Proceedings of the 2008 IEEE Systems and Information Engineering Design Symposium, University of Virginia, Charlottesville, VA, USA, April 25, 2008

Collaborative Risk-based Preparedness for Pandemic Influenza in Southeastern Virginia

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Abstract— **There is consensus among preparedness experts, including epidemiologists, that another influenza pandemic is imminent [1], [2]. An influenza pandemic is a worldwide spread of a new, highly contagious strain of flu where little or no immunity exists and a vaccine is unavailable. The development of a preparedness plan before the next pandemic outbreak is vital because past pandemics have led to millions of American casualties and substantial economic losses. This project develops a set of risk mitigation strategies in the form of mask distribution for reducing the impact of an influenza outbreak in the Hampton Roads Planning District (HRPD). The project found a significant reduction in illnesses, hospitalizations, deaths, worker absenteeism, economic losses and medical surge for all strategies. However, an analysis of regional supply concludes that only partial mask strategies are feasible.**

I. Introduction

OVER the last several centuries, outbreaks of pandemic influenza have occurred every few decades [3], with the most recent in 1968. The deadliest of these, in 1918, killed an estimated 50 to 100 million people [3]. Within months, the virus spread across the globe and decimated the world's supply of medical resources [4]. Influenza experts estimate that the next pandemic may infect between 20-50% of the world population, and even in the best-case scenario two to seven million people around the world would die and tens of millions would require medical attention [5]. Developing mitigation strategies prior to the onset of the first influenza cases could save millions of lives and prevent significant regional economic deterioration.

Several risk mitigation strategies exist to decrease illness and preserve regional economic vitality, each with associated tradeoffs. This research focuses on the evaluation of protective face mask strategies. Two types of masks are considered: the N95 respirator and the basic surgical mask. This project evaluates various mask strategies according to consistent estimates of deaths, hospitalizations, medical surge, worker absenteeism and economic losses. These estimates are based on calculations of transmission probabilities, disease attack rates, strategy compliance levels, in addition to regional demographic, economic, and social interaction data specific to the HRPD.

Manuscript received April 7, 2008. This work was supported in part by the Virginia Governor's Office of Commonwealth Preparedness.

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II. Previous Work

Many strategies exist that successfully mitigate the effects of an influenza pandemic. These strategies include: vaccines which prevent flu contraction, antivirals which suppress flu symptoms and shorten duration, quarantine and social distancing which separate individuals and slow disease spread, and surgical masks and respirators which decrease the frequency of transmission, among others.

Vaccines are the only method that completely mitigates the effects of flu. In the event of a pandemic outbreak, developing a vaccine from a recently identified strain can take six to eight months [6], enough time for a significant portion of the world to become infected. In addition, current estimates of flu vaccination production capacity and logistic insufficiencies place it several billion doses under requirements for immunization [7].

Outside of vaccination, health leaders are exploring tamiflu and other antivirals as a response strategy. When taken correctly, these drugs are useful in suppressing transmission and shortening symptom duration [8]. Unfortunately, tamiflu production is significantly lower than what would be required to impact the spread of a pandemic [8]. The drug is also expensive, costing approximately $80 for a full treatment of a single person [8]. Moreover, there is speculation that wide-spread use of tamiflu could lead to mutation of antiviral resistant strains of flu [8].

Another strategy, which has been implemented in past pandemics, is social distancing. Social distancing comes in many forms, from encouraging people to remain indoors to full quarantines. Any reduction in face-to-face interactions will reduce the chance of disease transmission. A side effect of social distancing is significant workforce absenteeism due to efforts to reduce interaction between people. On a regional scale, this has a large effect on the economy through foregone wages and lost production. Certain sectors of the economy, such as communications, water, power, and agriculture cannot afford significant worker absenteeism [9].

The large scale use of face masks is a relatively unexplored strategy that has significant potential. The use of masks offers benefits similar to social distancing – a reduced virus transmission rate [10]; but can preserve some fraction of the workforce. In comparison to other methods, face masks are inexpensive, ranging from 16 cents to a dollar depending on the type of mask, thus offering hope of a cost-effective mitigation strategy. However, masks can only be worn for a limited period of time, and extensive questions exist concerning the current stocking practice in the US.

