# Understanding Health Disparities in an Influenza Epidemic

Lijing Wang* Jiangzhuo Chen*† Achla Marathe*

**Abstract**

Infectious disease epidemics such as influenza and Ebola pose a serious threat to global public health. Certain demographics and cohorts have higher risks of getting infected than others due to a variety of factors. In this research we explore the heterogeneities in individuals' demographic and socioeconomic attributes as the potential causes of health disparities in an influenza epidemic. We use an agent-based model to simulate an influenza epidemic over a synthetic social contact network of Montgomery county population in Southwest Virginia. We divide the population into age and income based cohorts and measure the direct and indirect economic impact from vaccination interventions for each cohort. The metrics used for measuring the economic impact include net return per capita, net return per vaccinated person, and net return per dollar spent. Results show significant health disparities in terms of attack rate across age groups and income groups, and economic disparities in terms of intervention efficiency among age groups.

## 1 Introduction

Infectious disease epidemics such as influenza and Ebola pose a serious threat to global public health. In the United States, it is estimated that in each year seasonal influenza causes 31.4 million outpatient visits, over 200,000 hospitalizations, 3,300-49,000 deaths, and is responsible for 44.0 million days lost (based on 2003 population, see [20]) [10, 25, 27]. Among the public health interventions for containing influenza epidemics, mass vaccination is among the most effective strategies. In fact, the United States Centers for Disease Control and Prevention (CDC) has recommended influenza vaccination for all persons aged six months and older since 2010 [10, 17].

There have been studies on the cost effectiveness of vaccination for children [9, 13, 16, 18, 21, 26], healthy working adults [7, 15], people of age 65 years and above [23]. These works focused on direct and indirect impact that takes medical cost and productivity loss into account, respectively. There are also studies on variations of the cost of influenza infections due to different outcomes: death, hospitalization, outpatients, ill but no medical care [4, 6, 14]. Prior work did not study the health disparities originated from differences in individual level attributes, such as age, income, etc.

Health disparities is defined as a particular type of health difference that is closely linked with social, economic, and/or environmental disadvantage. Health disparities adversely affect groups of people who have systematically experienced greater obstacles to health possibly due to their age; gender; geographic location; income level and other socioeconomic status; racial or ethnic

*Network Dynamics and Simulation Science Laboratory, Biocomplexity Institute, Virginia Tech, Blacksburg, VA 24061.

†Corresponding author. Email: chenj@vbi.vt.edu.

background; religion; mental health; cognitive, sensory, or physical disability; sexual orientation or gender identity; or other characteristics historically linked to discrimination or exclusion [12].

In this work we focus on the heterogeneities in individuals' demographic attributes (like age, gender) and socioeconomic attributes (like occupation, income). During infectious disease epidemics, individual social behavior, which depends on the individual's demographic and social economic attributes, affects his/her vulnerability (probability of getting infected if being susceptible) or infectivity (probability of infecting others if being infectious), as well as his/her compliance with interventions. At cohort level, this leads to different attack rate (overall fraction of a subpopulation being infected), peak infection number (largest daily infection number), and time to peak, as well as consumption of health care and interventions resources and effectiveness of public health interventions. Therefore, the heterogeneities at individual level can lead to significant difference in health outcomes and economic returns at subpopulation level, i.e., significant population health disparities [1, 2, 11, 22, 28].

In this paper our objective is to learn heterogeneities in which individual level attributes may have an impact on health outcomes and economic cost, using an agent-based model. By simulating epidemics where vaccine-based interventions are applied to either randomly selected or targeted groups of people in the population, we study health disparities among different age groups and income groups.

**Our contributions**: (i) We use an agent-based model to study health disparities among age and income-based groups during an influenza epidemic, in the Montgomery county of Southwest Virginia. (ii) We provide a methodology to explore and evaluate vaccination strategies in term of specific objectives by using simulations, and identify the optimal vaccination priority. The findings have significant policy implications that may assist public health decision making in assigning limited pharmaceutical resources.

## 2 Methods

In this study, we apply EpiFast, an agent based epidemic simulation model, to simulate the spread of influenza in a synthetic population through a people to people contact network. We choose Montgomery county of Virginia to run our simulation experiments for analyzing health disparities. The synthetic population of Montgomery county (available at [24]) is constructed to be a realistic representation of the real population [1, 3, 22, 28]. It includes individual level demographic, socioeconomic, geographic attributes, and daily mobility and activities of each individual. From colocation of people a synthetic social contact network is constructed to allow simulations of epidemics at person to person transmission level in this population.

