Paid Sick-Leave: Is It a Good Way to Control Epidemics?

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Abstract. This research considers an economic intervention i.e. a paid sick leave policy to control an Influenza epidemic. Research has shown that "presenteeism" i.e. sick workers coming to work, costs employers more than "absenteeism" because sick workers put their coworkers at risk and are less productive.

We examined the costs and benefits of a paid sick leave policy through its effect on productivity, medical costs and attack rate. We considered two kinds of workers' behavior: honest and rational. Honest workers take sick leave for days they are sick; but rational workers take all available sick leave. We ran agent-based epidemic simulations on large scale social contact networks with individual behavior modeling to study the coevolution of policy, behavior, and epidemics, as well as their impact on social welfare.

Our experimental results indicate that if the workers behave honestly, the society's economic benefits increase monotonically with the number of paid sick days, however if the workers behave dishonestly but rationally, the society's welfare is maximized when the number of paid sick days is equal to the number of mean days of sickness. This research shows that paid sick leave can be used as an effective policy instrument for controlling epidemics.

Keywords: epidemics, simulation, influenza, public health, economic analysis, social welfare, sensitivity analysis.

1 Introduction

Global disease outbreaks, such as H1N1 and H5N1, have severe morbidity, mortality, and economic consequences. For instance, the World Bank estimated in 2008 that a flu pandemic could cost $3 trillion, affect 70 million people worldwide and decrease the world gross domestic product by 5% [9]. Small and timely interventions can sometimes prevent isolated outbreaks from becoming epidemics or they may hold back the epidemics enough to deploy vaccines to the masses. In the absence of vaccines or antivirals, social distancing may be the only viable measure available in the early period of the epidemics. Previous researchers have studied a variety of intervention strategies, both pharmaceutical and non-pharmaceutical, to control the spread of an infectious disease. These include

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social distancing strategies such as school closure, work place closure and quarantine [5,13]; and pharmaceutical strategies such as distribution of vaccines and antivirals [8,18,19], as well as herd immunity [1,2].

This paper focuses on an economically driven intervention, i.e. a paid sick leave policy that allows the workers to stay home from work without loss of income. The authors believe that the sick leave policy as a tool to contain epidemics has not been studied in detail in the health care literature, but noteworthy exceptions are [11–13, 17]. Work by Gilleskie [11] explores the endogenous decision making of medical care consumption and absenteeism by sick employees in order to understand the behavior that contributes to increasing health care costs. The study of [17] goes one step further and incorporates an epidemiological model to the labor market and its consequent impact on absenteeism. It examines the endogenous determination of the optimal sick leave ratio. In particular, it looks at how sick leave serves to decrease the transmission rates, reduce the spread of disease and increase the social welfare, using a theoretical model. Authors in [12] show that sick leave results in an abrupt decrease in the magnitude of the epidemics. Work by [13] simulates the effectiveness of a set of potentially feasible intervention strategies including the liberal leave policy using three different simulation models developed separately. Simulation results show that the liberal leave policy along with increasing community and workplace social distancing can reduce the disease prevalence significantly. This paper uniqueness lies in the fact that it uses an individual based detailed simulation model to do a parameterized study and considers both epidemiological and economic factors in detail.

Previous researchers have pointed out that presenteeism may be more damaging than absenteeism [14]. From public health viewpoint, it is desirable to reduce the disease *attack rate*, defined as the fraction of the population being infected. A liberal sick leave policy will discourage sick employees from coming to work which will help contain the disease; but it will affect the productivity of the society. To see whether a sick leave policy is indeed an effective tool for controlling the epidemics and whether it is economically efficient, our paper considers a variety of sick leave policies and worker behavior. The analysis takes a social welfare point of view to study the cost effectiveness by comparing the productivity loss of the sick workers with the socio-economic gain caused by a lower attack rate in the population.

A detailed experimental design considers a variety of scenarios based on the number of paid sick days allowed, disease type, the behavior of the workers and the compliance level of the employers with the sick leave policy. The worker behavior is assumed to be of two types: *rational* and *honest*. In case of rational behavior, the workers take the maximum number of sick days available regardless of how long they are sick for, but in case of honest behavior, a sick worker takes off only the number of days s/he is sick for. Honest behavior can also be thought of as a proxy for full information sharing, or symmetric information between the employer and employees; and the rational behavior can be interpreted as partial information sharing or asymmetric information between the employer and employees [17]. Our simulation results show that if employees behave honestly, a liberal sick leave policy would maximize the social benefit but if they behave rationally, the social benefit is maximized when the paid sick days are equal to the mean number of sick days. In the rational case, a liberal sick leave policy reduces the overall social welfare.

