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ECONOMIC AND SOCIAL IMPACT OF INFLUENZA MITIGATION STRATEGIES BY DEMOGRAPHIC CLASS

Pro. Caritt D[1]; Bechman P[2]; Karatheo T[3],

[,2,3,1] *faculty in Department Of Geography in University of British Columbia.*

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Corresponding Author:

Pro.Caritt D [1.]

[1] *faculty In Department Of Geography In University of British Columbia .*

cadhu.df@gmail.com

ABSTRACT

We aim to work out the economic and social impact of typical interventions proposed by the general public health officials and preventive behavioral changes adopted by the private citizens within the event of a “flu-like” epidemic.

Method

We apply an individual-based simulation model to the New River Valley area of Virginia for addressing this critical problem. The economic costs include not only the loss in productivity thanks to sickness but also the indirect cost incurred through disease avoidance and caring for dependents.

Results

The results show that the foremost important factor to blame for preventing income loss is that the modification of individual behavior; it drops the entire income loss by 62% compared to the bottom case. the subsequent most vital factor is that the closure of faculties, which reduces the full income loss by another 40%.

Conclusions

The preventive behavior of the private citizens is that the most vital consider controlling the epidemic.

KEYWORDS: Computational epidemiology; Demographics; Intervention strategies; Antiviral distribution.

INTRODUCTION

The threat of a world disease outbreak, like pandemic Influenza, is a crucial public ill health facing the globe. This potential for a H1N1 or H5N1 pandemic underscores the conspicuous risk to public health and global economy. so as to plan and respond proportionately to such pandemics, public health officials must have a scientific assessment of the socio-economic and health impact of the disease, interventions, and other mitigation efforts (Blendon et al., 2008, Epstein, et al. 2007, Philipson, 2000). Policy makers desire an understanding of intervention possibilities and pitfalls for limiting pandemic risk and assisting vulnerable populations (Fineberg & Wilson, 2009). These interventions may include social distancing, a prioritized governmental distribution of vaccines and antiviral medications, and pharmaceutical consumption within the private sector (Bruin et al., 2006, Whitley et al., 2006).

Individuals may possess strong private incentives to avoid the disease and are willing to self-impose social distancing measures. Traditional models in epidemiology and economics specialize in the prevalence of the disease and therefore the cost of treatment respectively but the price of disease avoidance should be considered moreover (Philipson, 2000). With the assistance of simulations, current research aims to fill this gap and capture the price of the disease avoidance caused by the modified behavior (Philipson & Posner, 1993).

The focus of this research is to know how individuals in various demographic classes react to a scourge given possible behavioral changes and the way this modified behavior affects the spread of the disease. it's well-known that individuals adapt their behavior in response to a threat posed by a possible epidemic, but a scientific study of this type of behavior has not been undertaken thus far. Our previous work shows that certain behavioral changes have potentially harmful side effects during outbreaks (Barrett, et al., 2008a). Personal behavior during a scourge depends on a person's socio-economic status yet as their perception of the epidemic within the community (Fischhoff et al., 1997). People maximize their well being by choosing levels of prevention and techniques with relevancy their own constraints. A national survey by the Harvard School of Public Health Project was recently conducted to measure public reaction to social distancing and other non-pharmaceutical interventions that will be enforced during a severe pandemic (Blendon et al., 2008). The survey highlights the very fact that different demographics of individuals will react differently to the interventions. This research undertakes the important task of measuring the economic and social effects of various social distancing and pharmaceutical interventions that are normally adopted by the general public health officials and personal citizens in a shot to contain a "flu-like" epidemic. The importance and effects of faculty closures, antiviral distributions, and personal social distancing measures are specifically analyzed. It's into the fairness of various intervention strategies by examining their economic impact within specific demographic classes. to know the total impact of a disease, it's important to calculate not only the price of the disease but also the price of disease avoidance. The results identify population strata by demographics that are likely to win or lose under such policies. Variety of recent reports and Hurricane Katrina has underscored the importance of this type of labor (Blaser, 2006, National Research Council, 2003).