The high performance computing based epidemic simulation model, EpiFast [5], adopts the susceptible-exposed-infectious-recovered (SEIR) epidemiological model for within-host disease progressing and can be used to study the transmission dynamics of an influenza-like-illness with individual level details in a synthetic population like the aforementioned one of Montgomery county. From the simulation output we know which people are infected, on which days they are infected, and who infect them. We choose to simulate two scenarios regarding interventions: **base case**, where there is no intervention to contain the epidemic; and **intervention case**, where an intervention is applied to a subset of the population. The intervention may be targeted (towards a subpopulation chosen by individual's specific attributes) or completely random (every person may be intervened probabilistically). In this research we focus on mass vaccination, which is applied at the beginning of the epidemic. Each person chosen to be vaccinated complies with a specified probability, called compliance rate.

Each infected person can have one of four health outcomes attributed to influenza infection: death, hospitalization, outpatient, ill but not seeking medical care. The health outcome of an infected person depends on his or her age and underlying risk condition. One's risk condition (high risk/non-high risk) depends on his/her age too. In our simulation we assign health outcomes to each infected person with a conditional distribution of outcomes given his/her age and risk condition [17]. Once we know the individual level outcomes, we can calculate health outcomes for each age or income cohort.

The vaccination cost is estimated as $30.53 [19]. The economic cost of an epidemic includes medical costs related to treatment of infected cases (direct costs) and socio-economic costs related to productivity loss of infected people (indirect costs). Costs of an infected individual depend on his/her age, risk condition, and outcome; such estimates are adopted from [8] and adjusted to year-2016 USD.

By aggregating individual total cost at cohort level or population level, and comparing the base case and the intervention case, we can compute the net return of a vaccine-based intervention as:

$$net\ return = total\ cost(base\ case) - total\ cost(intervention\ case) - vaccination\ cost$$

Note that our individual based model allows us to calculate net return for any subpopulation and for any health outcome. More details will be shown in Section 3.

# 3 Experiments

In this section, we first present our simulation settings, then analyze some of the interesting results as well as policy implications regarding both age groups and income groups. For sensitivity, we vary the compliance rate of vaccination intervention in the simulations to study the robustness of our observations.

## 3.1 Simulation settings

In this experiment we focus on the Montgomery county of Virginia. It is a rural region with a population of about 77,000 people. We run epidemic simulations on the synthetic contact network of this region and analyze the simulation output of individual infections, joined with the synthetic demographic and socioeconomic data of these infected individuals. The disease model parameters are calibrated such that the attack rate when no intervention is applied is about 40%; the corresponding transmissibility (probability of disease transmitting from an infectious person to a susceptible person in every minute of contact time between them). Details about interventions are shown in Table 1: Compliance rate is the probability that a chosen person for an intervention complies with it. We assume that the vaccine has a 90% efficacy, i.e., it reduces the probability of disease transmission (a susceptible person being infected or an infectious person infecting other people) by 90%. Note that these parameter values do not correspond to any specific epidemic, as they vary from season to season and differ between populations. We choose realistic values for them in this study. For each parameter setting, we run the simulation for 30 replicates.

Table 1: Simulation settings

| | base-case | intervention-case |
|---|---|---|
| transmissibility | 0.00007 | 0.00007 |
| intervention | – | vaccination |
| compliance rate | – | 0.5 |
| efficacy | – | 90% |

## 3.2 Health disparities among age groups

To study health disparities due to age, we divide the population into four age groups: 0-4 years old (preschool); 5-19 years old (school age); 20-64 years old (adult); 65 years old and above (senior).

### 3.2.1 Health disparities of vulnerability and outcome

In Table 2 we compare the attack rates in different age groups. The t-test results suggest that the attack rate is significantly different between any two age groups. This shows that there are health disparities among age groups, specifically the school age people are much more vulnerable to influenza infections than other age groups.

Table 2: Disparity analysis of attack rate (AR) among age groups: p-value (base-case)

| | preschool | school | adult | senior |
|---|---|---|---|---|
| preschool ($\overline{AR} = 44\%$) | - | 0.0001*** | 0.0001*** | 0.0001*** |
| school ($\overline{AR} = 70\%$) | - | - | 0.0001*** | 0.0001*** |
| adult ($\overline{AR} = 34\%$) | - | - | - | 0.0001*** |
| senior ($\overline{AR} = 22\%$) | - | - | - | - |

Two-tailed test $*p < .05, **\,p < .01, ***p < .001$. Note $\overline{AR}$ is the average attack rate computed from 30 simulation replicates.

In Table 3 we show the fractions of people in each age group have different outcomes in base-case. Please note that although from [17] we obtain conditional distribution of outcomes given the age and risk condition of each infected individual, Table 3 shows the distribution of these outcomes among *all people including infected and uninfected*, which can only be computed from simulation output.

The most interesting observation from Table 3 is that the death rate of the senior age group is significantly higher than the other age groups. In Table 4, we compare the death rate among age groups with $t$-tests. The results imply statistically significant difference between any two age groups. Although death rate is the smallest among four outcomes, it is an important outcome because of its severe consequence for infected people and the related high costs.