The paper is organized as follows: Section 2 explains the disease model, experiment parameters and the methodology. Section 3 describes the simulation results and provides a discussion from both epidemiology and economics point of view. In Section 4 shows results of the sensitivity analysis and the final section concludes the paper.

2 Methodology

2.1 Disease Model

This study assumes that an "Influenza-like-illness" is spreading across a synthetic population representing the city of Miami, Florida, via people-to-people contacts. The simulation is run using EpiFast, a fast agent-based epidemic simulation tool [6]. The disease model, the synthetic population modeling, and the people-to-people contact network model are described in detail in [3,4,7,10]. Our disease model assumes that the probability of transmission depends upon the health states of the individuals and the duration of their simultaneous presence in a small area.

The progression of disease within the host is based on the usual SEIR model and the duration of each state [13, 15]: at any given time, each individual in the population is in one of four health states: *susceptible, exposed, infectious*, or *removed* (SEIR). For each individual, the incubation period duration is sampled from a discrete distribution with mean 1.9 days and standard deviation 0.49 day; the infectious period duration is sampled from a discrete distribution with mean 4.1 days and standard deviation 0.89 day.

We assume that only 66.7% are symptomatically sick and of those only two-thirds are correctly diagnosed [13]. Only symptomatic people go to see the doctor and encounter medical costs. The asymptomatic individuals behave as healthy individuals but they can transmit the disease, although they are only half as infectious as the symptomatic ones. The epidemic is seeded with five randomly chosen individuals. Every day five new infections from external sources occur within the population in addition to those generated by transmission. The simulation is run for 300 days. Reported results are based on an average of 25 simulation replicates.

2.2 Factorial Experiment Design

We consider the following 5 factors in our experimental design: disease type, compliance level, maximum number of sick days allowed, workers' behavior and the productivity level of workers who work while they are sick. The disease types are moderate flu or catastrophic flu. The compliance levels of the employers/workplace are set at 50% and 100%, which refers to the fraction of work

Table 1. Factorial Design

Factor	Description	Values
Dis	disease types: catastrophic and moderate flu.	Cat, Moderate
Comp	compliance: probability each workplace complies with the sick leave policy	50%, 100%
$D_{\max}$	sick leave policy: max number of sick days allowed to diagnosed workers	3, 4, 5, 6
Beh	workers' behavior towards the sick leave policy: take the exact sick days off (honest) or take the maximum possible days off (rational)	rational, honest
e	productivity level of those working while sick	20%, 50%, 80%

locations that comply with the sick leave policy. In the 50% compliance case, only 50% of the work locations choose to comply and provide paid sick leave to its employees. In the 100% case, all work locations and hence all workers are given paid sick leave. However note that only diagnosed workers are allowed to take sick leave.

Regarding the number of maximum paid sick days, workers can take sick leave up to $D_{\max}$ =3, 4, 5, or 6 days without any income loss. Workers' behavior is considered to be of 2 types, rational and honest; if rational, workers take all available sick leave so the actual number of sick leave days taken is $D_{sl} = D_{\max}$. In the honest case, eligible workers take off only when they are sick: $D_{sl} = \min(D_{sick}, D_{\max})$, where D_{sick} is the actual number of sick days. All of the experimental factors are summarized in Table 1.

2.3 Interventions

2.4 Cost and Benefit Estimates

The procedure below describes the methodology used in estimating the economic costs and benefits of a paid sick leave policy. The costs include medical costs and loss in productivity of the sick workers. Benefits include lower attack rate and hence gain in productivity. Information used to calculate the costs and benefits include workers' income, medical costs for treating sick workers, health status, number of sick days, number of paid sick leave days used, and the age of workers. Workers' productivity is calculated based on their income in the following manner: $y_i = 1.154 I_i$ where y_i is the daily productivity of worker i and I_i is the income generated by worker i. We use a multiplier of 1.154 which reflects the ratio of productivity to income in the US i.e. Gross National Product (GNP) to Gross National Income (GNI) is $GNP/GNI = 1.154$.[1]

Let's assume h_i represents the health status of worker $i, i \in [1..n]$ and h_i is a binary variable that takes value 1 if i is symptomatic and 0 if i is healthy

[1] The ratio is calculated based on the US indices for year 2010. Data source: The World Bank.

or asymptomatic. Let $\epsilon_i = 1$ represent that i is diagnosed and 0 otherwise. We assume that the healthy and asymptomatic workers work at their full productivity level but if a worker is symptomatic and working, the productivity is $e < 1$. In our experiment design different parameter values are considered for e: $e = 0.2, 0.5, 0.8$.