Methodology

we use an individual-based modeling environment called Simdemics (Barrett, et al., 2008b) for simulating epidemic outbreaks. Simdemics may be a network-based epidemiological modeling framework that simulates the spread of a phenomenon across a social contact network. Simdemics builds upon individual-based mobility, activity, and disease transmission models, see Table 1. this kind of model allows one to perform studies at a personal level to judge the results of public policy during an emerging communicable disease. See Barrett et al. (2005), Eubank et al. (2004), Ferguson et al. (2005), Ferguson et al. (2006), Germann et al. (2006), and Meyers et al. (2003) for recent results and discussion on disaggregate models. The simulation approach taken during this study relies on three interacting models: Step 1—statistical models for the creation of synthetic populations, Step 2—an activity-based model for creating time-varying social contact networks, Step 3—a model of disease transmission. to take care of the readability of the paper, these steps are described, in detail, within the Appendix, furthermore as a conference version of this paper (Barrett et al., 2009b).

Table 1. Models and modeling approaches employed in Simdemics.

 Pro. Caritt D[1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

Models	References
Urban Population Mobility Models	Barrett et al. (2009a), Bowman et al. (1998), TRBC (1995), and, TRB (1998–2006)
Natural Disease History	Bailey (1975), Elveback et al. (1976), Halloran et al. (2008), Hethcote (2000), and Longini et al. (2005)
Transmission Models	Halloran et al. (2008), Hethcote (2000), and Longini et al. (2005)
Social Network Models	Eubank et al. (2004), Halloran et al. (2008), Newman (2003)
Types of Interventions	Ferguson et al. (2005), Ferguson et al. (2006), Halloran et al. (2002), and Halloran et al. (2008)

THE EXPERIMENTAL DESIGN AND ITS RATIONALE

Demographic classes and intervention strategies
This study estimates the differences within the economic and social impact on demographic classes caused by the varied public antiviral distribution and social distancing strategies similarly as private behavioral strategies. The study simulates a "flu-like" epidemic within the river Valley (NRV) region of Southwest Virginia, containing about 150,000 people, using an individual-based simulation model. The synthetic population is generated from US Census data as provided in PUMA (Public Use Microdata Area) and SF3 files (www.census.gov). Demographic classes are supported the three social factors, i.e., household income, family size, and also the age of the individual. it's been shown that these factors are highly correlated with most other demographic factors like education, ethnicity, employment, etc., and are hence appropriate for stratification. Individuals are aggregated into demographic classes for interpretation of outputs.

Income-based classes are low, medium, and high, and that they correspond to families who make but $25,000, $25,000–75,000, and over $75,000 annually, respectively. Similar income thresholds are utilized by other researchers (Blendon et al., 2008). Classes supported household size are defined as those containing one member, two to a few members, and quite three members. Age-based categories are juveniles (0–18), working adults (19–64), and retirees (65+). Demographic classes were formed through combinations of every of the three factors leading to a complete of 27 different classes (Thompson et al., 2006). However, 3 of the 27 classes were empty and hence are excluded from the tables. Table 2 displays the categories still because the proportion of individuals (in parentheses) in each demographic class. The results for the center groups (e.g., middle income, small families, and adults) are presented within the Appendix (Additional analysis section) to simplify the reporting of the more interesting groups on the extremes of every demographic factor. In Table 3, the column "class" lists the classes with a precise count of the individuals within the class. If any adult children live with their parents, they're counted as adults and assumed to behave like adults.

Table 2. Demographic classes are supported age, household income, and size.

HHIncome (population frac)	HHSize (population frac)	Age (population frac)
0–25 K (.32) Poor	1 (.11) Single	0–18 (.20) Child
25–75 K (.52) Medium Inc.	2–3 (.54) Sm. Family	19–64 (.69) Adult
75 K + (.16) High Inc.	4+ (.35) Lg. Family	65+ (.11) Elderly

Table 3. Demographic classes and their respective thresholds to trigger public and personal intervention strategies.

Demographic	Global threshold	Local threshold
Class (population size)	(%Sick in the society)	(%Sick in class)
Low income—(48,493)	None	None
High income, single, elderly (131)	1	2
High income, lg. fam., child (4430)	.5	None
High income, lg. fam., elderly (275)	1.5	1
Public-antivirals and close schools	1	None

Individual strategies

Pro. Caritt D[1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

People with different socio-economic backgrounds follow different preventive strategies to accommodate their personal constraints. These strategies are supported how people perceive society as doing additionally as how their own peer group/demographic class is doing. We project that change in individual behavior is triggered by the prevalence level of the virus within the overall society (global prevalence) in addition as within one's own demographic class (local prevalence). To model that, thresholds for these two factors were set for every class as shown in Table 3. the essential principles followed in setting these thresholds are (i) the upper the income level, the lower is that the overall tolerance for disease risk and hence lower the worldwide threshold, (ii) children have the bottom thresholds since adults are protective of the kids and monitor reports of widespread illnesses and absenteeism among children, and (iii) adults have the best thresholds since they're the foremost healthy group. because the main income earners, adults should take more risk with their health although some individuals with a high risk of complications may take less risk with their health. The private interventions are triggered as soon because the local or the world prevalence threshold is met for the category. the brink is reached supported the aggregated number of latest infections in a very day exceeding a tolerable limit. Please note that only 1 set of parameters has been considered here supported our greatest guess. In world, there's likely to be a variation within the application of those thresholds across people.

