non-slum
25 population), and 5% of the individuals can stay home (692,183 individuals; this is
26 applied to only the infected individuals). Note that an individual may receive a vaccine
27 and also stay at home if this individual, in spite of being vaccinated, gets infected.
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33 We consider 4 different ways of applying interventions to 10% of the total population: (i)
34 apply both interventions to slums, i.e. give all vaccines to slums and apply SHO only in
35 the slums (VsSs); (ii) apply all interventions to non-slum areas (VnSn); (iii) give vaccines
36 to slums and SHO to non-slums (VsSn) and (iv) give vaccines to non-slums and apply
37 SHO to slums (VnSs).
38
39

40 For both types of intervention, the same number of individuals is chosen randomly from
41 slum or non-slum areas. 10% of the total Delhi population amounts to 76.5% of slum
42 population, 11.5% of the non-slum population, or a combination of 38.25% of the slum
43 and 5.75% of the non-slum population (i.e. half from slums and half from non-slums).
44 Figure 5 shows the mean cumulative infection rates, as well as the number of infected
45 from the entire population of Delhi, the slums, and non-slum areas under each of the
46 four scenarios. The first 3 columns refer to Network 2 and the last column shows results
47 for Network 1. Since Network 1 does not distinguish between slum and non-slum areas,
48 the infection rates in each subpopulation remain the same as for the total population.
49
50
51

52 Comparison of the last two columns in Figure 5 indicates that the non-slum population
53 in Network 2 faces 3-5% additional disease risk compared to Network 1 in all cases.
54 This is primarily driven by the increased interactions within slum populations and
55 between slum and non-slum populations in Network 2.
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4 In Figure 5, all four intervention strategies produce essentially the same total attack
5 rates (around 43% to 44%), a drop of 4% to 5% over the base case. The dominant
6 effect on Network 2, is the benefits that primarily accrue to the slum population for the
7 VsSs and VsSn strategies because they drive down the fraction of infected slum
8 residents from 0.74 to 0.55 or 0.58. Also, as described in the context of Figures 4 and
9 S6 above, social distancing of the non-slum residents helps to isolate them from the
10 infected slum residents. Results such as these may be helpful to policy makers in
11 breaking the poverty trap in economically poor regions.[43]
12

13
14 Also, the strategy of vaccinating non-slums and social distancing slums (VnSs) is not as
15 effective as the interventions in rows 1 and 2 of Figure 5. This is a counterintuitive
16 result, since the density of population is much higher in the slums, which may lead to
17 the belief that social distancing in slums will break up the dense clusters. However, a
18 careful examination shows that keeping slum residents home is not an effective social
19 distancing strategy because their family size is, on average, almost 3 times the family
20 size of non-slum households.[27] The high level of mixing at home makes social
21 distancing ineffective in slums unless the infected individual is completely isolated.
22 However, complete isolation is not viable in slum areas where the entire household may
23 live in a single room.
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29 Figure 5 goes here
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32 DISCUSSION 33

34 With slum populations expected to grow to 2 billion by 2030,[44] it is becoming
35 increasingly urgent to understand how to control the spread of infectious diseases in
36 slum areas and measure its effect on urban populations. To our knowledge, a detailed
37 study of interventions to control influenza epidemics in slums, using an agent-based
38 simulation model, has never been done before. Slum conditions are important for a city
39 beyond the direct effects of disease transmission. For example, civil wars may be
40 precipitated or exacerbated by disease outbreaks because they decrease social health
41 and welfare.[45]
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43
44

45 Even though slum regions contain only 13% of the total population of Delhi, Chen et
46 al.[4] show that omitting their attributes leads to underestimation of the overall infection
47 rate and the peak infection rate of the epidemic. This paper extends that work by
48 evaluating the differential impact of interventions on slum and non-slum regions.
49 Various vaccination and social distancing strategies are analyzed under different
50 scenarios that show that the slum population is more prone to infections under the same
51 control measures. Furthermore, taking account of slum populations significantly alters
52 the disease dynamics in the *entire* population. Differences in key measures are
53 demonstrated between the cases of accounting for slum populations and not: e.g., a
54 100% increase in the peak attack rate in some cases when slum regions' characteristics
55 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;