Let med represent the medical costs of treatment per person. For ages between 0-19, the average medical cost for treating flu is \$249 per person; for 20-64, \$400.7 per person; and for 65 and above, it is \$415 per person. These numbers are based on estimates given in [16]. We assume that the asymptomatic people do not have medical expenditure.

$$med = (249 \times N_{0-19}) + (400.7 \times N_{20-64}) + (415 \times N_{65+}) \tag{1}$$

where N_x is the number of symptomatic people within x age bin.

The simulation experiments are done for a total of $T = 300$ days for the city of Miami, Florida. Equation 2 shows the for worker i for the honest case i.e. $prod^H$, when the sick leave policy is in effect, while equation 3 shows the same for the rational case ($prod^R$). $D_{sick,i}$ is the number of sick days for worker i and $D_{\max}$ is the maximum number of sick-leave days allowed by the policy. The first line of both equations shows the productivity of the healthy and asymptomatic workers as represented by $h_i = 0$. The second line shows the productivity of the workers who are symptomatic ($h_i = 1$) but undiagnosed ($\epsilon_i = 0$). The third line represents the productivity of workers who are symptomatic ($h_i = 1$) and diagnosed ($\epsilon_i = 1$).

$$\begin{aligned} prod_i^H =&(1-h_i)\sum_{t=1}^{T} y_{it} \\ &+ h_i(1-\epsilon_i)\left[\sum_{t=1}^{T-D_{sick,i}} (y_{it}) + \sum_{t=1}^{D_{sick,i}} (y_{it})e\right] \\ &+ h_i\epsilon_i\left[\sum_{t=1}^{T-D_{sick,i}} (y_{it}) + \sum_{t=1}^{\max(D_{sick,i}-D_{\max},0)} (y_{it})e\right] \end{aligned} \tag{2}$$

$$\begin{aligned} prod_i^R =&(1-h_i)\sum_{t=1}^{T} y_{it} \\ &+ h_i(1-\epsilon_i)\left[\sum_{t=1}^{T-D_{sick,i}} (y_{it}) + \sum_{t=1}^{D_{sick,i}} (y_{it})e\right] \\ &+ h_i\epsilon_i\left[\sum_{t=1}^{T-D_{\max}} (y_{it}) - \sum_{t=1}^{\max(D_{sick,i}-D_{\max},0)} (y_{it})(1-e)\right] \end{aligned} \tag{3}$$

The loss in productivity for the above scenario is calculated by taking the difference between the productivity when there is no sickness in the society and the productivity as calculated in equation 2 or 3 for the honest or rational case respectively. Finally,

$$\text{Net Social Benefit} = \text{Productivity} - \text{Medical Costs} \tag{4}$$

3 Results

3.1 Effect of the Sick Leave Policy on Epidemics

The epidemic curves derived from our simulation results are displayed in Figure 1 for the catastrophic flu and Figure 2 for moderate flu. In both figures, we show the epidemic curve for the base case (i.e. no sick leave at all) and the curves for $D_{\max}$ values set at 3 days and 6 days only. The epidemic curves for $D_{\max} = 4$ and $D_{\max} = 5$ are very close to the 3-day and 6-day cases and are hence omitted to avoid clutter. Table 2 shows the total attack rate, peak day and peak size for all values of $D_{\max}$ and compliance levels.

It is important to note that the epidemics do not change across honest and rational cases, because in the SEIR model a recovered individual does not transmit the disease to others and cannot be infected by others either. The honest case and the rational case differ only when a sick worker recovers before $D_{\max}$ is reached: an honest worker will then go back to work while a rational worker will remain off. But it does not matter any more with respect to the disease spread because this worker is already recovered. Therefore the epidemic curves are the same under these two cases and we show the curves only once.

Figure 1 and Table 2 clearly show that the sick leave policy has a significant effect on the epidemic dynamics in catastrophic case. At 50% workplace compliance, the sick leave policy of 5 days can reduce the peak size from 19,000 to 16,000, i.e. by 15%. It can be reduced by another 15% to 13,600 if the compliance goes up to 100%. The effect is more prominent than it appears because