This threshold measure assumes active surveillance, monitoring, and reporting of infection counts per day by public health officials. Three interventions available to the people are buying antivirals for prophylactic use,1 eliminate unnecessary trips like trips to shopping malls and recreational facilities, and depend on protection resulting from others taking antivirals. The model assumes that when the brink is crossed, all affluent household members choose the primary option, i.e., purchase over the counter antivirals with an occasional .3 efficacy for prophylactic use because (1) they will afford to spare resources for the antivirals and (2) this strategy is least intrusive to their lifestyle. Members of the middle-income class choose the second strategy and modify their daily activity schedule by eliminating unnecessary trips. This social distancing technique reduces their potential contact with the infected individuals in society. The individuals from the poorest income class opt to depend upon protective steps being taken by the opposite members of the society.

The individuals from the poorest income class opt to depend upon protective steps being taken by the opposite members of the society. They find it too expensive to buy antiviral, and that they already take only a few unnecessary trips. We assume that every one individual in their demographic classes strictly follow their respective strategies. this might not be true in point of fact.

Table 3 tabulates the private strategies implemented by the various income classes and also the measurements used for global and native thresholds.

Public strategies

We simulate two common strategies available to public health officials: distribution of antivirals to individuals and college closures, see Table 4. The trigger threshold for the general public intervention is about at 1% of the overall population becoming infected. the general public stockpile of antiviral courses is restricted to 10,000.2 The antiviral courses are distributed to the individuals supported the subsequent four selection techniques: randomly selected individuals, poorest individuals, first sick individuals, and people with the very best simulation infection risk probability (high-risk).

Table 4. Government and personal intervention descriptions.

Pro. Caritt D[1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

Intervention	Description
Poor	Antivirals given to the 10,000 poorest individuals
Random	Antivirals given randomly to 10,000 individuals
High risk	Antivirals given to the 10,000 most often infected in previous simulations
Sick	Antivirals given to the first 10,000 who fall sick
CS	Schools are closed for a period of 2 weeks
Social distancing	Eliminate unnecessary trips and activities

The simulation infection probability of a personal is defined because the probability with which the individual gets infected when the disease starts from a random person within the population (Barrett, et al., 2008c). We empirically estimate the infection probability of all individuals within the population by running 100 simulation runs of the epidemic where each run starts from a special random individual. To calculate the proportion, we determine the amount of times a personal gets sick and divide it by the full number of runs. as an example, if a personal got infected five times during the hundred runs, his simulation infection probability was .05. Under the high infection risk strategy, the antiviral courses were distributed to people who had the very best risk value as calculated by the above procedure. This group is that the optimal group to figure with, because it is that the presumably set of people to become infected. While identifying this group wouldn’t be implementable, it provides a benchmark for strategy comparisons with less optimal groups. It’s important to show that this group doesn’t include those who are at high risk of complications like obesity, diabetics, pregnancy, HIV +, etc. the sole demographic wont to distribute public antivirals is that the income level. Note that under all the above strategies, the general public stockpile of antiviral is distributed only after the world threshold is met.

For the close school strategy, the trigger threshold is additionally set at 1% of the whole population becoming infected. the colleges are kept closed for a period of two weeks. When the colleges are closed, a minimum of one adult should be home to worry for young children, age 13 or less, who don’t remain alone reception. within the case of both parents working or all adults working, one working parent or adult stays home. We assume that 75% of the kids reside home when their schools are closed. the opposite 25% of scholars follow they’re after-school activities and hence mix with other children outside the varsity environment. The 75/25 split is predicated on the Activity Survey Data described within the Appendix. However, this split is also different when the faculties close during the conventional term.

Overall, there’s a limited mixing of kids during the college closure as compared to the regular school environment. We try various combinations of interventions including school closure and distribution of public antiviral courses, leading to nine distinct governmental strategies. See Table 5 for previous work investigating these governmental strategies and individual behaviors.

