Information and Risky Behavior: Model and Policy Implications for COVID-19

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June 16, 2020

Abstract

This paper studies a contagion model where individuals can take risky or safe actions to study the effects of testing and fines on disease spread and welfare. Testing gives agents knowledge to better assess the costs of exposing themselves to a disease. Whether testing increases or decreases disease spread depends on the private costs of the disease. If the private costs are small enough, then testing individuals increases infection. If the private costs are large enough, then testing individuals decreases infection. Punishing individuals for exposing themselves and others to the disease while also providing testing can also increase disease spread. Welfare in the economy is also examined in a simplified version of the model. Policy implications for public health responses to pandemics are discussed along with an application to crime.

1 Introduction

With the massive economic and health impacts of COVID-19 it is crucial to understand how policies will effect disease transmission and welfare. This paper takes an economic approach to understanding the effects of different policies on infection and welfare taking into account how behavior changes.

Medically testing the population has been noted to have major benefits during a pandemic. It can allow medical experts to track the spread of the disease and assess the potential consequences. While the data collected from testing individuals are surely useful in this capacity, very little is understood about how medical testing could affect individual behavior and disease spread. For example, could testing the population lead to increased infection?

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The answer to this question depends on how healthy and sick individuals choose to expose themselves to others in the face of better information on their health status. In particular consider a simple example of a sick and healthy individual interacting in a community. Perhaps they could meet at a restaurant or while grocery-shopping. The amount of disease spread in the economy depends on their interaction - only if both of them decide to go out to the restaurant or shop is there the possibility of disease spread.

If the healthy individual does not want to catch the sickness, then her equilibrium choice will depend on the choice of the sick individual. Suppose the sick person is willing to run their errand. If the cost of getting sick is high enough and the benefit of the errand is low enough, then the healthy individual will stay home.

Now consider the possibility that neither individual knows their health status. In particular, the sick individual may be asymptomatic or have only mild symptoms, but is still contagious. What is the effect of telling the individuals their health status on disease spread? In the simple two person example under the assumptions made above, disclosing the information can only decrease the amount of disease spread, since the healthy person does not want to risk their health status.

If a slight adjustment is made to the model, though, the result is ambiguous. Suppose now that there are four individuals, two of them are sick and two are healthy. The probability of getting sick if you are healthy is increasing in the number of sick people eating out. From each of the sick and healthy individuals, one has a very high benefit from eating at a restaurant - so high that they will not be deterred by getting sick at all - and the other has a low benefit so that if any sick people are out, they want to stay home.

Without medical testing, one sick and one healthy person go out to eat. When testing is introduced though, both sick people go out since they have no cost of getting the disease in the future. The high benefit person continues to go out to restaurants as well, and the rate of disease spread increases.

This paper analyzes this problem more formally in a model. In the model, individuals have heterogeneous benefits of exposing themselves to others, taking the "risky action", but internalize that getting sick is costly. The more sick people exposing themselves, the more likely it is for a healthy person to be infected. If a healthy person does not expose themself with the risky action, taking the "safe action", they have no risk of getting infected.

The equilibrium in this model is characterized by a threshold so that all agents with a benefit of taking the risky action larger than some cutoff take the risky action. A stark assumption is made between the regimes with and without testing: without testing it is assumed that individuals have no information on their health status, while with testing it is assumed that they perfectly observe their health status. Thus, when there is testing, the equilibrium threshold also depends on the health status of the agent.

The main result of this paper is that when testing is introduced, it is ambiguous whether infection increases or decreases. If the costs of getting sick are high enough, then infection decreases, while if the costs of sick are low enough, then infection increases. This ambiguity comes from the fact that healthy and sick individuals optimally adjust their exposure when learning their private information. More sick individuals always expose themselves while less healthy individuals expose themselves. This creates an ambiguity in infection that is resolved by the private costs of getting sick.

Consider also the possibility of enforcement on disease spread. For example, suppose that everyone that exposes themself by going out to a restaurant is fined some amount. Fines that target the entire population in this way will always reduce the amount of disease without testing, However when fines or lockdown procedures are combined with testing, the effect is ambiguous. The intuition is the same as above, since fines also reduce the mass of sick individuals exposing themselves. Fines that are targeted only towards sick individuals are not sufficient to overcome this issue.

The welfare implications of these different policies are also analyzed and compared. Fines that are targeted towards sick individuals who take the risky action can achieve a large proportion of the maximum possible social welfare if the number of initially sick individuals is small enough.

The policy implications of this analysis suggest that both testing and fines alone are not very useful. In fact, testing alone can lead to increased infection while fines alone do not increase welfare. Instead, the model suggests that testing and fines together can be a powerful tool to manage both disease spread and allow for many of the economic benefits lost to full lockdown to be regained. However, this relies on a potentially large fine being implemented and the ability to accurately monitor individual health status.

While the model focuses on disease spread, the model analysis also applies to other natural applications where heterogeneous individuals interact together to produce (negative) outcomes. In particular, an application is considered where there are criminals and non-criminals and the policy-maker can decide whether to disclose the location of the police. The model provides implications for how these policies are affected by crime. The intuition behind the main results is similar to Lazear (2006). Lazear (2006) studies a problem with exogenous policing and whether or not to announce where the police are located. This model extends that model by considering a heterogeneous group of agents that have different types. In other words, non-criminals are added to that model. The crime application is almost exactly analogous with the problem studied in that paper.

This paper is related to a large body of recent economics research inspired by the COVID-19 pandemic.[1] Many papers that study the implications of medical testing and other policy inter-

[1] A selection of papers: Akbarpour et al. (2020), Farboodi et al. (2020), Acemoglu et al. (2020), Eichenbaum et al. (2020b), Fernndez-Villaverde and Jones (2020)

ventions use tools from macroeconomics, building optimizing agent models on top of SIR epidemiology models to simulate the effects of different policy interventions such as lockdowns and quarantines. Similar to some of the results in this paper, some papers show that testing without quarantine can increase disease spread and suggest that combinations of lockdown and testing can deliver large social gains Eichenbaum et al. (2020a). This paper's novelty and value compared to those papers is specifying direct conditions on the primitives on the model to assess the efficacy of the policy, and providing qualitative intuition on when certain policies may or may not be effective.

On the microeconomic modeling side, a closely related paper to this paper is Deb et al. (2020). Their paper also shows that testing and fines (transfers in their setting) can have major gains over testing alone. A major departure from their model is that disease spread and welfare are directly modeled as an outcome to be achieved. Their model assumes the planner targets a certain infection rate. While this captures a similar trade-off between healthy and sick people taking certain actions which is central to the welfare claims made in this model, it does not allow for a clear understanding of how the primitives of the model map to the efficacy of certain policy interventions. Deb et al. (2020) also consider testing at home versus work, a policy margin not considered in this paper at all.[2]

The organization of the rest of this paper is as follows. The next section introduces a simplified version of the full model to build intuition on the effect of testing. Section 3 develops the full model that includes heterogeneous benefits and presents the main results on infection with testing. Section 4 considers other non-information based interventions separately and in combination with testing policies. Section 5 considers the welfare implications of the different policies. Section 6 discusses further applications in crime. Section 7 concludes.