Surgical masks offer less protection than disposable respirators (N95 masks), but are easier to use, can be produced more easily, and are less expensive. With the ability to filter smaller airborne particles, N95 masks are more effective at preventing transmission but are more costly as a result. Stockpiles of these masks are very limited outside of those for healthcare workers. In the aftermath of 9/11 the entire US supply of the N95 respirators was consumed in just over a week [11] by the New York City residents and response workers. If a mask distribution strategy is to be an effective mitigation policy, production must be increased and stockpiles strategically planned.

Given the economic structure and varying level of capability of regions across the US, it is expected that a mixture of the discussed strategies will serve as the best preventative strategy for a particular region. Because vaccines take months to develop and distribute, combinations of antivirals, social distancing, and mask strategies must be executed immediately upon a pandemic's outbreak in order to preserve a region's economic integrity. This paper will focus on the development of a modeling framework that enables the measure of protective strategies as it pertains to maintaining economic continuity and meeting health surge. We apply the framework to extensively analyze various mask distribution strategies.

III. Research Approach and Results

A. Integrative Framework

Our modeling approach integrates several components to systemically capture the effects of a pandemic. Fig. 1 outlines the architecture of our model.

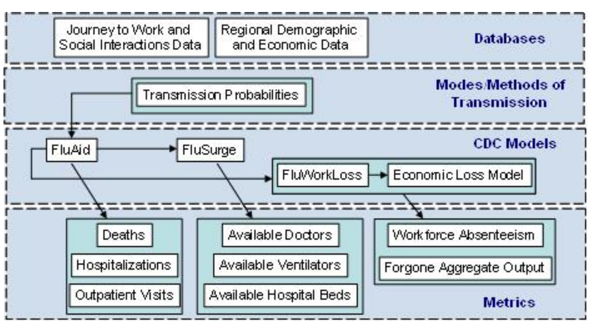

Fig. 1. Pandemic flu impact model

As shown in Fig. 1, the model requires demographic, employment, and behavioral data from various sources. The data are regionally focused on the HRPD. The data come from multiple sources, including the US Census Bureau and Bureau of Economic Analysis. Moreover, the data support all levels of the analysis. The second tier in Fig. 1 is a model that builds on fundamental research concerning the spread of disease in order to estimate the probability of transmission of the virus as a function of the mask strategy. It integrates data concerning modes of transmission, relative frequency of each mode, the relative effectiveness of masks, among other factors described subsequently.

The third tier of the pandemic flu model uses three Centers for Disease Control (CDC) pandemic loss models: FluAid, FluSurge, and FluWorkLoss. The output from the FluWorkLoss model integrates into a model that estimates economic losses. Each of these models requires gross attack rate (% population afflicted) in order to produce results. Transmission probabilities developed in tier two of the model map to the gross attack rate for input into the tier three modeling suite. The tier three models provide the metrics shown in tier four of Fig. 1, including: deaths, hospitalizations, outpatient visits, medical surge, foregone output, and absenteeism, among others. When analyzing different mask strategies, we observe how the reduction in the transmission probability will propagate downward through Fig. 1 and affect the various metrics.

B. Transmission Probabilities

A particle based infection model was developed due to the need to understand how wearing the two types of face masks influenced the probability of an infection occurring during a five minute encounter with an infected person. Using data from several different sources, the model traces the particles as they are expelled from an infected person's mouth and nose via talking, coughing, or sneezing. Once the particles have dispersed through the air, the model develops probabilities of entry through the mask and possible infection of a susceptible person.

Duguid [12] develops a distribution of the quantity of various sized particles expelled when a person talks, sneezes, and coughs. Moreover, Atkinson and Wein [13] develop probabilities of coughing and sneezing in a five minute interaction when at least one interaction participant is ill with influenza. Convolving the distributions from [12] and [13] results in a distribution of particles excreted. Particle distributions are reduced based on filtration efficiency of the mask worn by the primary interaction participant, which has different efficiencies for variously sized particles [10] (Fig. 2).

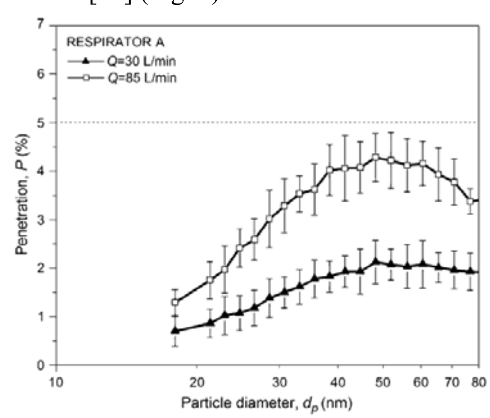

Fig. 2. Filtration efficiency of N95 masks [10]

Through the air, it is assumed that the particle concentration drops off with an inverse square of the distance between them (due to dispersion and gravity effects described by

[13]). Then, the particles are passed through a mask worn by the secondary interaction participant of a susceptible person, using the same filtration estimates. Finally, particles pass into the lungs, where the average number of viruses per particle is used to calculate infection probability using the tissue culture infectious dose for an influenza virus [13].