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3 this was only done here in Figure 5. However, to disambiguate results, it is prudent to
4 first examine individual interventions. (12) Effect of changing disease transmission rate
5 for different activity types. (13) Effect of changing contact times at different locations.
6 (14) To capture close-proximity transmission, one could use actual physical proximity.
7 Here, we use colocation. Finally, just as changes in modeling details can change model
8 results, so, too, changes in the conditions in actual outbreaks can change results; some
9 of these factors are listed above. It is essentially impossible to capture all of these
10 effects—many of which are unknown—down to the level of individual humans.
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14 Public health implications: This research demonstrates that modeling slum populations
15 is important, not only for understanding disease dynamics, but also for designing
16 effective control measures. Ignoring the influence of slum characteristics on their urban
17 environment will significantly underestimate the speed of an outbreak and its extent,
18 and hence will lead to misguided interventions by public health officials and policy
19 planners. Lessons from this research can be applied in the field and observations
20 collected from the field can provide valuable data to improve the models and validate
21 the results. For example, our results show that a slum resident has about 50% greater
22 total contact duration per day compared to a non-slum resident. This makes social
23 distancing based interventions more taxing in the slum population. Public health policy
24 makers may want to subsidize pharmaceutical resources for the slum population to
25 make them more affordable. Similarly, we find women in slums have a higher number of
26 contacts per day than their male counterparts whereas in non-slum regions, women
27 have a fewer number of daily contacts than their male counterparts. This kind of
28 information can be used to prioritize the distribution of limited resources, e.g. women
29 could be given preference over males for vaccination in slum areas. This research
30 provides simulation-based evidence that in general social distancing strategies are
31 ineffective in slums because of a large number of contacts at home. Unless one applies
32 complete isolation, which is not feasible in slums, just staying at home still keeps a large
33 number of contacts and pathways of spread intact.
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4 **Contributorship statement**

5 AA, SE, CJK, AM, MM, SS, AV designed and conceived the study. SC carried out the
6 experiments and simulations. SC, CJK, AM performed data analysis. CJK, BL, AM, MM,
7 EKN, MLW helped with reviewing the results and writing the paper.
8
9

10 **Competing Interests**

11 There are no competing interests.
12
13

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21 09S1).
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28 **Data Sharing Statement**

29 Data pertaining to figures and statistical analysis are partially provided in the
30 supplementary file, and also can be obtained by contacting the corresponding author
31 through email.
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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 ($\alpha = 30\%$, 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

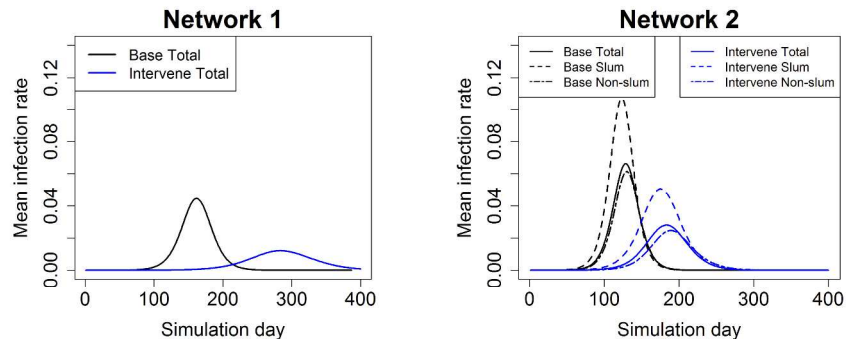
Figure 4. Heat map of cumulative infection rates in slum and non-slum regions of Network 2 under different intervention strategies. The colors of boxes correspond to the larger numbers in the boxes—the cumulative infection rates—and the two plots use the same scheme for comparisons. Darker colors correspond 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