2 Simplified Model

Suppose that there is a continuum of individuals of mass 1 with benefit $b > 0$ of taking a risky action. They can also take a safe action which yields a benefit of 0. They can be either sick or healthy, but their health statuses are unknown. The model takes place in a single period. If they are sick or get sick they pay a cost of $c > 0$ at the end of the period.

Disease is transmitted so that the total mass of infected people is equal to

$$\text{Infected} = \tau \cdot (\text{Healthy and Risky Action}) \cdot (\text{Sick and Risky Action}) \tag{1}$$

[2]Some older important economic work is also related to this paper. Philipson and Posner (1995) show that introducing voluntary medical testing in the market for STDs could increase the incidence of STDs. The major difference is that the economic mechanisms of their paper highlight a buyer-seller interaction with asymmetric information and uncertain quality. Here, the main mechanism is symmetric ignorance and symmetric informativeness.

which follows the epidemiological SIR model with the added nuance that only people taking the risky action can be either susceptible or can transmit the disease. $\tau \in (0,1)$ is the "infectivity" parameter, or how contagious the disease is. Proportion $p \in (0,1)$ of the population is sick. The objective function that the policymaker considers about is the total mass of individuals infected.

Equilibrium is given by a proportion $\mu_{nt}^* \in [0,1]$ of individuals taking the risky action and satisfies

$$b = \underbrace{(1-p)}_{\text{probability healthy}} \cdot \underbrace{[\tau \cdot p \cdot \mu_{nt}^*]}_{\text{probability get sick}} \cdot \underbrace{c}_{\text{cost of getting sick}} \tag{2}$$

so that the marginal community member is indifferent between taking the risky action and the safe action. This can be simplified to be

$$\mu_{nt}^* = \min\left\{\frac{b}{\tau p(1-p)c}, 1\right\} > 0 \tag{3}$$

and so the mass of infected people in the community is given by

$$D_{nt} = \tau(p\mu_{nt}^*)((1-p)\mu_{nt}^*) = \tau p(1-p) \cdot (\mu_{nt}^*)^2. \tag{4}$$

Suppose now the community tests everyone. For simplicity of the problem, testing is compulsive and free - this is not the most important margin of the problem for the purposes of this paper. Equilibrium is now described by two numbers (μ_h^*, μ_d^*) that describe the proportion of healthy and sick individuals, respectively, that take the risky action.

In this case, sick people have nothing to lose: they already suffer the cost c so they will take the marginal benefit b of going outside. Thus $\mu_d^* = 1$. Then consider the healthy people. Their benefit of the risky action is b while the cost is

$$[\tau \cdot p] \cdot c.$$

Their behavior is given by

$$\mu_h^* = \begin{cases} 1, & b > \tau pc, \\ 0, & b < \tau pc, \end{cases} \tag{5}$$

and so disease when testing is introduced is given by

$$D_t = \begin{cases} \tau p(1-p), & b > \tau pc, \\ 0, & b < \tau pc. \end{cases} \tag{6}$$

In this simplified model testing either leaves disease spread the same or reduces it:

Proposition 1. $D_t \leq D_{nt}$ and $D_t < D_{nt}$ if and only if $b < \tau pc$.

Proof. Suppose $b < \tau pc$. Then $D_t = 0$ and $D_{nt} > 0$ since (3) is strictly positive.

Suppose $b > \tau pc$. Then $D_t = \tau p(1-p)$. Also,

$$b > \tau pc \Rightarrow b > \tau p(1-p)c \Rightarrow \frac{b}{\tau p(1-p)c} > 1 \Rightarrow \mu_{nt}^* = 1$$

which implies that $D_{nt} = \tau p(1-p) = D_t$. □

Does this result imply that testing will always reduce disease? It may appear to suggest so, but this is a knife-edge result that is extremely sensitive to the assumptions made about homogeneous benefits. Introducing slight heterogeneity allows for the possibility that testing increases disease. To see how suppose that there are two types of people in the population those with low and high benefits, $0 < \underline{b} < \bar{b}$ with $\bar{b} > \tau pc$. This assumption guarantees the high benefit types are undeterred by the risk of catching the disease. Proportion q have high benefits and the distribution of benefits and the disease are independent. Without testing, all high benefit types take the risky action. If

$$\underline{b} < \tau pqc$$

then none of the low benefit types take the risky action without testing. This induces

$$D_{nt} = \tau p(1-p)q^2 \tag{7}$$

Now with testing, all sick individuals take the risky action. The low benefit healthy individuals continue to take the safe action, but the high benefit healthy individuals are undeterred - they continue to take the risky action. In this case

$$D_t = \tau p(1-p)q > D_{nt} \tag{8}$$

so that testing increases disease spread. The increase in the number of sick individuals taking the risky action is not compensated enough for the decrease in the number of healthy individuals taking the risky action. The strength of these two effects is what determines whether testing increases or decreases disease spread. The model in the next section allows for a general distribution of benefits $F(\cdot)$.

3 Model

Continue to assume that there is a continuum of individuals of mass 1 in a community interacting. Suppose now that instead of a single benefit characterizing all individuals, each individual i has a benefit b_i and an initial disease status d_i^0 where these are modeled as random variables distributed according to

$$b_i \sim F(\cdot),\ b_i \in [0, \bar{b}]$$
$$d_i^0 \sim \text{Ber}(p)$$

and that b_i and d_i^0 are independent. Moreover assume that F is continuous and atomless. All other assumptions from the model above remain the same.

Suppose that there is no testing so that no individuals observe their initial health status d_i^0. Individuals only observe their benefit of taking the risky action. In this case, and in all future cases, equilibrium is described by a threshold b^*_{nt} s.t. $a_i = \mathbf{1}\{b_i > b^*_{nt}\}$ where $a_i = 1$ is the risky action so that all people with benefits of going outside larger than the cutoff b^*_{nt} take the risky action.

Thus the equilibrium is completely characterized by the single number b^*_{nt}. Since the equilibrium is a threshold equilibrium, it must be that, in equilibrium, the individual i with $b_i = b^*_{nt}$ must be indifferent between taking the risky and safe action in terms of their expected utility. Indifference for an individual i is described by

$$b_i = \mathbb{P}\left(d_i^0 = 0\right) \cdot [\tau \cdot \underbrace{\mu_d}_{\text{mass of sick risky action individuals}}] \cdot c = (1-p) \cdot [\tau \cdot \mu_d] \cdot c \tag{9}$$

Note that if all $b_i > b^*_{nt}$ take the risky action, and proportion p of them are sick, then the mass of sick individuals taking the risky action as a function of the threshold can be expressed as

$$\mu_d = p(1 - F(b^*_{nt})). \tag{10}$$

Thus for a threshold b^*_{nt} and individual i with $b_i = b^*_{nt}$ we have that equilibrium is described by

$$b^*_{nt} = (1-p) \cdot [\tau \cdot p(1 - F(b^*_{nt}))] \cdot c. \tag{11}$$

Unpacking this equation, we see that as more individuals take the risky action, the expected cost of the risky action increases. This is because μ_d is increasing in the proportion of the population taking the risky action. Moreover, individuals with the highest benefit of taking the risky action are those that take the risky action in equilibrium.