The particle transmission model calculates infection probabilities for five mask strategies, characterized by mask type and compliance level: 100% N95 compliance, 60% N95 compliance, 100% surgical compliance, 60% surgical compliance, and no mask. The resulting probabilities, as well as attack rates, can be found in Table 1.

These results are built on input data that have a large amount of variability from source to source. For example, the distribution of the size of the particles expelled varies based on the experiment, with the most recent being used in this model (i.e., [12]). In addition, the filtration efficiency of the masks in question is the expected efficiency, according the results of [10]. In the real world, where moisture, human error, and other unknown variables enter into the equation, these filtration rates will likely drop by an unknown amount throughout the duration of a mask-wearing session. Finally, the complex behavior of very small particles on the micro-level in open air was not explored in this model, but may add additional uncertainty.

The modularity of the model structure allows the model to be updated as new experiments or literature provides new information. Moreover, the model can be expanded in complexity. These infection probabilities provide estimation on the effectiveness of face masks in curtailing the transmission of influenza, something largely unexplored in previous literature. In addition these provide a foundation for a consistent estimate of the tradeoffs among various mask distribution strategies.

TABLE I
PROBABILITY OF INFECTION AND ESTIMATED ATTACK RATES

	N95 Mask		*Surgical Mask*		*No Mask*
Compliance	*100%*	*60%*	*100%*	*60%*	
Probability of Infection (%)	1.3	11.6	5.2	11.8	27.0
Attack Rate (% of population infected)	1.7	15.0	6.7	15.2	35.0

In order to acquire results from the infection probabilities and resulting attack rates, the attack rates are applied to the various CDC models. The FluAid model determines how many deaths, hospitalizations, and outpatient visits result from the application of the various mask strategies. FluAid functions through the use of matrices populated with the likelihood of deaths, hospitalization, and outpatient visit based on age and vulnerability distributions in the HRPD.

C. *FluAid Results*

The FluAid model provides the backbone for the other models, FluSurge and FluWorkLoss, described subsequently. The base case scenario of a 35% attack rate was used on the basis that some action needs to be taken to reduce the spread of the virus. At this attack rate, the base case resulted in over 290,000 outpatient visits and over 1,300 deaths during an eight week period. As shown in Table 2, a 100% compliance rate using N95 masks proved to be the most effective way to decrease the stress on the medical sector and minimize deaths. A more reasonable assumption would be for a 60% compliance rate with either N95 or surgical masks. These cases proved effective in reducing hospital visits and deaths by over 50%.

TABLE II
FLUAID RESULTS FROM MOST LIKELY SCENARIO

Attack Rate(%)	*Mask and Compliance Level*	*Outpatient Visits*	*Deaths*	*Hospitalizations*
1.7	100% N95 Compliance	14,330	70	300
15.0	60% N95 Compliance	126,640	580	2,670
6.7	100% Surgical Compliance	56,200	260	1,190
15.2	60% Surgical Compliance	128,070	590	2,700
35	No Mask Compliance	294,900	1,360	6,230

D. *Hospital Surge*

During the outbreak of flu, one of the most heavily taxed sectors, in terms of criticality to regional recovery is the healthcare sector. Several issues arise that pose major threats to the safety of citizens. During normal conditions, hospitals operate at around 70% of their capacity, leaving about 30% available for sudden unexpected increases in demand [14]. Upon the outbreak of a pandemic, hospitals in the HRPD could fill above their normal operating levels and excess resources will be quickly consumed. If the outbreak is severe, hospitals may surpass their capacity and resources may become exhausted. The option of creating temporary facilities is very costly to set up and maintain. The Commonwealth of Virginia has drafted a preparedness plan that is scheduled to be released in the coming months [15].

Developing a model to predict how an untreated outbreak affects the region's healthcare is important for identifying any potential consequences. To estimate the probability of exceeding capacity, we integrate the FluSurge model into a risk analysis model for the HRPD medical facilities [14]. Sentara Healthcare, a major owner of healthcare assets in the region, provided regional data. Fig. 3 shows weekly hospital admissions by mask distribution strategy.