Table 5. Related work on behavior and policy.

Policies	Reference
Behavior and demographics	Blendon et al. (2008), Del Valle et al. (2005), and Mniszewski et al. (2008)
Social distancing and reducing trips	Davey et al. (2008), Ferguson et al. (2006), Germann et al. (2006), Inglesby et al. (2006), and World Health Organization Writing Group (2006)
Prophylaxis antivirals	Arinaminpathy and McLean (2008), Davey et al. (2008), Ferguson et al. (2006), Germann et al. (2006), Longini et al. (2004), McCaw and McVernon (2007), and Sander et al. (2008)
Treatment antivirals	Arinaminpathy and McLean (2008), Davey et al. (2008), Germann et al. (2006), McCaw and McVernon (2007), and Sander et al. (2008)
Close school duration	Blendon et al. (2008), Cauchemez et al. (2009), Germann et al. (2006), Inglesby et al. (2006), Sander et al. (2008), and World Health Organization Writing Group (2006)

RESULTS

To assess the economic impact of varied intervention strategies by demographic class, we develop seven distinctive scenarios supported individual and governmental actions. Five of those scenarios involve private and public interventions. A base case is conducted to see the economic loss and also the size of the epidemic within the absence of any interventions. Finally, a scenario is developed where no government intervention takes place and only private strategies are implemented. This scenario helps isolate the socio-economic effect of the private strategies. The economic costs for every strategy are derived from direct,

Pro. Caritt D [1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

indirect, preventive, and treatment costs. The direct costs are composed of income losses thanks to an ill worker not reporting to figure. This cost combines personal and company economic losses for salaried, wage, and self-employed workers. Indeed, all leaves don't necessarily end in income loss to the individuals thanks to the supply of paid sick leave for several individuals. However, leave of absence still ends up in productivity loss, which causes loss of income to society as a full. Therefore, we count all income losses in our calculation. Direct costs also include the price of treatment like outpatient visits, prescription costs, co-payments, hospitalization, etc. The indirect costs are because of parents staying home to worry for ill children. The preventive costs are composed of the governmental actions of distributing 10,000 antiviral kits and shutting schools for a 2-week period.The prices of closing schools are determined by the lost wages for folks staying home to produce child care and workers related to the college system. Costs for treating infected individuals through hospitalizations and outpatient care are calculated supported (Meltzer et al., 1999) and provided as health care costs. Also, the rates of outpatient care and hospitalizations of the sick were supported the fractions given in (Meltzer et al., 1999).

The costs for people in each strategy are aggregated and compared to the bottom case to explain the economic benefits of every strategy to every demographic group also because the amount of cash spent by the govt per person as compared to the bottom case epidemic. Al together of the scenarios, the interventions by the govt. and also the modified behavior of the private citizens greatly reduced the income loss and therefore the number of infections during the course of the epidemic. Even the smallest amount effective intervention diminished the full size of the epidemic to but half the bottom epidemic. The prevalence of the disease at its height was reduced by two-thirds. it's important to notice that the interventions not only caused the peaks to drop significantly but also delayed the outbreak and reduced the duration of the epidemic. The epidemic curves for every class and every strategy are shown within the Appendix. Please note that each one strategies reported here include behavior modifications by private citizens. the sole exception is that the base case.

Strategy label description

We now describe the strategies that are followed by the general public health officials and personal citizens during this study. Under all scenarios except the bottom case, the private citizens follow their respective strategies whenever their local or global thresholds are met. the whole public stockpile of antivirals is distributed by the govt to the subsequent people: poorest, highest risk, first sick, and randomly selected individuals. These are labeled as poor (P), high-risk (HR), sick(S), and random (R) strategies. CS strategy closes schools for 14 consecutive days. CS + R strategy refers to closing schools additionally as distributing the general public stockpile of antiviral to the population haphazardly. Similarly, CS + P, CS + HR, and CS + S talk to closing schools plus giving public antiviral to the poorest, highest risk, and sick people, respectively. NoGovt strategy implies that there's no intervention by the govt, i.e., no antiviral are distributed and therefore

The schools remain open. This strategy helps isolate the results of individual behavior.