Importantly note that $b^*_{nt} < \bar{b}$, so that $1 - F(b^*_{nt}) > 0$, some people in the population take the risky action.[3]

[3]Proof: Suppose $b^*_{nt} = \bar{b}$ in equilibrium. Then $\mu_d = 0$ and so there is no cost to taking the risky action and so there is an incentive to take the risky action.

Disease spread in this case is given by

$$D_{nt} = \tau(p(1 - F(b^*_{nt})))((1 - p)(1 - F(b^*_{nt}))) = \tau p(1 - p)(1 - F(b^*_{nt}))^2 \tag{12}$$

Suppose now that all individuals are tested (compulsively and costlesly) and each individual i observes their health status d^0_i. Similar to above, the equilibrium will feature a threshold. Since individuals observe both their health status and their benefit, this threshold will also depend on health status. Thus, equilibrium will be described by a threshold for sick people $b^*_t(1)$ and a threshold for healthy people $b^*_t(0)$ so that all individuals of health status d^0 with $b > b^*_t(d^0)$ will take the risky action.

First consider the incentives of sick individuals. Under the assumptions of the model, these individuals already pay a sunk cost of c at the end of the period independent of their behavior so there is no further risk of getting infected. Since $b_i \geq 0$ and risky actions are always beneficial without the risk of sickness, it must be that $b^*_t(1) = 0$. Thus all sick individuals take the risky action when there is free testing available. This result only depends on the assumption that risky actions are preferred when individuals are immune to the disease.

For a healthy individual i, the payoff to the safe action is 0 while the payoff to the risky action is

$$b_i - [\tau p] \cdot c$$

and so the equilibrium for risky individuals will have

$$b^*_t(1) = \tau pc \tag{13}$$

Disease spread with testing is thus given by

$$D_t = \tau(p)((1 - p)(1 - F(\tau pc))) = \tau p(1 - p)(1 - F(\tau pc)). \tag{14}$$

Equations (12) and (14) show that testing reduces disease spread if and only if

$$1 - F(\tau pc) \leq (1 - F(b^*_{nt}))^2. \tag{15}$$

Equation (15) shows that the effect of testing is ambiguous since $b^*_{nt} < \tau pc$.[4] The two competing forces are similar to those described in the simplified model above. First, testing induces less healthy people to take the risky action. Second, testing induces more sick people to take the risky

[4] To see why note that

$$b^*_{nt} < \tau pc = b^*_t(1)$$

since $(1 - p)(1 - F(b)) < 1$.

action. So while the number of susceptible people decreases, the probability of infection for those that remain susceptible increases. These two offsetting forces make it ambiguous to know exactly how testing will affect disease.

The following proposition provides a resolution of this ambiguity in terms of the economic primitives of the model.

Proposition 2. Let $p < 1/2$. For any concave $F(\cdot)$ with a non-decreasing hazard rate $h(x) = \frac{f(x)}{1-F(x)}$ and finite support on $[0, \bar{b}]$, there exists some $c^* \in (0, \bar{b})$ s.t. if $c < c^*$ then $D_{nt}(c) < D_t(c)$ and otherwise $D_{nt}(c) \geq D_t(c)$. This c^* is decreasing in p, so more diseased people initially makes it easier for testing to have a positive impact, and decreasing in τ, so higher contagion makes it easier for testing to have a positive impact.

Proof. This result is established by a series of four claims. Let $\kappa = \tau pc$ and consider the functions $D_{nt}(\kappa)$ and $D_t(\kappa)$. These claims are

- $D_{nt}(0) = D_t(0)$
- There exists a $\bar{\kappa}$ large enough that $D_{nt}(\bar{\kappa}) > D_t(\bar{\kappa})$
- $|D'_{nt}(0)| > |D'_t(0)|$
- The function $g(\kappa) = D_{nt}(\kappa) - D_t(\kappa)$ satisfies the weak single crossing property for $\kappa > 0$.[5]

To see how these three claims establish the result, note that they establish that $D_{nt}(\kappa)$ and $D_t(\kappa)$ cross only on some connected interval starting at some $\kappa^* \in (0, \bar{b})$. Moreover, note that there exists some $\kappa_2^* \geq \kappa^*$ s.t. $D_{nt}(\kappa) > D_t(\kappa)$. This is because they establish that there is some values κ_1, κ_2 s.t. $g(\kappa_1) < 0$ (the first and third claim) and $g(\kappa_2) > 0$ (the second claim), and $g(\kappa)$ has a connected set of interior zeros. That connected set could be a singleton. In fact, it will be a singleton if the hazard rate is strictly increasing.

The first claim is a computation: when $\kappa = 0$ we have that $\tau pc = 0$ and the cost of taking the risky action is 0 so that $b^*_{nt} = 0$ is the equilibrium threshold. Thus

$$1 - F(\tau pc) = 1 - F(0) = 1 = (1 - F(0))^2 = (1 - F(b^*_{nt}(0)))^2$$

Now let $\bar{\kappa} = \bar{b} + \epsilon$ for some very small $\epsilon > 0$. Then $\tau pc > \bar{b}$ and so $b^*_t = \bar{b}$ so that no healthy people will take the risky action. Then

$$D_t(\bar{\kappa}) = 1 - F(\bar{b}) = 0$$

[5]The weak single crossing property states that $g(c) = 0$ implies that $g'(c) \geq 0$. This implies that the zero set of the function must be connected.

In the no testing equilibrium we have that

$$b_{nt}^* = (1-p)\bar{\kappa}(1 - F(b_{nt}^*)) < \bar{b}$$

which can be seen by assuming that $b_{nt}^* \geq \bar{b}$ then $1 - F(b_{nt}^*) = 0$ and so the cost of taking the risky action is 0 and so any type has an incentive to deviate. Thus

$$D_{nt}(\bar{\kappa}) > 0$$

and the second claim is established.

For the third claim, note that

$$\begin{aligned} D_t'(\kappa) &= -f(\kappa) \\ D_{nt}'(\kappa) &= -2(1 - F(b_{nt}^*))f(b_{nt}^*)b_{nt}^{*'}(\kappa) \end{aligned} \tag{16}$$

and using the equilibrium condition (12) we get that

$$\begin{aligned} b_{nt}^{*'}(\kappa) &= (1-p)(1 - F(b_{nt}^*)) - (1-p)\kappa f(b_{nt}^*)b_{nt}^{*'}(\kappa) \\ \Rightarrow b_{nt}^{*'}(\kappa) &= \frac{(1-p)(1 - F(b_{nt}^*))}{(1-p)\kappa f(b_{nt}^*) + 1} (\geq 0) \end{aligned}$$

Then we can write

$$D_{nt}'(c) = -2\frac{(1-p)f(b_{nt}^*)(1 - F(b_{nt}^*))^2}{(1-p)\kappa f(b_{nt}^*) + 1} \tag{17}$$

Evaluating these derivatives at 0 yields

$$\begin{aligned} D_t'(0) &= -f(0) \\ D_{nt}'(0) &= -2\frac{(1-p)f(0)}{(1-p)(0)f(0) + 1} \\ &= -2(1-p)f(0) \end{aligned}$$

and then since $p < 1/2$ we have that, $|-2(1-p)f(0)| = 2(1-p)f(0) > f(0) = |-f(0)\tau p|$ and so $|D_{nt}'(0)| > |D_t'(0)|$. This implies that there exists a $\kappa_1 > 0$ s.t. $g(\kappa_1) < 0$.