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3 intervention strategies (vaccination (VAX), close-schools (CS), stay-home (SHO) and
4 isolation (ISO)) are considered. For vaccines, three different trigger points are
5 considered: when cumulative infection rate reaches 0% (VAX0), 1% (VAX1) and 5%
6 (VAX5). For close-schools, two trigger points are used: when the cumulative infection
7 rate reaches 1% (CS1) and 5% (CS5). Compliant individuals are selected randomly
8 from the entire Delhi population, and the mean infection rates are calculated separately
9 for the slum and non-slum subpopulations. Although not reported here, qualitatively
10 similar results are found for other transmission rates, as well as for higher vaccine
11 efficacy (70%). Base is the baseline case with no interventions. The smaller-font
12 numbers under the infection rate show the actual number of infected individuals.
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16 **FIGURE 5:** Mean cumulative infection rates for each category listed on the x-axis, for
17 Network 2 and Network 1, under four different intervention scenarios. The color scheme
18 of the boxes are based on the large values in the boxes—the cumulative infection rates.
19 Darker colors correspond to higher infection rates. Smaller font values are the number
20 of infected individuals. The vaccine efficacy is set at 30%. VsSs refers to the case when
21 vaccines and social distancing are both applied to slum residents; VnSn refers to the
22 case when vaccines and social distancing are applied to non-slum residents. Similarly,
23 VsSn means vaccines are given to slums and stay home is applied to non-slums; and
24 VnSs means vaccines are given to non-slums and stay home is applied to slums. Base
25 refers to the case where no intervention is applied. The smaller-font numbers under the
26 infection rates show the actual number of infected individuals in each category listed on
27 the x-axis.
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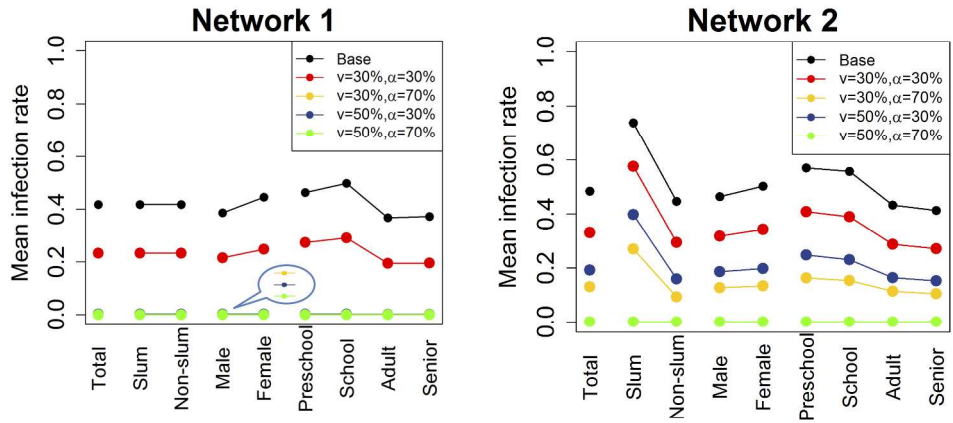
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Intervention	Base	C ₁	C ₂	S ₁	S ₂	I ₁	I ₂	V ₁	V ₂
V ₁	0.36	0.23	0	0	0				
V ₂	5038837	3228985	20921	221	97				
I ₁	0.37	0.25	0.11	0.04	0.02				
I ₂	5061754	3405459	1549547	539181	322258				
S ₁	0.37	0.27	0.19	0.13	0.1				
S ₂	5146506	3802876	2618588	1781022	1318401				
C ₁	0.3	0	0	0	0				
C ₂	4158127	648	62	35	23				
S ₁	0.36	0.12	0	0	0				
S ₂	4939914	1659965	241	89	51				
I ₁	0.36	0.24	0.14	0.08	0.06				
I ₂	5017949	3367475	1880956	1121321	881914				
C ₁	0.37	0.27	0.19	0.15	0.16				
C ₂	5112280	3738161	2615064	2125815	2169135				
Base	0.42	0.42	0.42	0.42	0.42				
	5772516	5772516	5772516	5772516	5772516				