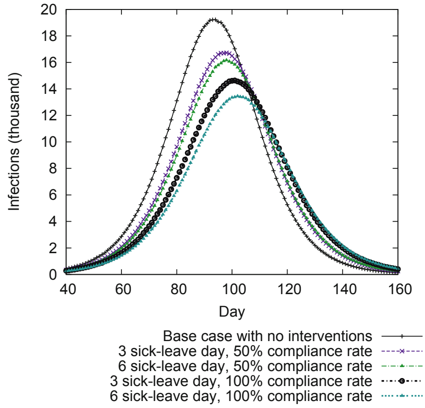

Fig. 1. Epidemic curves under the catastrophic flu case

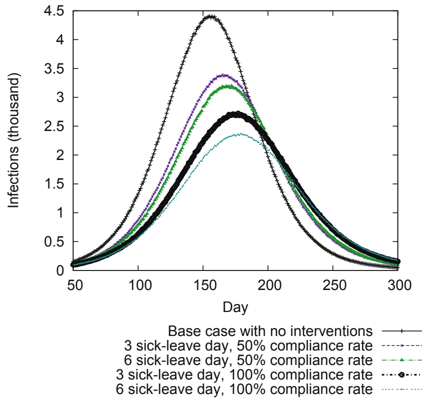

Fig. 2. Epidemic curves under the moderate flu case

Table 2. This table shows the percentage of people infected (attack rate), peak infection day (peak day), and the maximum number of infections on one day (peak size) in the catastrophic and moderate flu cases along with the base case (no intervention)

scenario	catastrophic flu			moderate flu		
	attack rate	peak day	peak size	attack rate	peak day	peak size
base case	40.0%	93	19,000	20.0%	155	4,400
Comp=50%, $D_{\max}$=3	37.3%	98	16,700	17.4%	165	3,400
Comp=50%, $D_{\max}$=4	36.5%	98	16,200	16.9%	169	3,200
Comp=50%, $D_{\max}$=5	36.2%	99	16,000	16.7%	168	3,200
Comp=50%, $D_{\max}$=6	36.1%	98	16,000	16.7%	170	3,200
Comp=100%, $D_{\max}$=3	34.5%	101	14,600	15.1%	177	2,700
Comp=100%, $D_{\max}$=4	33.1%	101	13,800	14.3%	177	2,500
Comp=100%, $D_{\max}$=5	32.5%	101	13,600	13.9%	180	2,400
Comp=100%, $D_{\max}$=6	32.4%	102	13,400	13.8%	179	2,400

the targeted intervened people only account for at most 6% (in case of 100% compliance rate) or 3% (in case of 50% compliance rate) of the total population.[2] The results show that the higher the compliance, the lower is the overall attack rate and changes to the maximum number of sick days by even a single day can cause statistically significant change to the attack rate and the medical costs. See Section 4.1 for details. A longer sick leave results in lower attack rates which is not surprising but the marginal effect due to an extra day of sick leave is nonlinear. The sick leave policy can help postpone the peak day by 5-8 days depending upon the compliance rate.

Similar pattern is found in Figure 2 and Table 2 for the moderate case. The policy has even more significant effects. It reduces the peak size by 27% compared to the base case (from 4400 to 3200) when compliance is at 50%. At 100% compliance the peak size is reduced by another 25%. The peak day can be delayed by 15 days at 50% compliance and another 10 days at 100% compliance.

For both catastrophic flu and moderate flu, the marginal effect of additional one day sick leave is decreasing. When $D_{\max}$ changes from 3 to 4, the effect on attack rate reduction is fairly large but as we increase $D_{\max}$ to 5 and 6 days, the marginal effect of additional sick days on attack rate starts to decrease. This can be explained by the fact that the mean infectious period is 4.1 days (see Section 2.1) and hence most people stay infectious for 4 days; there are relatively fewer people who stay sick for 5 or 6 days. Therefore the greater number of sick leave days are not needed for a large proportion of the population and the marginal improvement in the attack rate from the additional days drops.

3.2 Economic Benefit and Loss

In this section, we compare the economic gains and losses from the sick leave policy. Our earlier analysis shows that the sick leave policy can significantly

[2] This is because only one third of the population is workers. In addition, the attack rate is at most 40%, the symptomatic rate is 2/3, and diagnosed rate is 2/3 which makes the targeted people only a small fraction of the society.

reduce the epidemic, but it is important to understand the cost as a result of the policy. Sick leave policy gives opportunity to not only the sick workers to stay home but also to recovered workers if they behave dishonestly. This results in big loss in productivity which may not necessarily be offset by the benefit of smaller attack rate and lower medical bills. We take a societal point of view to see if there is an overall net benefit to the society from the sick leave policy.

We split the scenarios in 4 cases and describe the results of each case in the following subsections. Case 1 assumes people's behavior to be "honest" and flu to be of type "catastrophic". Case 2 assumes the behavior to be "honest" and flu to be of type "moderate". Similarly, case 3 and case 4 assume behavior to be "rational" and flu to be "catastrophic" and "moderate" respectively.