We aim to show that $g(\kappa) = 0$ implies that $g'(\kappa) \geq 0$. Note that

$$g'(\kappa) = D_{nt}'(\kappa) - D_t'(\kappa) = -\left(\frac{2(1-p)f(b_{nt}^*)(1 - F(b_{nt}^*))^2}{(1-p)\kappa f(b_{nt}^*) + 1} - f(\kappa)\right)$$

using (16) and (17).

We now aim to show that if $g(\kappa) = 0$ then $g'(\kappa) \geq 0$. To show that this is non-negative, we need to show that the term inside the big brackets is non-positive. First, note that because $g'(0) < 0$, $\exists \kappa_2$ s.t. $g(\kappa_2) > 0$, and $g(\kappa)$ is continuous, we have that $\mathcal{K} = \{\kappa : g(\kappa) = 0\}$ is non-empty.

Let $\kappa_1 = \min\{\mathcal{K}\}$. Since $g'(0) < 0$ we have that $g'(\kappa_1) \geq 0$. Since $g(\kappa_1) = 0$ we know that

$$1 - F(\kappa_1) = (1 - F(b^*_{nt}(\kappa_1)))^2$$

and so we can write

$$\begin{aligned} g'(\kappa_1) &= -\left(\frac{2(1-p)f(b^*_{nt})(1-F(b^*_{nt}))^2}{(1-p)\kappa_1 f(b^*_{nt}) + 1} - f(\kappa_1) \right) \\ &= -\left(\frac{2(1-p)f(b^*_{nt})(1-F(\kappa_1))}{(1-p)\kappa_1 f(b^*_{nt}) + 1} - f(\kappa_1) \right) \end{aligned}$$

and since $g'(\kappa_1) \geq 0$ we have that

$$f(\kappa_1) \geq \frac{2(1-p)f(b^*_{nt})(1-F(\kappa_1))}{(1-p)\kappa_1 f(b^*_{nt}) + 1} \Leftrightarrow \frac{f(\kappa_1)}{1-F(\kappa_1)} \geq \frac{2(1-p)f(b^*_{nt})}{(1-p)\kappa_1 f(b^*_{nt}) + 1}$$

Now to establish the weak single crossing property, let $\kappa' \in \mathcal{K}$. We aim to show that $g'(\kappa') \geq 0$. Note that $\kappa' \geq \kappa_1$ by construction of κ_1. Now we have that

$$\begin{aligned} \frac{f(\kappa')}{1-F(\kappa')} &\geq \frac{f(\kappa_1)}{1-F(\kappa_1)} \text{ by hazard rate non-decreasing} \\ &\geq \frac{2(1-p)f(b^*_{nt}(\kappa_1))}{(1-p)\kappa_1 f(b^*_{nt}(\kappa_1)) + 1} \\ &\geq \frac{2(1-p)f(b^*_{nt}(\kappa'))}{(1-p)\kappa' f(b^*_{nt}(\kappa')) + 1} \text{ since } \kappa' \geq \kappa_1, b^{*'}_{nt}(\kappa) \geq 0 \text{ and } F(\cdot) \text{ concave} \end{aligned}$$

which implies that

$$g'(\kappa') \geq 0.$$

This establishes the single crossing property.

The later parts are simple implications of the fact that $\kappa = \tau pc$. □

The economic intuition for this result is simple. When testing is introduced, all sick individuals take the risky action exposing themselves, increasing the mass of sick individuals exposing to others. If c is small, then a sufficient number healthy individuals will still insist on taking the risky action, since the private costs of disease are small enough, increasing overall disease spread. If c is large, healthy individuals will be sufficiently deterred from the increase in sick individuals in the community to reduce the infection rate.

The technical conditions of the proposition may appear somewhat specific and I discuss them more in depth now. A concave cdf implies that the probability density is decreasing. In words, this condition states that in the population, for any two values $b_1 > b_2$, the likelihood of a person having value b_1 is less than the likelihood of a person having value b_2.

The condition on the hazard rate is one that is not completely unfamiliar to economists. For example, a non-decreasing hazard rate for the distribution of bidder values is also a sufficient condition for the virtual valuations $v - \frac{1-F(v)}{f(v)}$ to be monotonic increasing, which allows for tractability and simplicity in the auctions literature in deriving the optimal mechanism (Myerson, 1981).

In general, the hazard rate and concavity assumptions on the distribution can be relaxed to prove a weaker result, in which there exists a $\underline{c}^*$ and $\bar{c}^*$ s.t. $D_{nt} > D_t$ if $c < \underline{c}^*$ and $D_{nt} < D_t$ if $c > \bar{c}^*$. This does not use the single crossing property in the proof, but instead only the comparisons of the derivative of infection at $c = 0$ and the large enough c s.t. $D_{nt} > D_t$. This contains much of the same economic content as the stated proposition.

Finally, the finite support distribution assumption is crucial to the proof. However the (infinite support) exponential distribution as a leading example for $F(\cdot)$ is analyzed now and it is shown that the properties of the Proposition hold. Importantly, multiple simulations for other infinite support distributions such as the chi-squared and log-normal distribution shown in the Appendix show that the same threshold condition on c^* holds. This gives me strong confidence that this economic property is more general than what can be shown here.

Consider the case in which $F(\cdot)$ is the exponential CDF with parameter $\lambda > 0$. Then we can write

$$1 - F(\tau pc) = \exp\{-\lambda \tau pc\}$$

The equilibrium without testing is described by

$$b^*_{nt} = \tau p(1-p)c \exp\{-\lambda b^*_{nt}\}$$

and the condition on the ranking of infection is given by

$$D_t \leq D_{nt} \Leftrightarrow \exp\{-\lambda \tau pc\} \leq \exp\{-2\lambda b^*_{nt}\}$$

and this can be simplified to

$$\tau pc \geq 2b^*_{nt}.$$

Note that the equilibrium condition for no testing above states that

$$b_{nt}^* = W(\tau p(1-p)c\lambda)/\lambda$$

where $W(\cdot)$ is the product log or Lambert W function.[6] Note that $W(x) < \log(x)$ for $x > e$ (Hassani, 2005) and so

$$2b_{nt}^* < 2\log(\tau p(1-p)c\lambda)/\lambda$$

and so there exists a c large enough s.t. $\tau pc \geq 2b_{nt}^*$ since τpc grows linearly in c and b_{nt}^* grows at most logarithmically in c.

4 Fines and Enforcement

The previous results suggest that giving individuals information through testing can increase disease spread. Now consider the possibility that the policymaker has fines or other tools available to punish individuals for taking the risky action and exposing themselves to the disease. Can these fines offset this potential infection effect when combined with testing? How do they compare to testing when used in isolation? Does it matter how the fines are administered? These questions are addressed using the model in this section.