Table 3: Outcome rates in age groups under base-case (outcome count/group size)

| age group | death | hospitalization | outpatient | ill (no medical care) |
|---|---|---|---|---|
| preschool | 0.00035 | 0.00167 | 0.23425 | 0.20635 |
| school | 0.00046 | 0.00254 | 0.36719 | 0.32517 |
| adult | 0.00069 | 0.00200 | 0.12787 | 0.20526 |
| senior | 0.00296 | 0.00364 | 0.10521 | 0.11310 |

Table 4: Disparity analysis of death rate (DR) between age groups: p-value (base-case)

| | preschool | school | adult | senior |
|---|---|---|---|---|
| preschool ($\overline{DR} = 0.00035$) | - | 0.0181* | 0.0001*** | 0.0001*** |
| school ($\overline{DR} = 0.00046$) | - | - | 0.0001*** | 0.0001*** |
| adult ($\overline{DR} = 0.00069$) | - | - | - | 0.0001*** |
| senior ($\overline{DR} = 0.00296$) | - | - | - | - |

Two-tailed test * $p < .05$, ** $p < .01$, *** $p < .001$. Note $\overline{DR}$ is the average death rate computed from 30 simulation replicates.

#### 3.2.2 Health disparities of economic costs and intervention efficiency

**Observation 1: Vaccination intervention is economically more efficient in school age and senior groups than in pre-school and adult groups.**

In Table 5 we show net returns of intervention-case. The total net return can be attributed to either reduction in direct costs (direct net return) or reduction in indirect costs (indirect net return). To account for difference in age group sizes, as well as numbers of vaccines applied to the groups, we show the net return per capita (NRPC), per vaccinated person (NRPV), and per dollar spent (NRPD).

Table 5: Net Return Per (NRP)

| | NRPC $ | | | NRPV $ | | | NRPD $ | | |
|---|---|---|---|---|---|---|---|---|---|
| age groups | direct | indirect | total | direct | indirect | total | direct | indirect | total |
| preschool | 118.88 | 541.01 | 675.13 | 238.19 | 1083.96 | 1352.67 | 7.80 | 35.50 | 44.31 |
| school | 270.19 | 817.19 | 1102.65 | 540.38 | 1634.40 | 2205.31 | 17.70 | 53.53 | 72.23 |
| adult | 157.01 | 615.64 | 787.86 | 315.16 | 1235.75 | 1581.45 | 10.32 | 40.48 | 51.80 |
| senior | 398.43 | 736.86 | 1150.47 | 801.32 | 1481.96 | 2313.81 | 26.25 | 48.54 | 75.79 |

NRPC - net return per capita; NRPV - net return per vaccinate; NRPD - net return per dollar spent.

Table 5 shows that indirect net returns (blue parts of Figure 1) are much larger than direct net

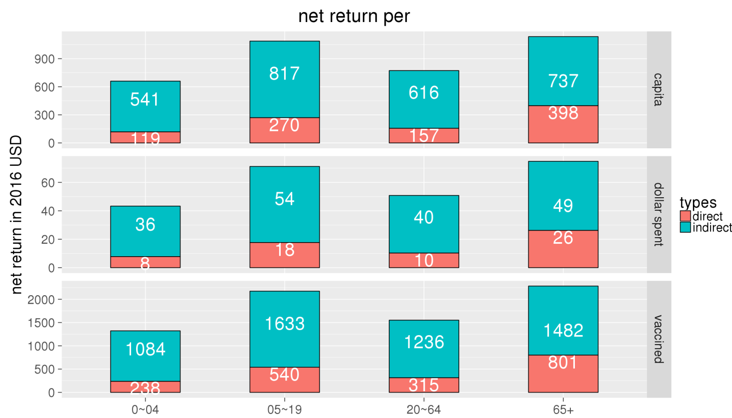


Figure 1: Direct and indirect net returns per capita/dollar spent/vaccinated person of different age groups. Total net return = direct net return + indirect net return.

returns (red parts of Figure 1) in each age group. Another interesting observation from Table 5 is that the school and senior groups have significantly higher total net returns than the other two groups. School and senior groups seem to be similar, however; pre-school and adult groups look similar too. Table 6 is the statistical significance test comparing net return per dollar spent between age groups; and the results support our observation. We observe similar results for net return per capita and per vaccinated person, which are omitted for the sake of brevity.

Table 6: Disparity analysis of NRPD among age groups: p-value

| | preschool | school | adult | senior |
|---|---|---|---|---|
| preschool ($\overline{NRPD} = 44.31$) | - | 0.0001*** | 0.14 | 0.0001*** |
| school ($\overline{NRPD} = 72.23$) | - | - | 0.0001*** | 0.44 |
| adult ($\overline{NRPD} = 51.80$) | - | - | - | 0.0001*** |
| senior ($\overline{NRPD} = 75.79$) | - | - | - | - |

Two-tailed test * $p < .05$, ** $p < .01$, *** $p < .001$. Note $\overline{NRPD}$ is the average net return per dollar spent computed from 30 simulation replicates.