Intervention	Base	C ₁	C ₂	S ₁	S ₂	I ₁	I ₂	V ₁	V ₂
V ₁	0.44	0.33	0.19	0	0				
V ₂	6070999	4584539	2669426	18530	206				
I ₁	0.44	0.34	0.21	0.1	0.04				
I ₂	6087287	4654816	2967789	1350667	554670				
S ₁	0.44	0.35	0.26	0.17	0.13				
S ₂	6146453	4898048	3594239	2329038	1818146				
C ₁	0.39	0.03	0	0	0				
C ₂	5465084	478780	85	37	23				
S ₁	0.44	0.31	0.08	0	0				
S ₂	6047827	4323509	1098024	543	83				
I ₁	0.45	0.37	0.31	0.29	0.27				
I ₂	6191602	5188739	4357831	4018271	3675802				
C ₁	0.47	0.44	0.43	0.42	0.4				
C ₂	6470698	6101056	5883830	5766943	5600599				
Base	0.48	0.48	0.48	0.48	0.48				
	6704038	6704038	6704038	6704038	6704038				

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		0.69	0.58	0.4	0	0
	V _{air0}	1263625	1041034	719517	7505	66
	V _{air1}	0.69	0.58	0.43	0.24	0.1
	V _{air5}	1296162	1052247	775240	426160	166606
	V _{air7}	0.7	0.6	0.49	0.36	0.29
	V _{air9}	1265497	1094158	890080	649544	525620
	ISO	0.65	0.08	0	0	0
	ISO	1168239	146106	20	7	3
	SHO	0.71	0.61	0.25	0	0
	SHO	1279142	1102671	460613	301	30
	CS ₁	0.72	0.7	0.67	0.66	0.65
	CS ₁	1311761	1260823	1215625	1194938	1171916
	CS ₃	0.73	0.72	0.72	0.71	0.71
	CS ₃	1326417	1309021	1298824	1292254	1283791
	Base	0.74	0.74	0.74	0.74	0.74
	Base	1337160	1337160	1337160	1337160	1337160
		10%	30%	50%	70%	90%
		Compliance				

		0.4	0.29	0.16	0	0
	V _{air0}	4817373	3542870	1921714	11025	139
	V _{air1}	0.4	0.3	0.18	0.08	0.03
	V _{air5}	4831106	3602969	2192949	924508	368084
	V _{air7}	0.41	0.32	0.22	0.14	0.11
	V _{air9}	4880956	3803892	2704160	1679494	1292525
	ISO	0.36	0.03	0	0	0
	ISO	4298845	332875	65	30	20
	SHO	0.4	0.27	0.05	0	0
	SHO	4768685	3220638	637412	242	53
	CS ₁	0.41	0.33	0.26	0.23	0.21
	CS ₁	4879841	3927917	3142206	2823334	2503886
	CS ₃	0.43	0.4	0.38	0.37	0.36
	CS ₃	5144281	4792032	4585006	4474690	4316809
	Base	0.45	0.45	0.45	0.45	0.45
	Base	5366878	5366878	5366878	5366878	5366878
		10%	30%	50%	70%	90%
		Compliance				

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V_{sSs}	0.44 6043049	0.55 989079	0.42 5053971	0.37 5176345
V_{sSn}	0.43 5938919	0.58 1042116	0.41 4896803	0.36 4995753
V_{nSs}	0.44 6023678	0.67 1217415	0.40 4806263	0.36 4986302
V_{nSn}	0.44 6104571	0.72 1309577	0.40 4794993	0.36 5016324
Base	0.48 6704038	0.74 1337160	0.45 5366878	0.42 5772516
	Total Network 2	Slum Network 2	Non-slum Network 2	Total Network 1

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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

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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.

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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

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

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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.