Effect of preventive behavior

The results show that the foremost significant reduction within the income loss and therefore the size of the epidemic was caused by the preventive behavior undertaken by the individuals. This could be seen by observing Table 6 where the No Govt. strategy performs 60% better in terms of the entire costs and 65% better in terms of attack rate compared to the bottom strategy. Under the No Govt. strategy, only the private citizens modified their behavior once alerted to the very fact that several peers in their demographic class and also

The society is infected. With in the No Govt. strategy, there's no intervention by the govt... The strategies with school closures and antiviral distributions together with preventive behaviors only slightly outperform No Govt. This means that personal psychotherapy was the most consider reducing the income loss and therefore the size of the epidemic all told these strategies.

Pro. Caritt D[1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com*.

Table 6. Important statistics by strategy (Std. Dev. supported 100 simulation runs).

Strategy	Attack rate (σ)	Sick days	Indirect income loss ($ million) due to care taking	Direct income loss ($ million) due to illness	Preventive costs ($ million), govt.	Preventive costs ($ mil), private	Hospital and outpatient cost ($ million)	All costs ($ million)	Benefits ($ million)	$ Spe per pers save
Base	.732 (±.001)	581567	10.43 (±.011)	30.32 (±.031)	0	0	25.07 (±.035)	65.82 (±.077)	0	0
No govt. (No AV dist.)	.263 (±.007)	204930	4.24 (±.028)	11.02 (±.072)	0	1.21	9.38 (±.228)	25.86 (±.329)	39.95	231.
Random	.260 (±.006)	201767	3.82 (±.026)	9.94 (±.068)	.50	1.21	8.88 (±.239)	24.35 (±.334)	41.46	216.
CS + R	.154 (±.006)	119898	.96 (±.007)	7.89 (±.055)	18.43	1.21	5.71 (±.242)	34.21 (±.304)	31.61	324.
CS + P	.156 (±.006)	119096	.93 (±.006)	7.87 (±.052)	18.43	1.21	5.68 (±.228)	34.13 (±.285)	31.69	325.
CS + HR	.090 (±.011)	88951	.74 (±.009)	6.25 (±.075)	18.43	1.21	4.48 (±.416)	31.12 (±.500)	34.69	273.
CS + S	.120 (±.011)	107730	.76 (±.009)	8.12 (±.093)	18.43	1.21	5.54 (±.397)	34.07 (±.498)	31.75	307.

The runner-up reduction within the size of the epidemic came from the govt. strategies that included closing schools, which dropped the overall income loss and also the attack rate by another 40%. However, this strategy increased the preventive costs by about 18 million dollars. Among the general public antiviral distribution strategies, the distribution of the antivirals to the best infection risk individuals proved to be the foremost effective. Surprisingly, it performed better than the sick strategy within which antivirals are distributed to the primary sick individuals. Compared to the sick strategy, the high-risk strategy performed 25% better in terms of the attack rate. We believe that this can be because sick individuals don't visit school and work, which reduces their exposure to individuals whereas the high-risk people still mingle in society. Giving antiviral to the high-risk group keeps them from being inadvertently infected by an outsized number of people in society. Strategies involving school closures shifted the height of the epidemic curves by several days, and also the number of infected individuals also tailed off earlier compared to the strategies without school closures. The delay of the epidemic peak is very important in real situations for preparing additional responses and medical services. Fig. 1, Fig. 2, Fig. 3 show the value of strategies by demographic class.

Fig. 3. Total costs include direct income loss, indirect income loss, preventive, and health care costs.

Fig. 2. Total costs include direct income loss, indirect income loss, preventive, and health care costs.

Fig. 1. Total costs include direct income loss, indirect income loss, preventive, and health care costs.

Effect old

Comparing the performance of intervention strategies across demographic classes highlights their strengths and weaknesses in controlling the epidemic and their usefulness in targeting particular strata of the population. Please see Fig. 1. as an example, closing schools for two weeks had the most effective impact on reducing the children's attack rate, although it created an oversized economic burden on the society, a complete of $25 million, of which nearly $19

 Pro. Caritt D[1.]; *Faculty In Department Of Geography In University of British Columbia; cadnu.dj@gmail.com.*

million is in preventive costs. With this government intervention, the disease was almost eliminated within the kids segment because the attack rate dropped from .84 within the base case to .07 within the children class. While closing schools was socially beneficial to the youngsters, the elderly witnessed a more modest improvement.