4.1 Coarse Fines and Lockdown

A common policy response to COVID-19 is lockdown - punishing either explicitly or implicitly any type of behavior that causes someone to expose themself to another. What are the disease implications of lockdown? It will be shown that whether lockdown reduces or increases disease spread depends on the information available to individuals. Similar to the intuition above, if individuals have knowledge about their health status, then lockdown policies can actually *increase* disease spread.

The implications of lockdown are derived by modifying the benefits for individual i to be

$$b_i(K) = b_i - K$$

where K is the expected punishment individuals face from disobeying lockdown orders and exposing themselves to others through the risky action.

Equilibrium analysis when individuals have no information about their health status, i.e. without testing, is very similar to the case above. In this case, the indifference condition can be written

[6] The product log function is defined by $W(x)e^{W(x)} = x$.

as

$$b_i - K = (1-p) \cdot [\tau \cdot \mu_d] \cdot c$$

and so the equilibrium is described by

$$b^*_{nt}(K) = K + (1-p)[\tau \cdot p(1 - F(b^*_{nt}(K)))] \cdot c \tag{18}$$

and it is easy to see that $b^{*'}_{nt}(K) > 0$.

Disease spread can then be written as

$$D_{nt}(K) = \tau p(1-p)(1 - F(b^*_{nt}(K)))^2 \tag{19}$$

and since $b^{*'}_{nt}(K) > 0$, it is clear that $D'_{nt}(K) < 0$. Lockdown without testing does indeed reduce the disease spread in the community. So, for reducing infection, lockdown appears to be a more robust solution than testing.

What about combining something like lockdown with testing? This could take a few different forms and two important cases are analyzed here.

Consider the case where individuals observe their health status thanks to testing. The behavior of sick individuals depends only on the fine. Sick individuals benefit from taking the risky action is now $b_i - K$ and so the equilibrium threshold for sick individuals is given by

$$b^*_t(1, K) = K.$$

Given sick individuals fixed behavior, one can solve for the healthy individuals equilibrium threshold as

$$b^*_t(0, K) = K + \tau p(1 - F(K))c$$

using the fact that the mass of sick individuals is $\mu_d = p(1 - F(K))$.

Disease spread with both lockdown K and testing can be written as

$$D_t(K) = \tau p(1-p)(1 - F(K))\Big(1 - F\big(K + \tau p(1 - F(K))c\big)\Big), \tag{20}$$

Similar to the intuition above, the derivative $D'_t(K)$ has an ambiguous sign. Formally we can write

$$D'_t(K) = -\tau p(1-p)\Big[f(K)(1 - F(d(K))) + f(d(K))(1 - F(K))d'(K)\Big] \tag{21}$$

where $d(K) = K + \tau p(1 - F(K))c$. Equation (21) shows that if $d'(K) \geq 0$, then that is sufficient for $D_t'(K) < 0$. The derivative $d'(K)$ is given by

$$d'(K) = 1 - \tau pcf(K)$$

and so the intuition is similar to before: if any of τ, p or c are large enough, then punishing individuals for exposure while also giving them information about their health status can increase infection. As with Proposition 2, one could write down a cutoff structure. Also, note that if $f(\cdot)$ is decreasing (i.e. $F(\cdot)$ is concave) and τpc is small enough, then there exists a K^* large enough after which it is guaranteed that $D_t'(K) < 0$.

It is informative to see these ideas in a concrete example. Suppose $F(\cdot)$ is the exponential distribution with parameter λ. Then we can write

$$D_t'(K) = -\tau p(1-p)\Big[\lambda \exp\{-\lambda K\}\exp\{-\lambda(K + \tau p \exp\{-\lambda K\}c)\} \\ + \lambda \exp\{-\lambda(K + \tau p \exp\{-\lambda K\}c)\}\exp\{-\lambda K\}(1 - \tau p \exp\{-K\}c)\Big]$$

and so the sign of the derivative depends on whether

$$2 - \tau p \exp\{-K\}c > 0$$

and so if $\tau pc > 2$ then for $K < \log(\tau pc/2)$ the derivative is positive and for $K > \log(\tau pc/2)$ the derivative is negative. Similar to the intuition above, fines induce more infection (i.e. the measure of K for which $D_t'(K) > 0$ increases) when c (and the full term τpc) increases. Behaviorally, the intuition remains the same throughout this paper. Fines that are small relative to τpc reduce diseased individuals from exposing themselves enough to incentivize sufficiently enough healthy people to expose themselves leading to increased infection.

4.2 Targeted Fines and Legal Implications

Indiscriminate lockdown and coarse fines considered previously are a blunt policy instrument, and it is well-known in the mechanism design literatures that targeting transfers based on people's types can lead to large gains in efficiency. Importantly for this application, medical testing gives policymakers the potential to identify individuals types. To make the enforcement strategy more sophisticated, the model now considers fines that only target sick people who take the risky action. Healthy people who expose themselves are not punished.

These types of enforcement policies treat risky actions by sick people similar to criminal activity. Willingly going out in public while highly infectious with a deadly disease can be seen as a crime with some social cost. In the model so far, there are no such punishments for infecting others, only for bluntly taking the risky action. When a healthy and sick agent interact, the sick agent willingly endangers the healthy agent. This is similar to many other crimes. In fact, some states already have communicable (contagious) disease statuses.[7] Many of these deal with cases where an STD is willingly transmitted. The principle is the same here, and these types of legal mechanisms may indeed affect people's behavior in the real world.

To add this type of instrument to the model, assume that benefits are modeled in the following way

$$b_i(1, K) = b_i - K$$
$$b_i(0, K) = b_i$$

so that only sick agents that take the risky action pay the expected fine.

The equilibrium without testing is the same with coarse fines except that now the expected payment is $\tilde{K} = pK$ since individuals cannot observe their health status. There is also question of whether this enforcement is even possible without testing easily present. Can the government easily test people on the spot to identify criminals? In any case, the behavioral and welfare results are qualitatively the same as above.

The equilibrium with testing differs drastically since now K directly affects sick people's behavior and only indirectly affects healthy people's behavior through its effect on sick people.

The equilibrium thresholds are

$$b_t^*(1, K) = K$$
$$b_t^*(0, K) = [\tau p(1 - F(K))]c$$

Importantly, compared to the coarse fines case above, strictly more healthy people take the risky action while the same number of sick people take the risky action for the same K.

Using the equilibrium conditions above, infection can be written as

$$D_t(K) = \tau p(1 - p)(1 - F(K))\Big(1 - F\big(\tau p(1 - F(K))c\big)\Big) \tag{22}$$

Do targeted fines strictly decrease infection? Perhaps surprisingly, the answer is no. To see why consider

$$D_t'(K) = -\tau p(1 - p)\Big[f(K)(1 - F(d(k))) + f(d(K))(1 - F(K))d'(K)\Big]$$

[7] Source. Another source states: "A majority of states have communicable disease laws that make it a crime to expose another person to a contagious disease on purpose. Even without a specific communicable disease statute, all states have general criminal laws?such as assault, battery, and reckless endangerment?that can be used to prosecute people for spreading diseases intentionally or recklessly." Source.

where

$$d(K) = \tau pc(1 - F(K)) \Rightarrow d'(K) = -\tau pcf(K) < 0.$$

Since $d'(K) < 0$ it is possible that $D_t'(K) > 0$, similar to the case with coarse fines.