Case 1: Honest and Catastrophic. This section calculates the net benefit to the society when the workers' behavior is honest and the flu is of catastrophic type. We measure change in attack rate, change in productivity (at different levels of e) and change in the medical costs and compare it with the base case of no sick leave. The results are shown in Table 3.

Results in Table 3 show that higher compliance rate and more sick leave lead to lower attack rate and higher net social benefit to the society. As $D_{\max}$ increases, the diagnosed workers take more days off which changes the social contact network and the probabilities for disease transmissions. The disease spread slows down which is reflected in the lower attack rate compared to the base case.

However, the marginal effect of each additional sick day is decreasing since most people are sick for 4 days according to the disease model. When $D_{\max} = 3$, not enough sick leave is being given to cover the period of sickness so when it increases from 3 to 4, there is a much higher drop in attack rate than when $D_{\max}$ increases from 4 to 5 or from 5 to 6. The change in productivity is greatly affected by the parameter e which represents the level of productivity of sick

Table 3. Case 1: behavior is "honest" and flu type is "catastrophic". Comp shows the compliance rate, D_{max} represents the maximum number of sick days allowed, ΔAttack rate, ΔProductivity, ΔMedical and ΔNet Benefit represent the change in attack rate, change in productivity, change in the medical costs and change in net social benefits respectively as compared to the base case. The variable e represents the level of productivity of people who are working while sick.

Comp	D_{max}	ΔAttack Rate	ΔProductivity(millions) $e = 0.2$	$e = 0.5$	$e = 0.8$	ΔMedical (millions)	ΔNet Benefit(millions) $e = 0.2$	$e = 0.5$	$e = 0.8$
0.5	3	-0.029	10.007	-0.362	-10.731	-15.450	25.457	15.088	4.719
	4	-0.036	12.928	0.650	-11.628	-19.179	32.107	19.829	7.551
	5	-0.039	14.025	1.072	-11.881	-20.675	34.700	21.747	8.794
	6	-0.040	14.369	1.188	-11.993	-21.140	35.509	22.328	9.147
1	3	-0.056	19.865	1.677	-16.511	-29.344	49.209	31.021	12.833
	4	-0.069	25.298	4.241	-16.815	-36.189	61.487	40.431	19.374
	5	-0.075	27.543	5.415	-16.714	-39.147	66.690	44.562	22.434
	6	-0.076	28.310	5.863	-16.584	-39.902	68.212	45.765	23.318

workers. If e is small, there are fewer gains to be had from keeping sick workers at work who are likely to spread the disease by just being present.

Hence at low levels of e, the gain in productivity caused by the lower attack rate outweighs the loss in productivity caused by the sick leave policy. However, when the productivity of sick workers jumps to $e = 0.8$, the loss in productivity outweighs the gain, resulting in a net drop in productivity. Intuitively, this makes sense since at $e = 0.8$ the sick workers are 80% as productive as healthy workers so giving them sick time off will result in a big productivity loss. The change in medical bills column shows that as the attack rate goes down, the medical costs go down too.

The net benefit column in Table 3 accounts for both the productivity and the medical costs. As $D_{\max}$ increases the productivity increases, the medical costs go down, and the net benefits go up. The last three columns show that the optimal policy is $D_{\max} = 6$ because no matter what compliance rate is and what e is, the net benefit is the highest. Such a result should be expected given the assumption that workers behave honestly and take exactly the required number of sick days. Giving more sick days off will only result in the sick workers taking the extra sick days which will keep them out of the social network and hence keep them from transmitting the disease. This policy will lower the attack rate and yet not sacrifice productivity (because of no dishonest workers).

Case 2: Honest and Moderate. The results under this scenario, as shown in Table 4, are similar to case 1 in terms of the trend of the variables but the magnitude of the numbers is smaller for moderate flu as compared to the catastrophic flu. We still observe that $D_{\max} = 6$ is the optimal policy. The net benefit increases with the increase in the number of sick days. Compared to the catastrophic case, the policies are even more efficient when the productivity parameter $e = 0.8$ i.e. the loss in productivity is much lower. From both these cases, we can conclude that as long as workers are honest, a liberal sick leave policy is the best, no matter what the parameter settings are.