For the elderly, the attack rate dropped from .66 within the base case to .18 within the CS scenarios. Although the full number of infections is a smaller amount when the faculties are closed, the elderly suffered from increased infections immediately following the opening of colleges. This led to a spike in transmissions among all ages, which was then followed by a pointy decline within the epidemic curve. in step with the bottom case, the elderly portion of the population had a way lower risk of infection. The infection prevalence within the base case among the elderly was at 66% whereas it had been 84% for kids. The difference was likely caused by the isolation of the elderly from the remainder of the population. The population contains a generally higher mixing rate compared to the elderly. When the faculties were closed, the antiviral failed to play a key role in determining the end result of the epidemic. Among all the antiviral distribution strategies, the distribution of antiviral to the high-risk group achieved the biggest reduction within the attack rate.

Effect of family size

Family size is a crucial variable in determining somebody's chances of getting infected. Single individuals are the smallest amount likely to become infected as they spend several hours being alone reception without extensive exposure to members of the family. Fig. 2 shows the overall costs encountered by the family class. the massive families had to incur higher preventive costs for strategies involving school closure. Closing school strategy is least beneficial to singles since they need no exposure to children. Large families with four or more members almost certainly have multiple children, and also the impact of faculty closure is most important for this class. In general, school closures are very beneficial in reducing the epidemic among all demographics irrespective of the family size. The antiviral distribution strategy mixed with the college closures had the foremost significant impact on reducing the dimensions of the epidemic.

Effect of income

As Fig. 3 shows, individuals from different income classes were affected differently by the varied interventions. Costs from the low-income class varied across strategies way more than the prices from the high-income class. In terms of net benefits, the low-income class gained the foremost under the CS + HR strategy and least under the No Govt. strategy. For this class, all strategies involving school closure resulted in higher benefits than strategies with no school closures.

The government distribution of antiviral did little to scale back the prevalence of the virus. In general, after antiviral interventions, the attack rates end up to be almost the identical within the low class and therefore the high-income class while the low-income class had not taken any personal action whereas the high-income class had modified its behavior. Originally the high-income class had a 6% higher attack rate than the low-income class but the parity after interventions suggests that the upper income class's ability to vary its own behavior had an immense effect on the attack rate. Government interventions failed to help reduce the prevalence of the virus in higher-income individuals the maximum amount because the other classes since they might afford their own medications. However, this class did benefit indirectly by the closing of faculties since the epidemic was reduced within the remainder of the population. Antiviral distribution to the high-risk group had the best effect on the high incomes but not on the poorest segment.

Key findings

Table 6 outlines the direct and indirect income loss, private and public cost of disease avoidance, attack rate, epidemic size, and also the total number of sick days by each

Intervention. A summary of the results shown in Table 6 is provided below:

 Pro. Caritt D [1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

1.The strategy that leads to the littlest attack rate and therefore the smallest amount of direct and indirect income loss is CS + HR. This strategy drops the attack rate by 87% and therefore the total income loss by 82% compared to the bottom case. The visit lost income is 90% thanks to a come by illness and 10% because of reduced caretaking. Note that the CS + HR strategy performs better than the CS + sick strategy. Under the CS + sick strategy, the whole income loss drops by 80% compared to the bottom case. This result shows that a proactive strategy that targets the high-risk group performs better economically similarly as in containing the epidemic than the reactive strategy during which the sick people are targeted.

2. Private citizens can greatly influence the epidemic through behavior modifications as shown by the results of the No Govt strategy. Under this strategy, there’s no intervention from the govt like school closures or antiviral distribution; only the private strategies stated earlier, i.e., stopping all non-essential activities and taking antivirals prophylactically, are in situ. This alone causes a visit total income loss by 62% and a call in attack rate by 64% compared to the bottom case.

3. The performance of the No Govt and random strategies is statistically indistinguishable. this may be verified by comparing the attack rates, sick days, and income loss columns of those strategies. the same observation is also made for the CS + R and CS + P strategies. Given the numerical variation within the outcomes of both the strategies, they’re practically the identical in performance. Under the No Govt. strategy, the govt. doesn’t distribute any antivirals to people whereas within the random strategy the govt gives antivirals randomly. However, under of these strategies, the private citizens follow their modified behavior. this suggests that the distribution of antivirals has only a marginal effect in improving the socio-economic measures. the foremost significant contribution comes from the modified behavior of the citizens.

4. The average total cost of saving an individual is highest when schools are closed. this can be because of added preventive costs like the caretaking of healthy children.

5. The CS strategy together with the antiviral distribution to the high-risk class leads to rock bottom income loss, number of sick days, epidemic size, and attack rate.