As a concrete example, suppose $F(\cdot)$ is an exponential λ CDF. Then

$$\begin{aligned}
&f(K)(1 - F(d(k))) + f(d(K))(1 - F(K))d'(K) \\
&\quad = \lambda \exp\{-\lambda K\} \exp\{-\lambda \tau pc \exp\{-\lambda K\}\} + \lambda \exp\{-\lambda \tau pc \exp\{-\lambda K\}\} \exp\{-\lambda K\}(-\tau pc \exp\{-K\}) \\
&\quad = \lambda \exp\{-\lambda K\} \exp\{-\lambda \tau pc \exp\{-\lambda K\}\}(1 - \tau pc \exp\{-K\})
\end{aligned}$$

and so

$$D_t'(K) \leq 0 \Leftrightarrow 1 \geq \tau pc \exp\{-K\}$$

and so if $\tau pc \geq 1$, we get that for $K < \log(\tau pc)$ the derivative is positive and for $K > \log(\tau pc)$ the derivative is negative. Thus targeted fines are not sufficient for guaranteeing a decrease in infection.

The intuition is that targeted fines strictly decrease the incentives of sick people of taking the risky action. Healthy people will then optimally respond by exposing themselves more, and the total amount of infection depends on the magnitudes of these behavioral responses. When fines are targeted at sick individuals, we have the opposite heterogeneous behavioral implications than when testing is introduced.

4.2.1 Discussion on Fines vs. Monitoring

The fines discussed have the original flavor in the enforcement literature that they combine both the actual fine or cost imposed ϕ and a probability of detection q so that $K = q\phi$. The standard result in literature is that when detection is difficult, q is set low and ϕ is set large.

In this model and the application considered it is relatively easy to detect *any* risky action. Risky actions consist of going to work or exposing ones-self to others, which often may take place in public spaces. Policemen or other law enforcement officials could use one's presence in public spaces or commuting to work as a way to detect this crime. There could also be other social processes that enable monitoring, where neighbors report these types of activities.

However, targeted fines are much more challenging to administer properly. It seems difficult without a mobile testing mechanism to confirm that someone is both taking the risky action and sick in real-time, unless symptoms are extreme. Practically, this highlights the potential usefulness of a universal database to track which individuals are sick or the ability to test "on-the-go". Within the model, this highlights that implementing targeted fines should probably consists of a very large punishment if caught, since the probability of enforcement could realistically be very low.

5 Welfare Implications

This paper has explored the implications of disease in a contagion model of behavior. One benefit of the simplicity of the model is that it can also be used to assess welfare. To make the analysis more tractable, consider the baseline model again where $b_i = b$ for all i. To make welfare comparisons interesting and avoid extreme solutions, suppose that $b < \tau p(1-p)c$, otherwise the social planner will always choose for the entire community to take the risky action. Welfare is studied in both the no testing and testing regimes.

The social planner without testing solves the following problem

$$\max_{\mu} \mu b - \tau p(1-p)\mu^2 c - pc \tag{23}$$

where the control variable μ is the mass of the community taking the risky action. Taking the first order condition yields that the socially efficient mass of individuals in the community taking the risky action is given by

$$\mu_s^* = \frac{b}{2\tau p(1-p)c}. \tag{24}$$

Compared to the equilibrium behavior above, μ_{nt}^* in (3), we have that $\mu_s^* < \mu_{nt}^*$. The social planner reduces the mass of individuals taking the risky action due to the social externality of infection. In this model, risky actions are reduced by exactly *half* in the social planner's solution.

The social planner with testing solves the following problem

$$\max_{\mu_h, \mu_d} (p\mu_d + (1-p)\mu_h)b - \tau p(1-p)\mu_d \mu_h c - pc \tag{25}$$

The first order condition yields

$$pb - \tau p(1-p)\mu_h c = 0$$
$$(1-p)b - \tau p(1-p)\mu_d c = 0$$

and the implied social welfare from this solution is

$$W = \frac{b^2}{\tau c} - pc.$$

However, the extreme points $\mu_h = 1 - \mu_d \in \{0, 1\}$ have values

$$W_1 = (1-p)b - pc$$
$$W_2 = pb - pc$$

and so if p is small enough and $\tau c > b$,[8] then the social planner chooses

$$\mu^*_{h,s} = 1 \tag{26}$$
$$\mu^*_{d,s} = 0$$

so that all healthy people take the risky action and all sick people take the safe action yielding welfare

$$W^* = (1-p)b - pc. \tag{27}$$

The social welfare achieved in equilibrium is less than that achieved by the social planner when there is no testing. This is true simply because $\mu^*_s \neq \mu^*_{nt}$ as shown above.

Consider the equilibrium social welfare with testing. This is given by

$$W_t = pb - pc \tag{28}$$

using the fact that $b < \tau p(1-p)c \Rightarrow b < \tau pc$.

Comparing W^* and W_t we see that

$$W^* - W_t = (1-2p)b.$$

In realistic cases that motivate this model, p is very small, suggesting that $1-2p$ is a large percentage. Thus, testing alone achieves a very small proportion of the overall social gains available.

It also useful to compare the welfare from testing and not testing independent of the social planner's problem. Note that when $b > \tau pc$, the testing and no testing equilibria have the same behavioral features - the entire community takes the risky action. The interesting case is when $b < \tau pc$. The following result summarizes this comparison, showing that testing improves social welfare.

Proposition 3. If $b < \tau pc$ and $p < 1/2$ then $W_t > W_{nt}$.

Proof. Write

$$W_{nt} = \mu^*_{nt}(b - \tau p(1-p)\mu^*_{nt}c) - pc < \mu^*_{nt}(b - b(1-p)\mu^*_{nt}) - pc$$

Then write

$$\mu^*_{nt}(b - b(1-p)\mu^*_{nt}) = b \cdot [\mu^*_{nt}(1-(1-p)\mu^*_{nt})]$$

[8] This is implied by $b < \tau p(1-p)c$.

Now compare $g(\mu) = \mu(1 - (1-p)\mu)$ to p for $\mu \in [0,1]$. I aim to show that

$$g(\mu) \leq p, \forall \mu \in [0,1].$$

Note that $g(0) = 0$ and $g(1) = p$ and that $g''(\mu) = -2(1-p) < 0$ so that the function is strictly concave. The local max is then given by

$$g'(\mu_*) = 0 \Rightarrow \mu_* = \frac{1}{2(1-p)}$$

and the value is

$$g(\mu_*) = \frac{1}{2(1-p)}(1 - (1/2)) = \frac{1}{4(1-p)}$$

Now

$$p(1-p) \leq 1/4 \Rightarrow \frac{1}{4(1-p)} \leq p$$

and so $g(\mu) < p$ and $W_t > W_{nt}$. □

A natural question is whether the lockdown or targeted fine policies above can improve the social gains to testing. This question is similar to the ones asked by Deb et al. (2020).