**Observation 2: Cost is significantly higher in the case of death than other outcomes.**

In Table 7, we show the cost of each outcome per capita of each age group in both base-case and intervention-case. Figure 2 visualizes the base-case of Table 7. It is obvious that the per capita (over group size) cost of death is significantly higher than that of the other outcomes.

Figure 3 and Figure 4 show the outcome distribution and the corresponding cost distribution in each age group, respectively. We observe that for each age group, among all outcomes although death rate (red color) is the smallest, the cost of death (red color) is the largest.

Our observations suggest that death is an important outcome to consider while evaluating health disparities of economic efficiency and making public health policies to reduce health disparities.

Table 7: Economic cost per capita on outcomes ($) (cost/group size)

| age groups | base-case death | base-case hospital-ization | base-case outpa-tient | base-case ill (no medical care) | intervention-case death | intervention-case hospital-ization | intervention-case outpa-tient | intervention-case ill (no medical care) |
|---|---|---|---|---|---|---|---|---|
| preschool | 510.71 | 21.81 | 134.88 | 35.27 | 10.44 | 0.08 | 1.42 | 0.36 |
| school | 844.48 | 63.52 | 204.32 | 28.51 | 18.52 | 0.68 | 3.30 | 0.43 |
| adult | 650.11 | 53.51 | 88.89 | 18.00 | 5.97 | 0.52 | 0.79 | 0.15 |
| senior | 854.00 | 70.51 | 236.47 | 15.19 | 7.86 | 0.44 | 2.10 | 0.11 |

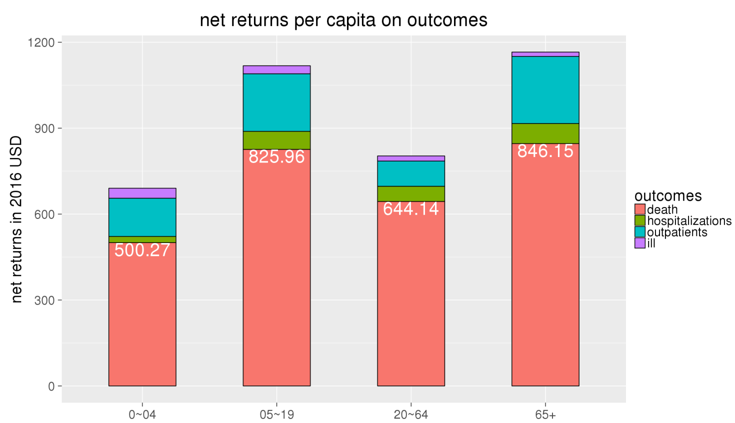


Figure 2: Net returns per capita on different outcomes of different age groups

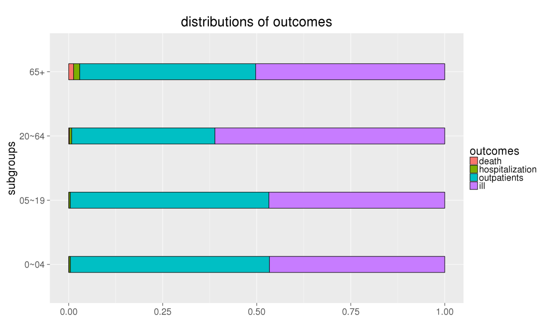


Figure 3: Distribution of death, hospitalization, outpatients, ill but no medical care, over all infections, in each age group.

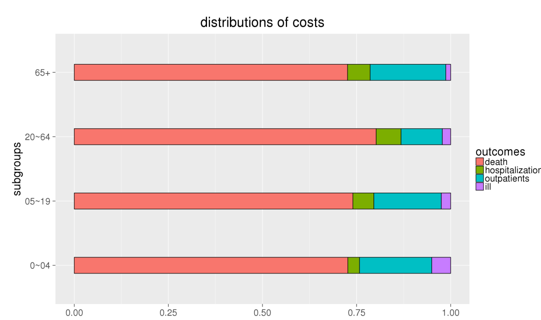


Figure 4: Cost distribution of death, hospitalization, outpatients, ill but no medical care in each age group.

### 3.2.3 Implications for policy

The public health authorities often publish recommendations of interventions to the population. In case of limited resources, e.g. when vaccines are not enough to cover the whole population, some subpopulations are given higher priorities, to optimize the efficiency of interventions towards specific objectives of containing the epidemic. In practice, age is often used to select subpopulations as targets. For example, in the recent CDC (Centers for Disease Control and Prevention) recommendations [10], it is suggested that "*when vaccine supply is limited, vaccination efforts should focus on delivering vaccination to ... all children aged 6 through 59 months; all persons aged* $\geq 50$ *years; ...*".