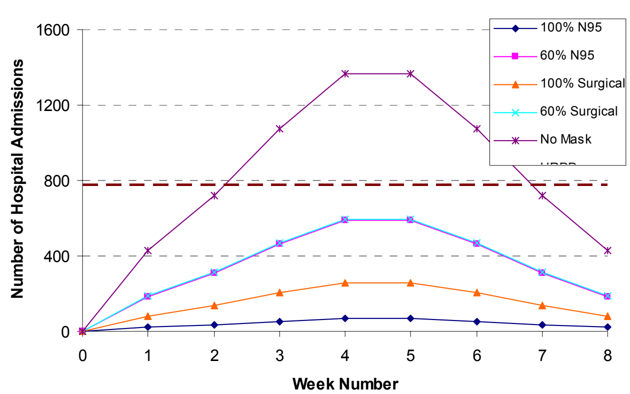

Fig. 3. Estimated weekly hospital admissions

If a virus attack rate were 35%, the medical sector would be crippled. The effect of masks decreases the number of hospitalized individuals and results in less demand for medical supplies. Fig. 3 shows the benefit that various mask strategies had on the medical sector.

Table 3 shows the peak demand for hospital resources during the FluSurge simulations at each compliance level. The base case results of no masks suggest that a mask strategy is necessary to estimate surge. All hospital resources exceed their capacity at some point during the outbreak, with hospital beds peaking at 143% of available capacity, ICU beds exceeding 200% of capacity, and the demand for ventilators rising above 150%.

TABLE III
ESTIMATED PEAK CAPACITY REQUIRED FOR MASK STRATEGIES

Attack Rate (%)	*Mask Strategy*	*Estimated Peak Capacity Required (%)*		
		Hospital Beds	ICU Beds	Ventilators
1.7	100% N95	7	11	8
15.0	60% N95	61	94	70
6.7	100% Surgical Mask	27	42	31
15.2	60% Surgical Mask	62	95	71
35.0	No Masks	140	220	160

Each of the mask strategies suggests significant improvement in reducing the demand for medical resources below capacity levels. The most effective reduction in demand occurs with 100% compliance of N95 masks. While 100% compliance by the public is the most effective case in reducing the demand for medical resources, it is unreasonable to assume that this compliance can be reached. A 60% compliance with surgical masks is a much more reasonable expectation. This policy decreases the demand below critical capacity levels throughout the outbreak. However, such a scenario would push hospital capacity to the limit and could lead to overflow in the event that a hospital is operating above the normal conditions. Another concern is whether the model is an accurate measure of the expected increase in demand. The model is unable to estimate the precise increase in demand that will result from the spread of the virus.

E. Economic Loss

Critical infrastructures and business operations in the HRPD depend on their workforce in different ways. However, pandemic flu may alter workforce dependence, perturbing operation continuity. Workforce continuity is critical for the essential functions of various systems to be carried out, especially those that require skilled workers [16]. For example, those operations that require high dependence on workforce will require power, communication, and transportation mobility to maintain the continuity and effectiveness of the workforce when distributed across their homes. Moreover, utility and telecommunications sectors that traditionally require lower levels of workforce for supervision and maintenance may surge their requirement for workers with specific skills to maintain the large shift in load to a residential workforce. Balaouras, a Forrester analyst, estimates that a 5000-person enterprise could have losses in the millions per day simply due to workforce disruption [17].

An outbreak of pandemic influenza in the HRPD has the potential to stress the productivity levels of various sectors of the economy and could result in a significant economic loss. Pandemic flu is unique among extreme catastrophes in that the mechanism of economic loss is not through infrastructure damage in any direct sense. It is through the loss of regional productivity resulting from missing people, skills, and innovation in the local economy. Health experts predict average illness length of two days, with a minimum of one day and a maximum of ten days [18]. However, even a very short illness length could result in many work days lost if the attack rate is high. Experts anticipate that 10-25% of the workforce will be absent at any given time due to illness or caring for an ill family member [18]. In a severe pandemic with a 40% attack rate, experts estimate at most 85% availability of normal workforce through the duration and 50-65% workforce availability for the peak three weeks [19]. An influenza pandemic thus could pose a serious threat to the workforce of the HRPD.