First, note that coarse fines are not effective in improving welfare. Without testing, individuals internalize the broad fines exactly so that the positive benefits given by less disease spread are exactly offset by the decrease in benefits from those who take the risky action. To see this, note that without testing, the new equilibrium is given by

$$\mu^*_{nt}(K) = \frac{b-K}{\tau p(1-p)c}$$

which yields that welfare is

$$W_{nt}(K) = (b-K)\mu^*_{nt}(K) - \tau p(1-p)(\mu^*_{nt}(K))^2 c - pc = -pc$$

When there is testing, if $b > K$ then the behavioral implications are unchanged, and individuals taking the risky action only suffer the fine, strictly *decreasing* welfare. If $b < K$, then welfare is $-pc$.

These results caution against the use of blunt policy instruments in combatting these properties. Do the same negative types of results hold for simpler targeted fines? Consider the case in which a fine of K is levied on sick people taking the risky action. In particular suppose that $K > b$. Then we have that

$$\mu^*_d = 0, \mu^*_h = 1$$

and

$$W_t(K) = (1-p)b - pc = W^*$$

so that the full social welfare is achieved. Thus, the combination of targeted fines and testing can bring about large societal welfare gains.

5.1 Discussion: Policy Implications

The policy implications of this discussion with respect to welfare suggest three main takeaways. One is that fines and blunt lockdown procedures are insufficient tools for bringing about large welfare gains. The second is that, similarly, testing alone is not likely to bring about large welfare gains. Importantly, the combination of targeted fines and testing can be an effective way to achieve higher social welfare. In particular, these policies resemble policies that punish sick people for exposing themselves to others. The key assumption for this implication is that p is small relative to $1-p$. These points are similar to those made by Deb et al. (2020). This paper nuances this observation by focusing on the implications of these types of interventions on infection.

6 Application: Disclosing Police and Crime

The model can be used to assess the impact of policies on other important social behaviors that involve the interaction of heterogeneous populations. One such important behavior is crime. Many crimes require two individuals to interact in a social setting. Oftentimes, individuals can reduce or increase their exposure to crime by making decisions. In the language of this model, we can say that

$$\text{Crime} = (\text{Mass of Non Criminals Interacting}) \cdot (\text{Mass of Criminals Interacting}).$$

This model of crime is a better description of crimes that involve social encounters or other crimes that can be affected by the behavior of non-criminals. For example, it is likely not a good model of property crime.

Note that the information intervention for testing is not intuitively interesting as a real-world experiment. In this case, it would be similar to telling people whether they are criminals or not. Criminal status is much easier observed privately, and does not require similar potential information interventions like medical testing does. Thus a different form of intervention is studied within this model.

A related policy experiment that can be conducted in this model in which a policymaker could provide useful information is on the location of law enforcement and deterrence. This mirrors the main policy experiment in Lazear (2006), where the policymaker can disclose the location of law enforcement, except that now there are two sides of the market reacting to such disclosures.

Suppose that there is a city with two areas where individuals interact. The policymaker can provide mass 1/2 of police to one of the two locations. There is a group of non-criminals in each location of mass 1/2 each. By exposing themself to crime, by interacting in their community for example, they get a benefit $b_i \sim F(\cdot)$. If they are a victim to a crime they pay a cost of c, and the probability of being a victim of a crime is equal to the total mass of criminals interacting in their location.[9]

There is a mass 1 of criminals. They have benefits of crime $b_{c,i} \sim F_c(\cdot)$, and are able to commit a crime and get this benefit with probability equal to the mass of non-criminals in that location. Criminals choose whether to attempt to commit a crime ("interact") and where to commit their crimes. If they commit a crime in a location with a police officer, they are arrested with probability equivalent to the mass of police officers in that location. If they are arrested they pay a cost k. Suppose that $\bar{b}_c < k/2$ so that if the full police force is used in a location, no criminals will want to commit crime there.

The amount of crime depends on the total interaction of non-criminals and criminals in each location:

$$C = (\mu_{nc}^1)(\mu_c^1) + (\mu_{nc}^2)(\mu_c^2)$$

where μ_{nc}^j is the mass of non-criminals interacting in location j and μ_c^j is the mass of criminals interacting in location j.

Consider two different policies: disclosing where the police are located and not announcing where the police are located. If it is not announced where the police are located and they are located uniformly across locations, then equilibrium is described by thresholds b^* and b_c^* for non-criminals and criminals so that all individuals in that group with a benefit above that threshold interact in the community. Note that because police are uniformly allocated across locations, the location decision of any criminal is irrelevant. Similarly, the behavior of non-criminals across locations can be treated symmetrically.

The criminal threshold is determined by

$$b_c^*(\mu_{nc}/2) = k/4$$

since the mass of non-criminals in each location is 1/2 and the mass of police in each location is

[9]Note that, unlike the SIRS infection assumption above, this assumption is not necessarily medically backed. This depends on the crime production function. If, for example, criminals and non-criminals are randomly matched in the community and criminals only have 1 chance to commit a crime, then this could differ. The model presented has the benefit of being simpler to analyze.

1/4 since they are uniformly distributed. The non-criminal threshold is determined by

$$b^*_{\text{no info}} = (\mu_c/2)c$$

where $\mu_c/2$ is the mass of criminals interacting in each location since criminals choices are symmetric between locations and the total mass of criminals is 1.

Because of heterogeneous benefits we have

$$\mu_{nc} = 1 - F(b^*_{\text{no info}})$$

and

$$\mu_c = 1 - F_c(b^*_c).$$

Thus the equilibrium without disclosing information is described by the system

$$b^*_c(1 - F(b^*_{\text{no info}})) = k$$
$$b^*_{\text{no info}} = (1 - F_c(b^*_c))c/2$$

and total crime is given by

$$C_{\text{no info}} = 2 * (1/2)(1/2)(1 - F(b^*))(1 - F_c(b^*_c)) = (1/2)(1 - F(b^*))(1 - F_c(b^*_c)) \quad (29)$$

Suppose now that the policymaker discloses that the full police force is being allocated to location 1.[10] In this case, since there is no risk of being caught in location 2, and $b_{c,i} \geq 0$, all criminals will go to location 2 and will interact and commit crimes. Then the decisions of non-criminals in location 2 are characterized by the threshold

$$b^*_{\text{disclose}} = c$$

since there is mass 1 of criminals. Thus, total crime with disclosure is given by

$$C_{\text{disclose}} = (1/2)(1 - F(c)) + (1/2)(0) = (1/2)(1 - F(c)) \quad (30)$$

and announcing where the police are located reduces crime if and only if

$$1 - F(c) \leq (1 - F(b^*_{\text{no info}}))(1 - F_c(b^*_c))$$

[10]The optimal allocation is not the focus of this exercise. Since everything is symmetric about the two locations, it should be irrelevant.

which is similar to (15). Once again, this comparison is ambiguous because $b^*_{\text{no info}} < c$ so that $1 - F(b^*_{\text{no info}}) > 1 - F(c)$.