Here we design different strategies of vaccine assignment among age groups, for four different objectives: minimum death rate, minimum death count, maximum net return per dollar spent on vaccination, maximum total net return from vaccination. For a specific objective, we rank the age groups with respect to the corresponding measure and assign priorities accordingly. For example, for death rate, we find that the senior group has the largest death rate, followed by the adult and the school age groups, and lastly the pre-school group (see Table 3); therefore we assign priorities in the same order for assigning vaccines. The priorities in different intervention strategies for four objectives are shown in Table 8.

Table 8: Priorities of vaccine assignment for four objectives

| | objective for prioritization | | | |
|---|---|---|---|---|
| priority | risk for death | total deaths | NRPD | total net return |
| 1(top) | senior | adult | senior | adult |
| 2 | adult | senior | school | school |
| 3 | school | school | adult | senior |
| 4(bottom) | preschool | preschool | preschool | preschool |

We run four additional sets of simulations, where we apply different vaccination strategies according to age group priorities in Table 8. We assume that the total vaccine supply covers 50% of the population, the same as in the previous intervention-case simulation. The vaccinated fraction of each age group is shown in Table 9. For example, in strategy 4-2-3-1, 4 denotes senior; 2 denotes school age; 3 denotes adult; 1 denotes pre-school; and the other strategies have a similar notation.

Table 9: Vaccinated fraction of each age group under different intervention strategies

| age groups | group sizes | no priority | 4-2-3-1 | 3-4-2-1 | 4-3-2-1 | 3-2-4-1 |
|---|---|---|---|---|---|---|
| preschool | 4617 | 0.5 | 0 | 0 | 0 | 0 |
| school | 13310 | 0.5 | 1 | 0 | 0 | 0 |
| adult | 52558 | 0.5 | 0.35 | 0.74 | 0.6 | 0.74 |
| senior | 7335 | 0.5 | 1 | 0 | 1 | 0 |

1:preschool, 2:school, 3:adult, 4:senior. The strategy 4-2-3-1 denotes the following vaccine assignment priority: first to senior group, then to school, adult, preschool subsequently in order.

Based on the simulation output, we calculate the death rate, death count, net returns per dollar spent, and total net returns under each strategy, and show the average (among 30 replicates in each simulation) in Table 10.

Table 10: Comparison of different strategies

| strategy | risk for death (%) | total death | NRPD ($) | total net return (million $) | AR(%) |
|---|---|---|---|---|---|
| base-case | 0.0845 | 66 | 0 | 0 | 40.00 |
| no priority | 0.0009 | 1 | 67.64 | 57.12 | 0.43 |
| 4-2-3-1 | 0.0006 | 1 | 67.88 | 59.54 | 0.42 |
| 3-4-2-1 | 0.0173 | 13 | 48.44 | 39.13 | 13.20 |
| 4-3-2-1 | 0.0158 | 12 | 47.11 | 38.46 | 14.64 |
| 3-2-4-1 | 0.0173 | 13 | 48.44 | 39.13 | 13.20 |

Surprisingly, the strategy 4-2-3-1 seems the most favorable in the sense that it minimizes death rate and maximizes net returns. The second favorable strategy is intervention with no priority. From Table 9, we notice that the main difference between these two strategies and the other strategies is that the school age group receives vaccines in the 4-2-3-1 and no priority cases; while it receives no vaccine in the other cases. This implies that school age group is a critical target when applying a mass vaccination intervention. A possible explanation is: students have long contact time with each other while at school; they form dense sub-networks at school locations in the overall social contact network; thus the epidemic spreads faster and more easily in the school age group. When the school age group receives no vaccine, the highly connected sub-networks of students remain to be able to spread the disease among students, impeding the intervention strategy to effectively reduce overall infections and costs. On the contrary, when the school age group are vaccinated, the epidemic is almost completely contained (less than 1% overall attack rate).

For public health policies, our results suggest that if vaccines are limited and a priority order is needed, then the school age group should be given high priority for maximizing overall net returns from vaccination and minimizing population death rate.

### 3.3 Health disparities among income groups

Now we divide the population into four quartile groups by household income: $0-$18400 (1st quartile); $18400-$41620 (2nd quartile); $41620-$75000 (3rd quartile); and above $75000 (4th quartile).

Similar to the analysis on age groups, we compare the attack rate of each income group and find similar results: there are health disparities between different income groups. When we look at each of the four possible outcomes, however, we find that while the other three outcomes still have significant difference between income groups, the death rate is not significantly different between any two income groups. Furthermore, other than that the net returns of the 4th and 3rd quartile income groups are slightly higher than those of the 1st quartile income group, there are no other evidence that is significant enough to establish economic disparities among all income groups.