SUMMARY AND CONCLUSIONS

This research shows, in detail, the socio-economic impact of public and personal mitigation efforts on different population strata. Note that the results are supported specific thresholds, strategies, and assumptions made on behalf of every demographic class. These are unlikely to play out exactly during this manner. However, the results still provide useful insights on the role of behavioral adaptation. They show that the modification of behavior by private citizens is that the most vital consider containing the epidemic. Behavior therapy alone drops the full income loss by 62% compared to the bottom case. Simply limiting the quantity of non-essential trips and taking antivirals prophylactically can reduce the spread of the virus to almost one-third of its base size. These results signify the importance of actions by the private citizens and have implications for his or her level of compliance to health officials’ demand social distancing and pharmaceutical measures. The closure of colleges ends up in a further 10–15% drop by infections after individuals have modified their behavior. simplest} and most effective strategy seems to be CS + HR, which needs school closures, public distribution of antiviral to the best risk individuals within the society, and behavior therapy by the private citizens.

In light of our results, we believe that activities like governmental policies and media campaigns that urge the general public to change their behavior to scale back exposure to a communicable disease are likely to greatly reduce epidemic attack rates. We discover that closing schools mitigate a scourge better than the supply of antiviral kits. The governmental actions of college closure are more practical although less economically efficient in preventing infections than the distribution of antiviral kits.

Pro. Caritt D[1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

APPENDIX

Assumptions

Below we offer a listing of the assumptions utilized in performing these experiments:

1. The epidemic starts from five index cases, chosen randomly.

2. All simulations were performed 100 times by changing the random seed. The economic and infection results are provided because the monetary value and mean several infections per group over the 100 iterations.

3. School closure always occurs for a 14-day period.

4. The antiviral prophylaxis course lasts for 10 days and therefore the treatment course lasts for five days.

5. Trigger thresholds for public and personal intervention strategies are stated in Table 2. All global thresholds are supported total disease prevalence level within the society and local/personal thresholds are supported people not reporting to figure in an exceedingly person's demographic class.

6. The private citizens take the subsequent preventive actions to avoid getting the disease. The high-income households buy antiviral, the medium-income households stop their non-essential activities like shopping and recreational trips, and also the lowest-income households hope their contacts are taking adequate preventative steps and hence take no action. When high-income households buy antiviral for prophylactic use, it's bought for each member of the household.

7. The public interventions are supported only the worldwide trigger, which is about at 1% of the entire number of individuals being sick in society. the general public interventions involve closing schools and distributing antivirals.

8. When a young child (age 13 or younger) is sick, a non-working older sibling or parent stays home but if all adults are working, a working adult misses work to remain home with a young child for the 2-week duration schools are closed. We assume that the adult can leave from work as required.

9. Infected individuals don't head to work or school. This leads to a schedule change for infected workers, infected children, and also the working parent of an infected child.

10. The income of the adult is calculated by dividing the household income by the entire number of working adults within the household.

11. The efficacy of the generic over-the-counter antiviral is assumed to be 30%.

12. The private stockpile of antiviral (or the quantity of courses available from the market) is unlimited but the general public stockpile is restricted to 10,000 courses.

Computational epidemiology models

Aggregate computational epidemiology models often assume that the population is partitioned into some sub-populations (e.g., by age) with a daily interaction structure within and between sub-populations. The resulting uniform mixing model can typically be expressed as a group of coupled ordinary differential equations. Such models specialize in estimating the amount of infected individuals as a function of your time and are useful in understanding population-wide interventions. as an example, they'll be wont to determine the amount of immunization required to guard a population from a pandemic. See Bailey (1975), Barrett et al. (2005), and Hethcote (2000) for more discussion on this class of models. The individual-based modeling framework we use is Simdemics (Barrett, et al., 2008b), which simulates epidemic outbreaks at the individual level of granularity. Simdemics belongs to a replacement emerging class of models called network-based epidemiological models that use a close representation of social contact networks; such a

 Pro. Caritt D[1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

representation is crucial for studying the questions associated with the role of individual behavior and public policies. This disaggregated agent-based model can represent each interaction between individuals and might thus be accustomed study critical pathways of the diseases. It is wont to study the effect of public policies and individual behavior on the dynamics of infectious diseases. Disaggregate models require neither partitions of the population nor assumptions about large-scale regularity of interactions. The three interacting models employed by Simdemics yield the diffusion of communicable disease across a network: Step 1—statistical models for the creation of synthetic populations, Step 2—an activity-based model for creating time-varying social contact networks, Step 3—the model of disease transmission. More discussion about Simdemics is found in Barrett et al. (2005) and Eubank et al. (2004).