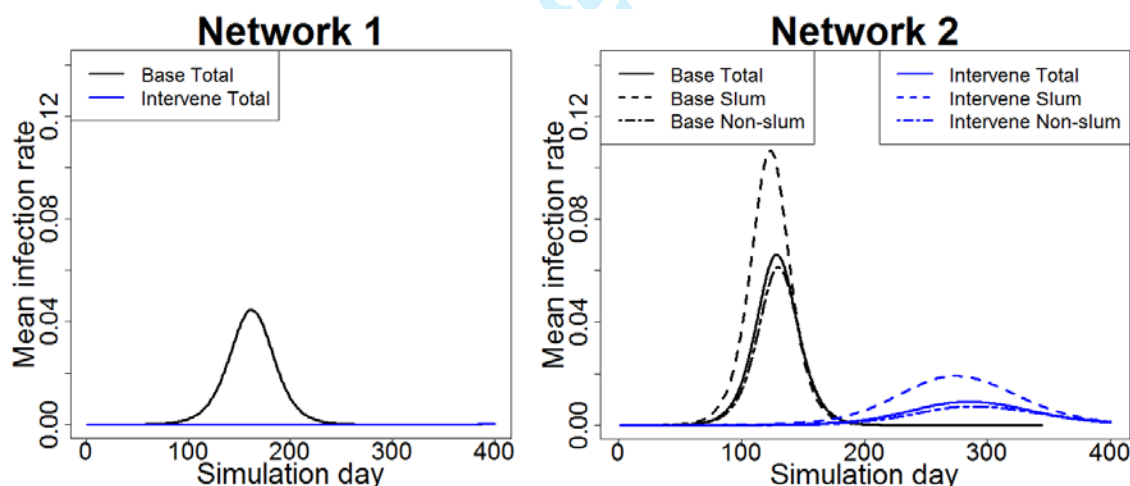


Figure S1: Epidemic curves for the base case and the vaccination case. The vaccines are given randomly to 50% of the entire population, and the vaccine efficacy is assumed to be 30%. The transmissibility is 0.000027.

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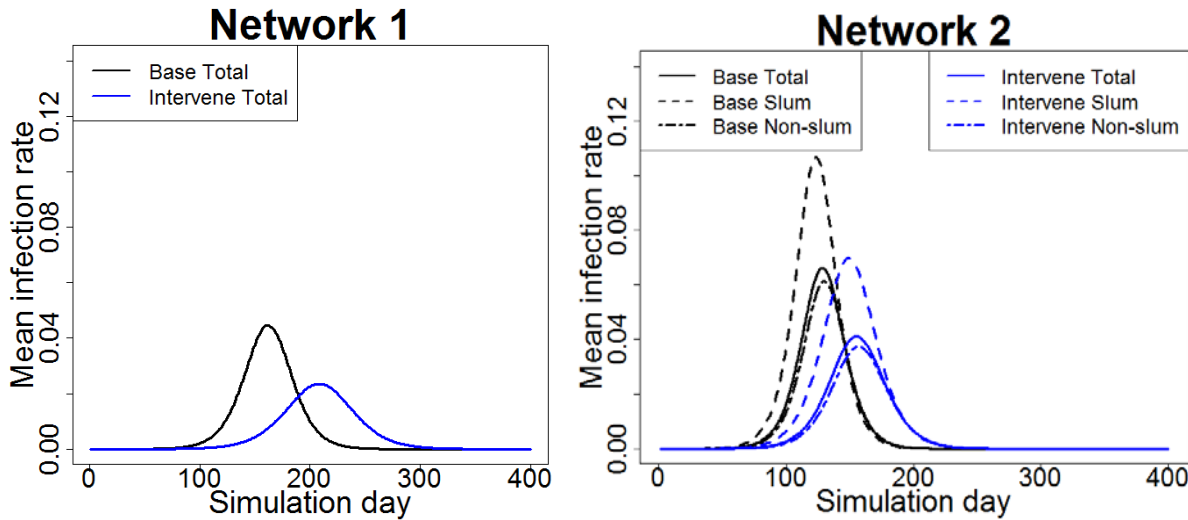


Figure S2: Epidemic curves for the base case and vaccination case. The vaccines are given randomly to 10% of the entire population and the vaccine efficacy is 70%. The transmissibility is 0.000027.