Note that this observation is somewhat different than what one expects. The productivity loss (indirect costs) of an infected person from a group of higher income is usually larger than that of one from a group of lower income, given that they have the same outcome. But in our experiment the indirect costs depend on age but not on income level (see data source [8]). To have a better understanding of the economic disparities among income groups, one needs to find a conditional distribution of indirect cost given the income of the infected person. Since we do not see significant difference between income groups either in death rate or in net returns to intervention, we do not study vaccination priorities among income groups in this work.

### 3.4 Sensitivity analysis regarding compliance rate

In this section, we study the sensitivity of our results with respect to compliance rate of vaccination interventions in our experiment. In a new set of simulations, we assume that the compliance rate is 0.25, i.e., each person selected for intervention has a probability of 0.25 to comply. The other parameters remain the same. We run the same analysis on health disparities based on age and income groups as we have done for 0.5 compliance rate. Note that the analysis in Section 3.2.1 on health disparities of vulnerability and outcome focuses on the base-case; the result is the same regardless of the intervention compliance rate. So in this section we will focus on analyzing economic disparities.

**Observation:** Vaccination intervention is economically more efficient in senior groups than in the other three age groups.

Again we identify economic disparities between different age groups. However, the observation is different than the corresponding one in the 0.5 compliance rate case. Figure 5 shows the net returns under 0.25 compliance rate. Comparing with Figure 1, we find that the difference between school age group and pre-school/adult groups becomes less significant, while the net returns of the senior group are still much higher than those of the other groups. The results of $t$-tests on net return per dollar spent support this observation. We omit the table of p-values to save space.

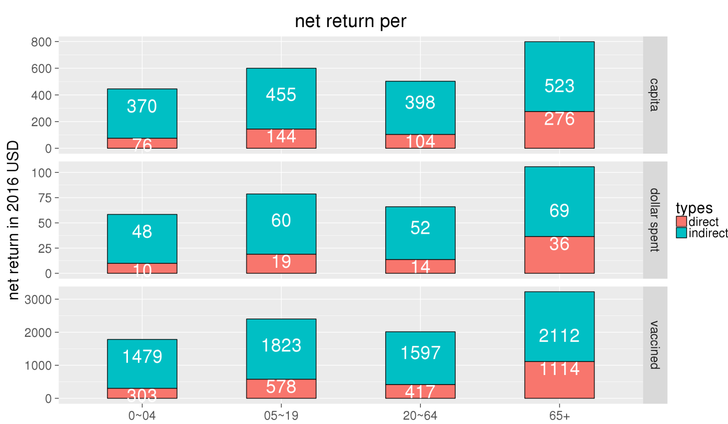


Figure 5: Direct and indirect net returns per capita/dollar spent/vaccinated people of different age groups. Total net return = direct net return + indirect net return. Compliance rate = 0.25.

To find out why the net returns in the school age group is not significantly higher than those of the pre-school/adult groups, we list the counts of different outcomes in each age group from the 0.5 compliance rate case (Table 12) and those from the 0.25 compliance rate case (Table 11). In Table 12, we find that with the intervention, counts of all outcomes drop by almost 100%. In Table 11, we find that with the intervention, outcome counts drop by about $\frac{2}{3}$ in the pre-school, adult, and senior groups, while the outcome counts drop by about half in the school age group. Comparing Tables 12 and 11, reduction of intervention compliance rate leads to $\frac{1}{3}$ decrease in net returns in the pre-school, adult, and senior groups, and about $\frac{1}{2}$ decrease in net returns in the school age group. Therefore, the difference in net returns between school age group and other groups becomes smaller.

The vaccination priority results are the same as those at 0.5 compliance rate. Strategies where school age group receives vaccines still have maximum overall net returns and minimum population death rate.

Table 11: Outcome counts in age groups under base-case (compliance=0.25)

| age groups | base | | | | intervention | | | |
|---|---|---|---|---|---|---|---|---|
| | death | hospital-ization | outpa-tient | ill (no medical care) | death | hospital-ization | outpa-tient | ill (no medical care) |
| preschool | 2 | 8 | 1082 | 953 | 1 | 3 | 423 | 370 |
| school | 6 | 34 | 4887 | 4328 | 3 | 16 | 2419 | 2138 |
| adult | 36 | 105 | 6720 | 10788 | 13 | 37 | 2409 | 3895 |
| senior | 22 | 27 | 772 | 830 | 7 | 9 | 254 | 280 |

All values are averages from 30 simulation replicates (rounded to integers).

Table 12: Outcome counts in age groups under base-case (compliance=0.5)

| age groups | base | | | | intervention | | | |
|---|---|---|---|---|---|---|---|---|
| | death | hospital-ization | outpa-tient | ill (no medical care) | death | hospital-ization | outpa-tient | ill (no medical care) |
| preschool | 2 | 8 | 1082 | 953 | 0 | 0 | 11 | 10 |
| school | 6 | 34 | 4887 | 4328 | 0 | 0 | 74 | 70 |
| adult | 36 | 105 | 6720 | 10788 | 0 | 1 | 58 | 92 |
| senior | 22 | 27 | 772 | 830 | 0 | 0 | 6 | 7 |

All values are averages from 30 simulation replicates (rounded to integers).