Developing a model to approximate the potential loss in economic output across each sector of the HRPD economy is important because it will give a consistent estimate for economic loss based on the parameters of the pandemic. These estimates can supplement and complement the estimates of illness, death, hospitalizations, and other factors that are significant to regional well-being. To estimate economic losses, we integrate the FluWorkLoss [14] model into a model that will estimate absenteeism across all sectors of the HRPD economy. The model will also evaluate how the lost work days in each sector affect the economy in terms of foregone wages and foregone aggregate output, as derived from industry earnings and production estimates. There are three basic components of the model, including the CDC FluWorkLoss model, the regional worker distribution model, and the regional sector output model.

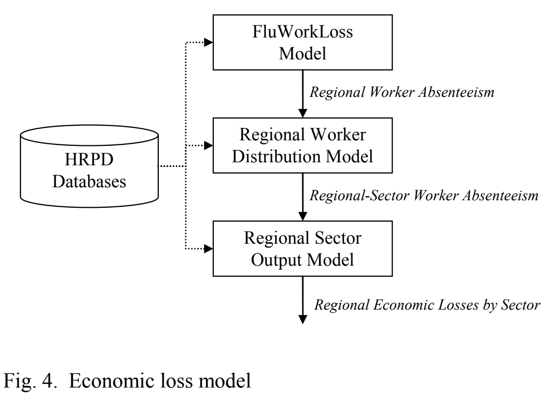

Fig. 4. Economic loss model

The CDC FluWorkLoss model estimates the number of workers absent in a region given flu parameters and regional demographics, and estimates concerning days that people spend to care for spouses and children. The regional worker distribution model estimates how regions' absences are distributed across sectors of the economy based on the concentration of workers in particular economic sectors. The regional sector output model estimates the foregone earnings of regions using expected paid wages to absent employees. This metric is then used to calculate economic loss using the output to earnings ratio recorded for the U.S. according to the Bureau of Economic Analysis (BEA). Absenteeism and economic losses are calculated using a triangular distribution that represents the minimum (best-case), most likely (mode), and maximum (worst-case) scenarios. Risk assessment evaluates two different types of protective face masks, the surgical mask and the N95 respirator, to examine how various levels of compliance will ultimately reduce absenteeism and economic losses sustained to the region.

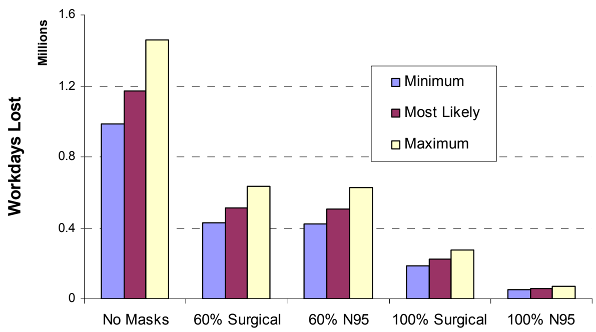

Fig. 5. Workdays lost for mask strategies

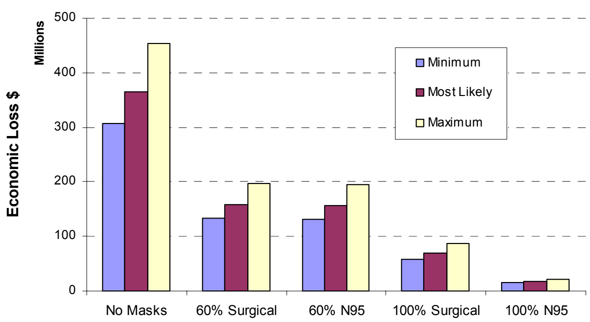

Fig. 6. Economic loss for mask strategies

With only 60% compliance, distributing surgical masks or N95 respirators will reduce economic losses by over 50%. With 100% compliance on N95 respirators, the HRPD (in the worst-case scenario) would only sustain roughly $2.2 million in losses due to reduced absenteeism. In the best-case scenario, the HRPD would incur close to $1.5 million in economic losses as derived from absenteeism. Taking no action could result in over $453 million in losses. Fig. 7 shows the concentration of economic losses in various sectors of the HRPD economy.

The government sector contributes approximately 41% of the economic losses. Comparatively, service sectors and manufacturing each contribute only 14%, meaning that the HRPD government and associated government enterprises play a vital role in stabilizing the regional economy. Workforce continuity is therefore most critical in the government sector of the HRPD. The distribution of a scarce supply of masks could be very beneficial in the government sector when trying to maintain economic stability.