Table 4. Case 2: behavior is "honest" and flu type is "moderate"

Comp	D_{max}	ΔAttack Rate	ΔProductivity(millions) e=0.2	e=0.5	e=0.8	ΔMedical (millions)	ΔNet Benefit(millions) e=0.2	e=0.5	e=0.8
0.5	3	-0.027	8.657	2.891	-2.874	-13.348	22.005	16.239	10.474
	4	-0.032	10.221	3.624	-2.974	-15.738	25.959	19.361	12.764
	5	-0.033	10.797	3.902	-2.993	-16.599	27.397	20.502	13.607
	6	-0.034	10.984	3.979	-3.026	-16.855	27.839	20.834	13.830
1	3	-0.049	15.507	5.984	-3.540	-24.108	39.616	30.092	20.568
	4	-0.057	17.853	7.264	-3.326	-27.849	45.703	35.113	24.523
	5	-0.060	18.811	7.849	-3.114	-29.493	48.304	37.342	26.379
	6	-0.061	19.068	7.992	-3.084	-29.904	48.972	37.896	26.820

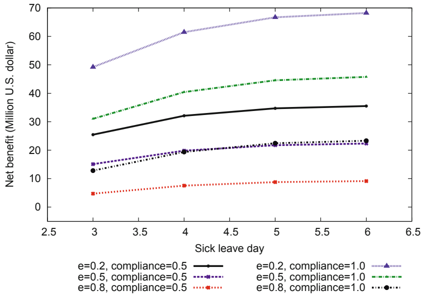

Fig. 3. Change in net benefit with honest behavior and catastrophic flu

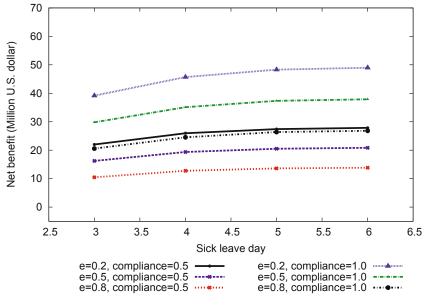

Fig. 4. Change in net benefit with honest behavior and moderate flu

Figure 3 and 4 show the net benefits for different policies for case 1 and case 2 respectively. The net benefit is monotonically increasing as $D_{\max}$ increases and all cases result in positive net benefit, suggesting that all intervention strategies are economically efficient.

Case 3: Rational and Catastrophic. Next we consider the scenario where the workers behave rationally and the flu type is catastrophic. In the rational case, the eligible workers use up all the available sick leave days.

Comparing the productivity in Table 5 with the productivity in the honest case in Table 3 shows that rational behavior results in lower productivity at all levels of e compared to the honest case. If workers stay home longer than they are sick for, it causes a pure loss to the society because there is no gain due to less disease transmissions. As a result the change in net benefit is smaller too. In this case, the optimal policy changes to $D_{\max} = 4$. The effect of $D_{\max}$ on net social benefit becomes non monotonic. As $D_{\max}$ increases from 3 to 4, the net benefit improves but when $D_{\max}$ increases from 4 to 5, the net benefit decreases. This is again because the mean sick days in our model is 4.1 so most of the people are sick for 4 days. If more than 4 days of sick leave is given, the loss in productivity outweighs any gains from lower attack rate. The optimal policy, $D_{\max} = 6$, under the honest case now becomes the least favorable especially when e is high.

Case 4: Rational and Moderate. Finally, results for case 4 where rational behavior is combined with moderate flu are presented in Table 6. Here the optimal policy is $D_{\max} = 5$ when $e = 0.2$, and $D_{\max} = 4$ when $e = 0.8$. Note that when $e = 0.2$, the productivity loss from the extra day off (i.e. $D_{\max} = 4$ vs. 5) by the sick workers is very little but their presence in the workforce increases the attack rate and the medical costs, which makes it socially optimal to have $D_{\max}$ set at 5. Increasing it further i.e. to $D_{\max} = 6$ does not help as much because the mean sick days are 4.1. However when $e = 0.8$ the productivity loss is high from the extra day off and hence the optimal sick leave policy changes to $D_{\max} = 4$.

Table 5. Case 3: behavior is "rational" and flu type is "catastrophic"

Comp	D_{max}	ΔAttack Rate	ΔProductivity(millions) e=0.2	e=0.5	e=0.8	ΔMedical (millions)	ΔNet Benefit(millions) e=0.2	e=0.5	e=0.8
0.5	3	-0.029	10.007	-0.362	-10.731	-15.450	25.457	15.088	4.719
	4	-0.036	11.323	-0.955	-13.233	-19.179	30.502	18.224	5.946
	5	-0.039	8.900	-4.053	-17.006	-20.675	29.576	16.623	3.670
	6	-0.040	4.742	-8.439	-21.620	-21.140	25.882	12.701	-0.480
1	3	-0.056	19.865	1.677	-16.511	-29.344	49.209	31.021	12.833
	4	-0.069	22.794	1.737	-19.319	-36.189	58.984	37.927	16.870
	5	-0.075	19.664	-2.465	-24.593	-39.147	58.811	36.683	14.555
	6	-0.076	13.713	-8.734	-31.182	-39.902	53.615	31.168	8.720

Figures 5 and 6 show the change in net social benefit when the behavior is rational and flu is catastrophic and moderate respectively. The net benefit is no longer monotonically increasing with the sick leave days.