# 4 Conclusions

In this paper, we apply an agent-based model to simulate influenza epidemics in a synthetic population of Montgomery county, Virginia, and study health disparities among age groups and income groups. Based on the analysis, we design four vaccine assignment strategies and identify the optimal strategy, which can guide vaccination priorities and public health policy.

We find health disparities between age groups as well as between income groups; and that economic disparities are significant among age groups, but not so among income groups.

For public health policy, we find if vaccines are assigned randomly without priorities, then the intervention is more effective for pre-schoolers, adults, and seniors than for school-aged children. Given the high connectivity of school aged children in the social contact network, they are at a disadvantage if the vaccine assignment is random. Simulations show that if priorities are considered for vaccine assignment, then the school-age group should be given high priority for maximizing net returns and minimizing death rate.

The policy implications of our findings are that death rate and economic return are impacted by vaccination priority. When prioritizing age groups, both attack rate and compliance rate should be considered carefully. Our research provides a general method to study health and economic disparities among subpopulations. Furthermore, it gives a methodology to explore and evaluate vaccination strategies in term of specific objectives, through simulations.

## 5 Future work

In the future work, we are going to use a survey to collect detailed real data on disease model parameters (e.g. attack rate), as well as intervention parameters (e.g. vaccine efficacies, vaccination compliance rates), and apply the same simulation based method to validate our findings on health outcome disparities and economic disparities among age-based and income-based groups. We also plan to study individuals' local and neighborhood structural properties in the social contact network and whether and how the differences in that cause health disparities among people.

## References


[1] J. Badham and R. Stocker. The impact of network clustering and assortativity on epidemic behaviour. *Theor Popul Biol*, 77(1):71–75, Feb 2010.

[2] C. Barrett, K. Bisset, J. Leidig, A. Marathe, and M. Marathe. Economic and social impact of influenza mitigation strategies by demographic class. *Epidemics*, 3(1):19–31, 03 2011.

[3] C. L. Barrett, R. J. Beckman, M. Khan, V. S. A. Kumar, M. V. Marathe, P. E. Stretz, T. Dutta, and B. Lewis. Generation and analysis of large synthetic social contact networks. In *Proceedings of the 2009 Winter Simulation Conference (WSC)*, pages 1003–1014, Dec 2009.

[4] M. Biggerstaff, C. Reed, D. L. Swerdlow, M. Gambhir, S. Graitcer, L. Finelli, R. H. Borse, S. A. Rasmussen, M. I. Meltzer, and C. B. Bridges. Estimating the potential effects of a vaccine program against an emerging influenza pandemic, United States. *Clinical infectious diseases*, 60:S20–S29, May 2015.

[5] K. R. Bisset, J. Chen, X. Feng, V. A. Kumar, and M. V. Marathe. EpiFast: A fast algorithm for large scale realistic epidemic simulations on distributed memory systems. In *Proceedings of the 23rd International Conference on Supercomputing*, ICS '09, pages 430–439, New York, NY, USA, 2009. ACM.

[6] R. H. Borse, S. S. Shrestha, A. E. Fiore, C. Y. Atkins, J. A. Singleton, C. Furlow, and M. I. Meltzer. Effects of vaccine program against pandemic influenza A(H1N1) virus, United States, 2009–2010. 19(3):439, 2013.

[7] C. B. Bridges, W. W. Thompson, M. I. Meltzer, G. R. Reeve, W. J. Talamonti, N. J. Cox, H. A. Lilac, H. Hall, A. Klimov, and K. Fukuda. Effectiveness and cost-benefit of influenza

vaccination of healthy working adults: A randomized controlled trial. *JAMA*, 284(13):1655–1663, Oct 2000.

[8] C. Carias, C. Reed, I. K. Kim, I. M. Foppa, M. Biggerstaff, M. I. Meltzer, L. Finelli, and D. L. Swerdlow. Net costs due to seasonal influenza vaccination  United States, 2005–2009. *PLoS ONE*, 10(7):1–15, 07 2015.

[9] W. P. Glezen, M. J. Gaglani, C. A. Kozinetz, and P. A. Piedra. Direct and indirect effectiveness of influenza vaccination delivered to children at school preceding an epidemic caused by 3 new influenza virus variants. *J Infect Dis*, 202(11):1626–1633, Dec 2010.

[10] L. A. Grohskopf, L. Z. Sokolow, K. R. Broder, S. J. Olsen, R. A. Karron, D. B. Jernigan, and J. S. Bresee. Prevention and control of seasonal influenza with vaccines. *MMWR Recommendations and Reports*, 65(5):1–54, Aug 2016.