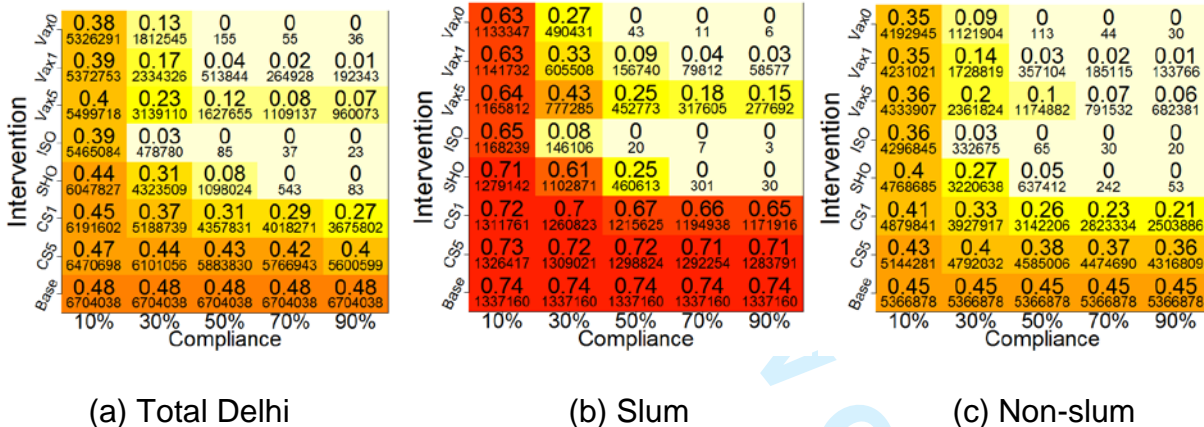


Figure S3. Heat map of mean cumulative infection rates in Delhi, and slum and non-slum regions under different intervention strategies for Network 2. The vaccination efficacy is fixed at 70%. Five different compliance rates, i.e., 10%, 30%, 50%, 70% and 90% and 4 types of intervention strategies, i.e. 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.

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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%,

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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

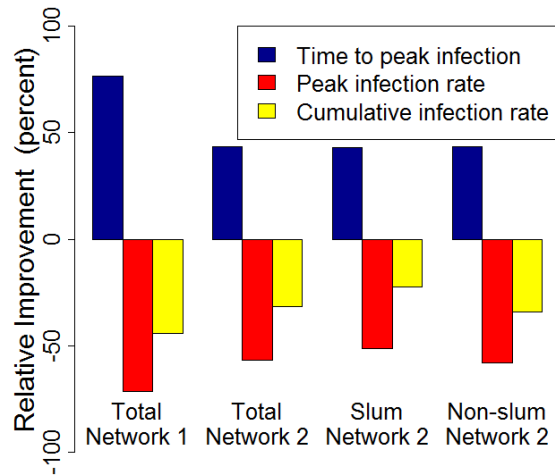


Figure S4: Effects of vaccination on time to peak infection, peak infection rate, and cumulative infection rate. The intervention is 30% vaccination rate and 30% vaccine efficacy. Each bar refers to the average value of the relative difference over 25 runs. Vaccination is more effective for Network 1 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 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