4 Sensitivity Analysis

4.1 Epidemiological Variables

This section performs a detailed sensitivity analysis of the compliance rate, disease type and the maximum number of sick leave available on the two response variables i.e. the attack rate and medical costs using *analysis of variance* (ANOVA). Given that the human behavior and productivity level (e) can only affect the economic variables but not the epidemiological variables, we consider them separately. There are three factors which affect the attack rate and the medical costs: maximum sick leave days ($D_{\max}$), compliance rate (C) and disease type (Di). The 3-factor ANOVA model below shows how the factors are related to the response variable:

$$y_{ijsk} = \alpha + \beta_j + \gamma_s + \delta_k + \beta\gamma_{js} + \gamma\delta_{sk} + \beta\delta_{jk} + \beta\gamma\delta_{jsk} + \epsilon_{ijsk} \qquad (5)$$

Table 6. Case 4: behavior is "rational" and flu type is "moderate"

Comp	D_{max}	ΔAttack Rate	ΔProductivity(millions) e=0.2	e=0.5	e=0.8	ΔMedical (millions)	ΔNet Benefit(millions) e=0.2	e=0.5	e=0.8
0.5	3	-0.027	8.207	2.598	-2.874	-13.348	22.005	16.239	10.474
	4	-0.032	9.172	2.731	-3.573	-15.738	24.910	18.469	12.165
	5	-0.033	8.452	1.713	-4.889	-16.599	25.051	18.312	11.710
	6	-0.034	6.984	0.136	-6.576	-16.855	23.840	16.991	10.279
1	3	-0.049	15.058	5.691	-3.540	-24.108	39.616	30.092	20.568
	4	-0.057	16.561	6.127	-4.169	-27.849	44.411	33.977	23.680
	5	-0.060	15.760	4.954	-5.716	-29.493	45.253	34.447	23.777
	6	-0.061	13.779	2.859	-7.923	-29.904	43.684	32.764	21.981

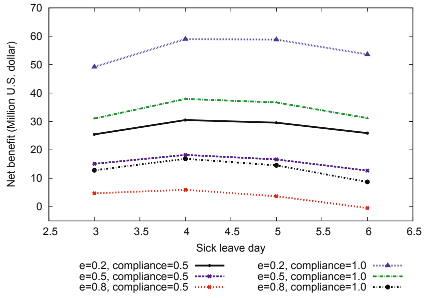

Fig. 5. Change in net benefit with rational behavior and catastrophic flu

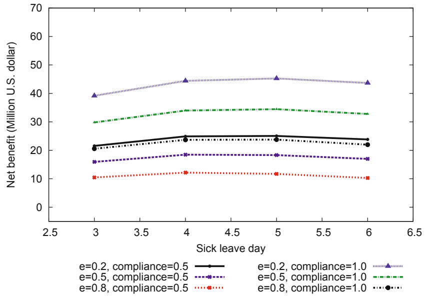

Fig. 6. Change in net benefit with rational behavior and moderate flu

where y represents the response variable i.e. attack rate and medical costs; α is the constant term, the main effects or factors are $\beta = D_{\max}$, $\gamma = C$, $\delta = Di$; ϵ is the error term and the rest are interaction terms. Subscript i represents replicates and takes values 1 … 25; j = 3,4,5,6; k = 50%, 100%; and s = catastrophic, moderate flu.

The sensitivity results as measured by ANOVA show that all three factors significantly affect the attack rate and the medical costs (p-value $< 1\%$). Both response variables are sensitive to the choice of policy days, disease type and the compliance rate. All interaction terms are significant too (p-value $< 1\%$).

In particular, we are interested in understanding if different number of sick leave days make a significant difference in the outcome variables. For this, we conduct *Tukey's honestly significant difference* (HSD) test to do a pairwise comparison. It considers all possible pairs of means and finds the ones that are significantly different. It is often used in conjunction with ANOVA. Suppose μ_i and μ_j are the means of two different treatments, and $\mu_i > \mu_j$, then Tukey's test statistic q_s is:

$$q_s = \frac{\mu_i - \mu_j}{SE} \tag{6}$$

where SE is the standard error of the data in question. The results of Tukey's test of different sick days ($D_{\max}$) are shown in Table 7 in the Appendix. All pairwise comparisons are significant, so 3, 4, 5, 6 days are all significantly different from each other in terms of their effects on the attack rate and the medical cost.