Statistical models of urban populations
Step 1 generates an artificial population by integrating a range of databases from commercial and public sources into a typical architecture for data exchange. the method preserves the confidentiality of the first individuals and produces synthetic agents with realistic attributes and demographics. The population may be a set of individuals and households related to a group of demographic variables drawn from the census. The population is comprised of a group of agent objects, each related to a collection of attributes. Each individual is placed in an exceedingly household with others, and every household is placed geographically in such the way that a census of our modeled population is statistically indistinguishable from the first census if aggregated to the block group level. Thus, the generated population utilized in simulations is statistically indistinguishable from the census data. See Beckman et al. (1996), Speckman et al. (1997a), and Speckman et al. (1997b) for added details.

Activity-based models of social contact networks
In Step 2, a collection of activity templates for households are determined supported several thousand responses to an activity or time-use survey. The modeling methodology is named activity-based travel demand models and is now accepted because the actual standard in transportation science (see Bowman et al., 1998, Bowman and Ben-Akiva, 2001 for recent overviews). Our early add this area (Beckman et al., 1996) played a very important role within the development of this system. The activity templates include the kind of activities each household member performs and also the time of day they're performed. Each synthetic household is then matched with one in all the survey households employing a decision tree supported demographics like the amount of workers within the household, number of youngsters, their ages, etc. The synthetic household is assigned the activity template of its matching survey household. for every household and every activity performed by this household, a preliminary assignment of a location is created supported observed land-use patterns, tax data, etc. For a city, demographic information for every person and site, a minute-by-minute schedule of every person's activities, and also the locations where these activities occur are generated by a mixture of simulation and data fusion techniques. These synthetic individuals interact, as real people do, with various degrees of fidelity, with one another and therefore the built infrastructure (shopping locations, offices, work, etc.) to supply a practical social contact network supported the movements and therefore the activities of each individual within the population. The social contact network from the above population is made as follows. We've got a labeled dynamic bipartite graph GPL, where P is that the set of individuals and L is that the set of locations. If someone $p \in P$ visits a location $\ell \in L$, there's a foothold $(p, \ell, \text{label}) \in E(GPL)$ between them, where "label" could be a record of the kind of activity of the visit and its start and end times. Each vertex (person and location) can even have labels. The person labels correspond to demographic attributes like age, income, etc. The labels attached to locations specify the location's attributes like its x and y coordinates, maximum capacity, etc. Note that there may be multiple edges between someone and a location recording different visits. This produces synthetic individuals that rather like real individuals can now perform other activities like eating, socializing,

 Pro. Caritt D[1.] ; *Faculty In Department Of Geography In University of British Columbia*; *cadhu.df@gmail.com.*

shopping, etc. a very important point to notice here is that such data are impossible to gather on this scale by measurements or surveys.

MODELS OF DISEASE TRANSMISSION

Step 3 consists of developing a computational model for representing the disease within individuals and its transmission between them. The model is viewed as a networked probabilistic timed finite state machine. Each individual is related to a timed probabilistic finite state machine. Furthermore, the automata are connected to other automata—this coupling springs from the social contact network. The state transition is probabilistic and is timed (e.g., may represent a distribution of incubation times). it should also rely on the attributes of the people involved (age, income, health status, etc.) additionally because the kind of contact (intimate, casual, etc.). Individual automata update their states in response to changes within the internal state and state of their neighbors. For this study, a potentially pandemic disease model for H5N1v influenza was utilized for tracking a human state throughout the stages of disease progression. By combing the disease model with information from the social network, contact timings with infected individuals, individual susceptibility, and therefore the potential use of antiviral medications, synthetic individuals may become infected and follow a probabilistically determined disease path. This culminates in returning to an uninfected state through the usage of antivirals or reaching the removed state where the individual isn't any longer infectious or susceptible. Fig. 4 displays the model employed in this study. Each node could be a finite state a personal remains in until a particular duration has elapsed. The duration distribution for intervals between 2 to five days and three to six days is included within the figure. the following state is decided probabilistically by selecting one in all the outgoing edges to a different state. Whether or not the agent has been treated with antiviral medications affects the sting probabilities within the disease model. For simplicity, the perimeters with a 1.0 probability don't seem to be labeled within the figure. This model has been calibrated through and utilize by previous research (Barrett, et al., 2008a, Epstein et al., 2008, Eubank et al., 2004, Halloran et al., 2008).

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