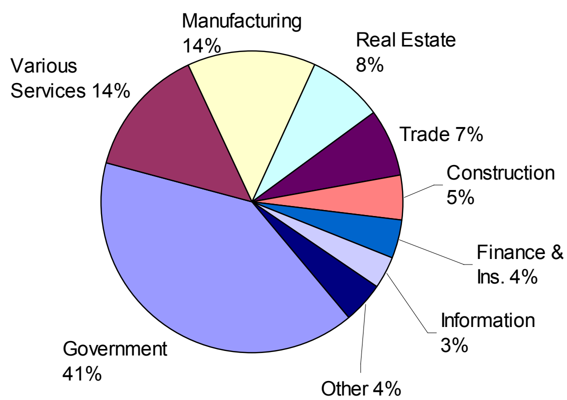

Fig. 7. Economic losses by sector of the economy

F. Mask Stockpiling

A systematic evaluation of stockpiling masks for the people of the HRPD considers multiple dimensions. The most important dimension is the costs and benefits of increasing third-party inventories in the area, and how that inventory will quantitatively decrease the transmission of influenza. Ultimately, any strategy for stockpiling masks will aid in mitigating the pandemic, but realistically, resources are extremely limited and economic sectors with the highest predicted economic losses may take priority in mask distribution in order to minimize the overall losses.

The stockpiling strategy depends greatly upon the economic considerations of the commonwealth. Funding already exists for distribution centers around the nation, but the addition of stockpiling masks for the entire population may not be economically viable [20]. To combat the funding problem, preparations would need to begin immediately and masks would need to be purchased and warehoused on a regular basis, preferably monthly.

When the outbreak finally occurs, shipments of masks from warehouses across the region will distribute supplies to local third-party vendors, improving the readiness of the region. Stockpiling at regional warehouses and purchasing steady supplies accounts for slow mask manufacturing times, and shipping supplies to local vendors ensures wide distribution. The government may subsidize the purchase of masks and the cost of their inventory.

The stockpiling method considered in this paper outputs the total cost of the strategy and the percentage of people in the region protected by masks. The stockpiling strategy bases its results on the construction of four regional stockpiles, and on other assumptions, such as the monetary amount the region is willing to invest in stockpiling masks, the native regional inventories, and on the regional mask manufacturing capabilities. The results are suggestive that there is a strong case for heavily stocking masks in the region, and the results provide a range of possible investments for the government to analyze.

TABLE IV
STOCKPILING METHOD BASELINE RESULTS

Best Case	
Time Prior to Outbreak (years)	10
Regional Stockpiles	4
To stock per month per stockpile	220,000
Final Stock after 10 Years	105,600,000
Storage Space Needed (ft^2)	146,700
Warehouse Cost per year	$704,000
Mask Cost per month	$55,000
Total Cost after 10 years	**$33,440,000**

Table 4 suggests that even in the best case (10 years of preparation and 880,000 masks stocked per month), the stockpile provides enough masks for less than half of the population and for only three-quarters of the working population when prioritized for the working class. A $45 million investment can provide the entire working class with masks for the duration of the pandemic, but this still leaves about half of the population unprotected and forces them to resort to other means such as quarantine and social distancing. It is important to note that the region cannot afford for workers to utilize these methods; masks are the only strategy that allows for people to continue working, which successfully minimizes economic loss.

The results provide a range of investment opportunities for the government, but to provide significant protection for the area, a sizeable investment is required. Despite the models assumptions and uncertainty, the results are strongly suggestive that even an incredibly ambitious stockpiling strategy cannot protect the entire population, and places these conclusions within the bounds of the models robustness.

IV. CONCLUSIONS

The economic losses saved during a pandemic outbreak in the HRPD by a surgical mask distribution policy ranges from $100 to $250 million at 60% compliance, which drastically exceeds the approximate $20 million cost of such a strategy (at the compliance level). Moreover, the strategy in the HRPD alone reduces expected illnesses by more than 300,000 persons, outpatient visits by approximately 160,000, hospitalizations by more than 3,500, and saves almost 800 deaths.

These numbers indicate that mask distribution strategies have a cost-effective and a significant impact on reducing the effects of pandemic flu in the region. However, given the extremely limited supply of masks, the effectiveness depends on the strategy's combination with other mitigation strategies. Future work should focus on how to direct strategic mask distribution strategies in combination with antivirals and limited social distancing, given regional constraints, until an adequate vaccination supply is available.

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