[11] M. E. Halloran, I. M. Longini, D. M. Cowart, and A. Nizam. Community interventions and the epidemic prevention potential. *Vaccine*, 20(27-28):3254–3262, Sep 2002.

[12] Healthy People. Disparities. Available at https://www.healthypeople.gov/2020/about/foundation-health-measures/disparities. Accessed September 1, 2016.

[13] J. C. J. King, D. Beckett, J. Snyder, G. E. Cummings, B. S. King, and L. S. Magder. Direct and indirect impact of influenza vaccination of young children on school absenteeism. *Vaccine*, 30(2):289–293, Jan 2012.

[14] D. Kostova, C. Reed, L. Finelli, P.-Y. Cheng, P. M. Gargiullo, D. K. Shay, J. A. Singleton, M. I. Meltzer, P.-j. Lu, and J. S. Bresee. Influenza illness and hospitalizations averted by influenza vaccination in the united states, 2005–2011. *PLoS ONE*, 8(6):1–8, June 2013.

[15] P. Y. Lee, D. B. Matchar, D. A. Clements, J. Huber, J. D. Hamilton, and E. D. Peterson. Economic analysis of influenza vaccination and antiviral treatment for healthy working adults. *Ann Intern Med*, 137(4):225–231, Aug 2002.

[16] I. M. Longini, M. E. Halloran, A. Nizam, M. Wolff, P. M. Mendelman, P. E. Fast, and R. B. Belshe. Estimation of the efficacy of live, attenuated influenza vaccine from a two-year, multicenter vaccine trial: implications for influenza epidemic control. *Vaccine*, 18(18):1902–1909, Mar 2000.

[17] M. I. Meltzer, N. J. Cox, and K. Fukuda. The economic impact of pandemic influenza in the united states: priorities for intervention. *Emerg Infect Dis*, 5(5):659–671, Sep-Oct 1999.

[18] M. I. Meltzer, K. M. Neuzil, M. R. Griffin, and K. Fukuda. An economic analysis of annual influenza vaccination of children. *Vaccine*, 23(8):1004–1014, Jan 2005.

[19] F. K. Meltzer MI, Cox NJ. The economic impact of pandemic influenza in the united states: priorities for intervention. *Emerging Infectious Diseases*, 5(5):659–671, 1999.

[20] N.-A. M. Molinari, I. R. Ortega-Sanchez, M. L. Messonnier, W. W. Thompson, P. M. Wortley, E. Weintraub, and C. B. Bridges. The annual impact of seasonal influenza in the us: Measuring disease burden and costs. *Vaccine*, 25(27):5086 – 5096, 2007.

[21] A. S. Monto, F. M. Davenport, J. A. Napier, and T. J. Francis. Effect of vaccination of a school-age population upon the course of an A2-Hong Kong influenza epidemic. *Bull World Health Organ*, 41(3):537–542, 1969.

[22] Y. Moreno, R. Pastor-Satorras, and A. Vespignani. Epidemic outbreaks in complex heterogeneous networks. *The European Physical Journal B - Condensed Matter and Complex Systems*, 26(4):521–529, 2002.

[23] J. P. Mullooly, M. D. Bennett, M. C. Hornbrook, W. H. Barker, W. W. Williams, P. A. Patriarca, and P. H. Rhodes. Influenza vaccination programs for elderly persons: cost-effectiveness in a health maintenance organization. *Ann Intern Med*, 121(12):947–952, Dec 1994.

[24] NDSSL. Synthetic data of Montgomery county, Virginia. http://ndssl.vbi.vt.edu/synthetic-data/, 2014.

[25] A. M. Presanis, D. De Angelis, A. Hagy, C. Reed, S. Riley, B. S. Cooper, L. Finelli, P. Biedrzycki, M. Lipsitch, and The New York City Swine Flu Investigation Team. The severity of pandemic H1N1 influenza in the United States, from April to July 2009: A bayesian analysis. *PLoS Med*, 6(12):1–12, 12 2009.

[26] L. A. Prosser, C. B. Bridges, T. M. Uyeki, V. L. Hinrichsen, M. I. Meltzer, N.-A. M. Molinari, B. Schwartz, W. W. Thompson, K. Fukuda, and T. A. Lieu. Health benefits, risks, and cost-effectiveness of influenza vaccination of children. 12(10):1548, 2006.

[27] C. Reed, S. S. Chaves, P. Daily Kirley, R. Emerson, D. Aragon, E. B. Hancock, L. Butler, J. Baumbach, G. Hollick, N. M. Bennett, M. R. Laidler, A. Thomas, M. I. Meltzer, and L. Finelli. Estimating influenza disease burden from population-based surveillance data in the united states. *PLoS ONE*, 10(3):1–13, 03 2015.

[28] E. Sydenstricker. The incidence of influenza among persons of different economic status during the epidemic of 1918. 1931. *Public Health Rep*, 121 Suppl 1:191–204, 2006.