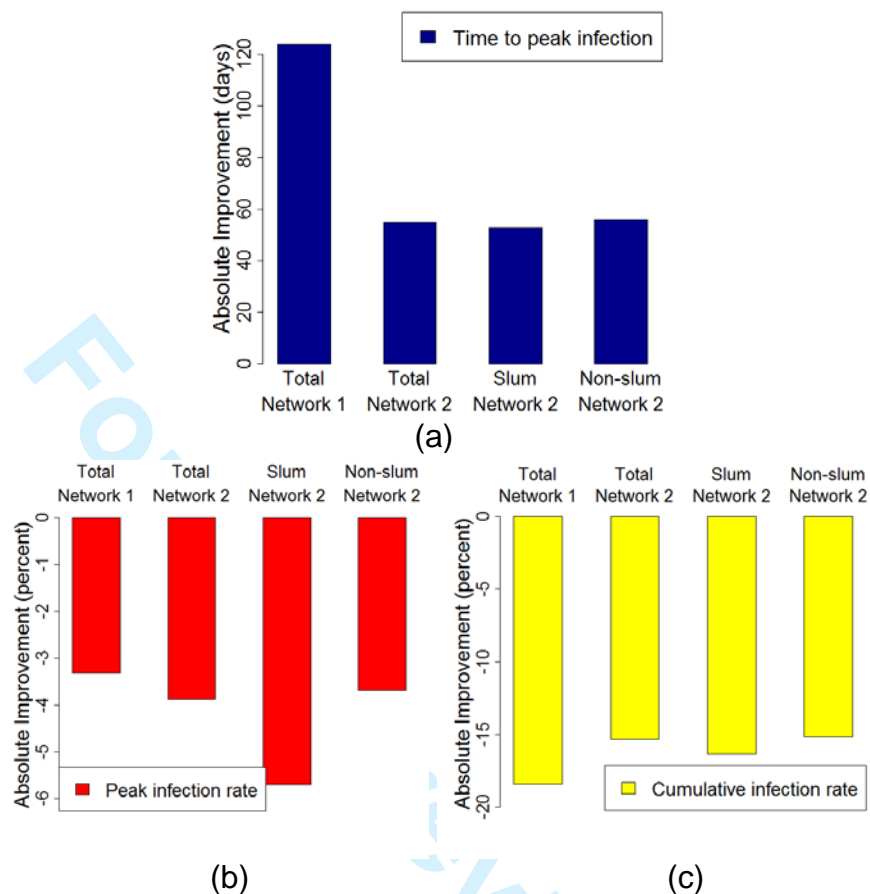
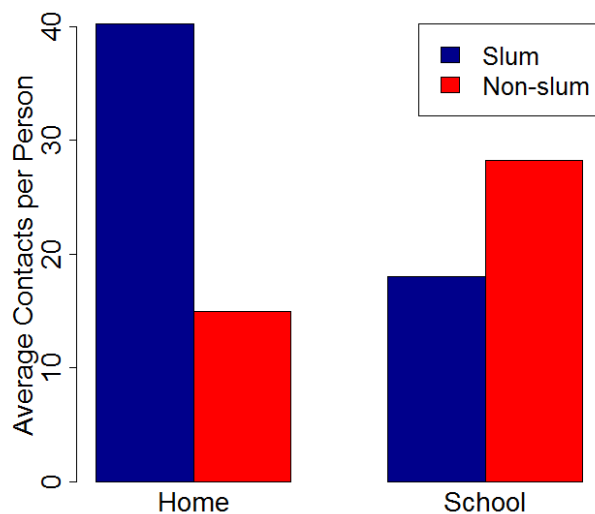


Figure S5: Comparison of absolute difference in improvement; the relative differences are shown in Figure S7. Absolute differences vary across the three parameters, so each is given on a separate scale. Data are summarized in Tables S7 and S9.

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).

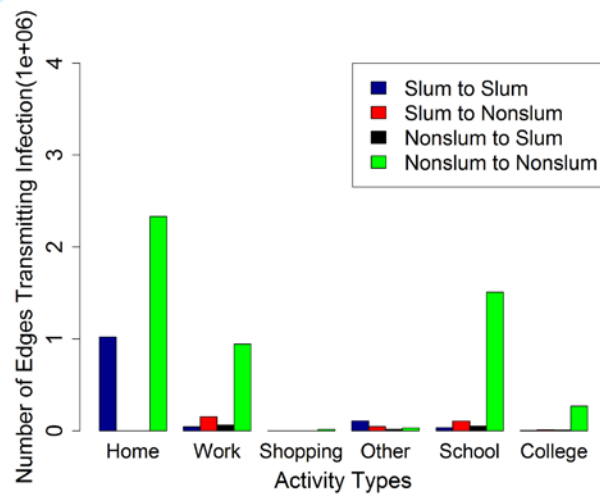


Figure S7. Data for Network 2. Number of edges transmitting infection (in millions) for each of the four types of interactions between slum and nonslum individuals (see legend) and for each activity type. The number of slum-to-nonslum edges is greater than nonslum-to-slum ones because once infection 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

References

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4. Jesan T, Menon G, Sinha S. Epidemiological dynamics of the 2009 influenza A(H1N1) v outbreak in India. *Current Science* (00113891) 2011; 100(7): 1051.