4.2 Economic Variables

Next, we analyze the sensitivity of the economic variables such as productivity and net social benefit. Besides the epidemiological factors, the economic variables are also affected by workers' behavior and their productivity levels during sick days. Hence we have a total of five factors i.e. $D_{\max}$, compliance (C), disease type (Di), behavior (B), productivity level of sick workers (e). Now the ANOVA model represents 5 factors:

$$y_{ijsklm} = \alpha + \beta_j + \gamma_s + \delta_k + \zeta_l + \lambda_m + I + \epsilon_{ijsklm} \tag{7}$$

where y represents the response variable i.e. productivity and net benefit. Note that this productivity is the overall productivity of the society as opposed to e which represents the productivity level of sick workers. $\beta = D_{\max}$, $\gamma = C$, $\delta = Di$, $\zeta = B$, $\lambda = e$, I represents all the interaction terms and ϵ is the error term. The sensitivity results as measured by ANOVA show that all five factors are significant (p-value $< 1\%$) in explaining productivity and the net benefit. Most interaction terms are significant too (p-value $< 1\%$). Due to space limit, in Table 8 we only show the interaction terms that are not significant at 1% level.

The results of Tukey's test (omitted due to space limit) show that $D_{\max} =$ 3, 4, 5, or 6 days are all significantly different from each other in terms of their effects on the productivity and net benefit (p-value $< 10\%$). Specifically, although $D_{\max} = 5$ and $D_{\max} = 6$ yield very similar net benefit in the honest case, and $D_{\max} = 4$ and $D_{\max} = 5$ have similar net benefit in the rational case, they are still statistically significantly different.

5 Summary and Conclusions

This research aims to study the role of an economic intervention i.e. a paid sick leave policy, as an instrument, to effectively control an influenza epidemic. A liberal paid sick leave policy discourages sick workers from coming to work which reduces the transmission of the disease among the workers and hence the society but affects the productivity of the society. The analysis takes a social planner's point of view to study the cost effectiveness of such a policy. We consider productivity loss due to the sick leave policy and compare it with the benefits from reduced attack rate and lower medical bills. Our experiments test a variety of scenarios based on the number of paid sick days and behavior of the workers. The number of maximum sick days considered are 3, 4, 5 and 6. The worker behavior is assumed to be of two types: rational or honest. In case of rational behavior, the workers take the maximum number of sick days available but in case of honest behavior, only the necessary number of sick days are taken. The simulation results show that if workers behave honestly, a liberal sick leave policy is the most optimal since the social gains increase with the increase in the number of paid sick days. If the workers behave rationally and take the maximum available sick days, however, it is optimal to have paid sick days to be equal to the mean number of sick days.

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Appendix: Tables for Sensitivity Analysis

Table 7. Pairwise comparison of factor $D_{\max}$. * represents significance at 10%.

	attack rate				medical cost			
grp vs grp	group means		mean diff	HSD-test	group means		mean diff	HSD-test
3 vs 4	-4.03	-4.84	0.81	61.21*	-20.56	-26.59	6.02	94.98*
3 vs 5	-4.03	-5.18	1.16	87.04*	-20.56	-25.31	4.75	74.91*
3 vs 6	-4.03	-5.28	1.25	94.08*	-20.56	-26.95	6.38	100.62*
4 vs 5	-4.84	-5.18	0.34	25.83*	-26.59	-25.31	1.27	20.07*
4 vs 6	-4.84	-5.28	0.43	32.87*	-26.59	-26.95	0.35	5.64*
5 vs 6	-5.18	-5.28	0.09	7.04*	-25.31	-26.95	1.63	25.71*

Table 8. Sensitivity analysis of economic variables. Only interaction terms not significant at 1% level are shown. All factors are significant at 1% level.

Factor	Productivity			Net Benefit		
	DF	SS	F value	DF	SS	F value
B:e	2	3.58E-28	2.23E-27	2	7.25E-28	5.24E-28
$D_{\max}$:B:e	6	4.28E-28	8.89E-28	6	3.43E-28	8.26E-29
C:B:e	2	1.67E-28	1.04E-27	2	1.64E-28	1.19E-28
Di:B:e	2	5.42E-29	3.37E-28	2	4.68E-28	3.38E-28
$D_{\max}$:C:B:e	6	1.31E-27	2.72E-27	6	1.46E-27	3.51E-28
$D_{\max}$:Dis:B:e	6	8.67E-28	1.80E-27	6	7.22E-28	1.74E-28
C:Di:B:e	2	1.19E-27	7.43E-27	2	6.17E-28	4.46E-28
$D_{\max}$:C:Di:B:e	6	4.10E-28	8.52E-28	6	1.56E-27	3.75E-28