The intuition is also similar: announcing where the police are forces criminals to a single location and increases overall criminal activity in that location. Then, depending on how non-criminals respond in that location determines the effect on overall crime. If non-criminals are deterred enough by the costs of crime, i.e. c is large enough, then they will respond in a strong enough way to reduce crime.

Thus, similar to the result above this inequality will be satisfied when c is large enough. An extra parameter in this analysis relative to the disease case considered previously is k, the magnitude of the punishment of criminals who are caught by the police. As k increases, more crime is deterred when criminals are uncertain where the police are. This is because when the location of police is announced, criminals can avoid punishment altogether by changing their behavior. This intuition is similar to that in Lazear (2006), but builds in the extra mechanism of endogenous behavior from non-criminals.

7 Conclusion

This paper considered the impacts of disclosing information on certain types of undesirable behavior that requires people to interact. The main application and motivation of this paper is disease spread in epidemiological models, but the model is relevant to other applications in which a policymaker is considered about certain types of bad interactions. For example, the same logic applies to interactions between criminals and non-criminals.

The main result is that policymakers may or may not encourage negative interactions when disclosing relevant information depending on the costs of such interactions. When the private costs of negative interactions are large enough, disclosing information will decrease negative interactions while if they are small enough, the amount of negative interactions could increase with increased information.

While this paper aims to inform understanding of how certain policies affect disease spread, it cannot make any strong quantitative or empirical conclusions to support certain policies. The main policy implication of this paper is that policymakers need to be careful with how they design both their lockdown and information dissemination policies together to achieve certain levels of disease spread. These policies also have important implications for welfare, and a careful mixture of them could be useful in substantially increasing welfare in the midst of a pandemic.

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8 Appendix

8.1 Simulations related to Proposition 2

8.1.1 Exponential Simulation

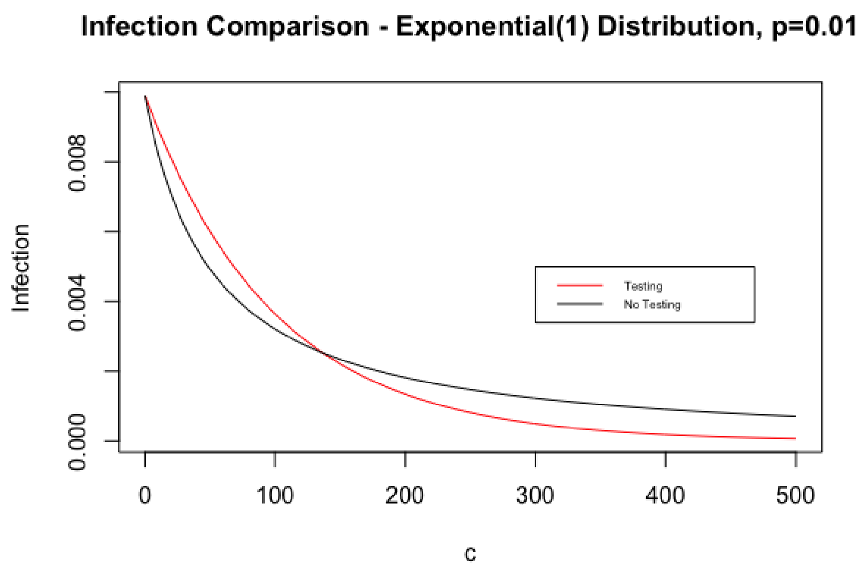

Figure 1: Exponential Simulation

8.1.2 Log-Normal Simulation

8.1.3 Chi Squared Simulation

8.1.4 Weibull Simulation

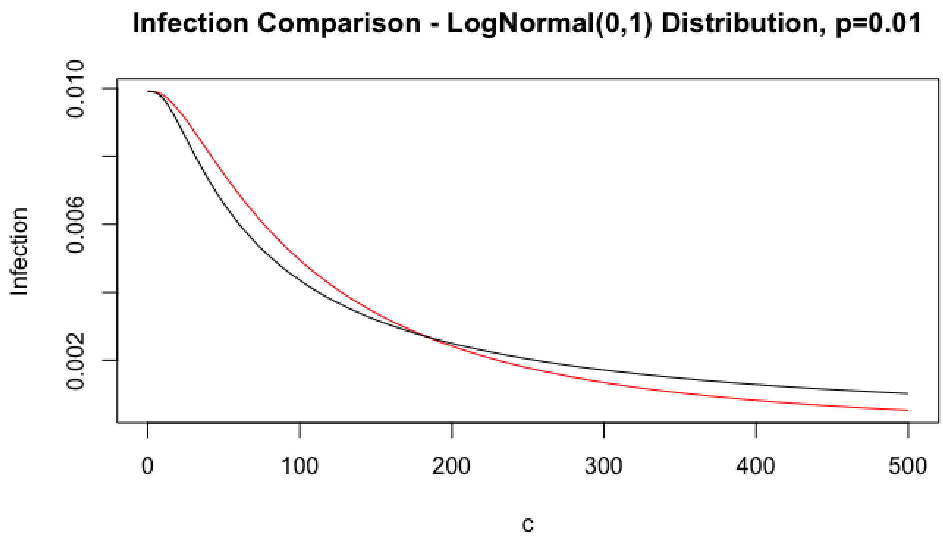

Figure 2: Log Normal Simulation

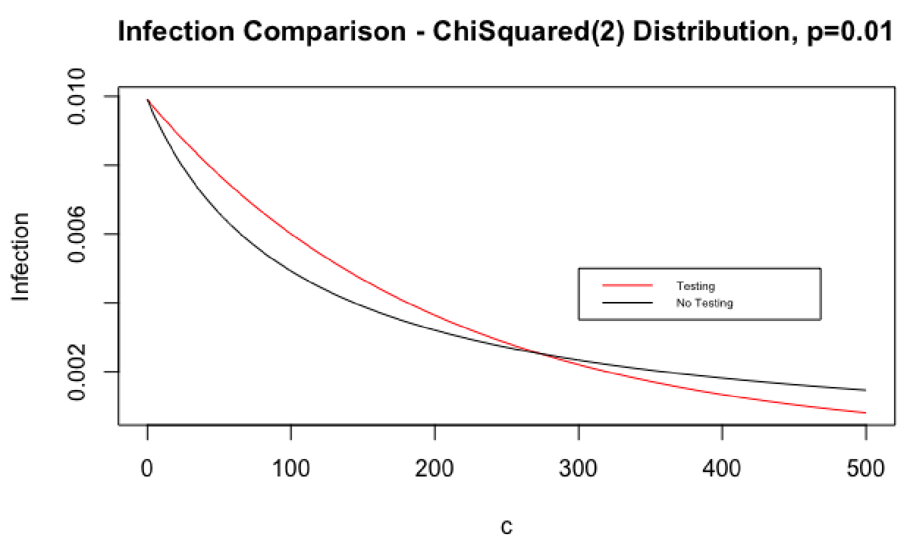

Figure 3: Chi Squared Simulation

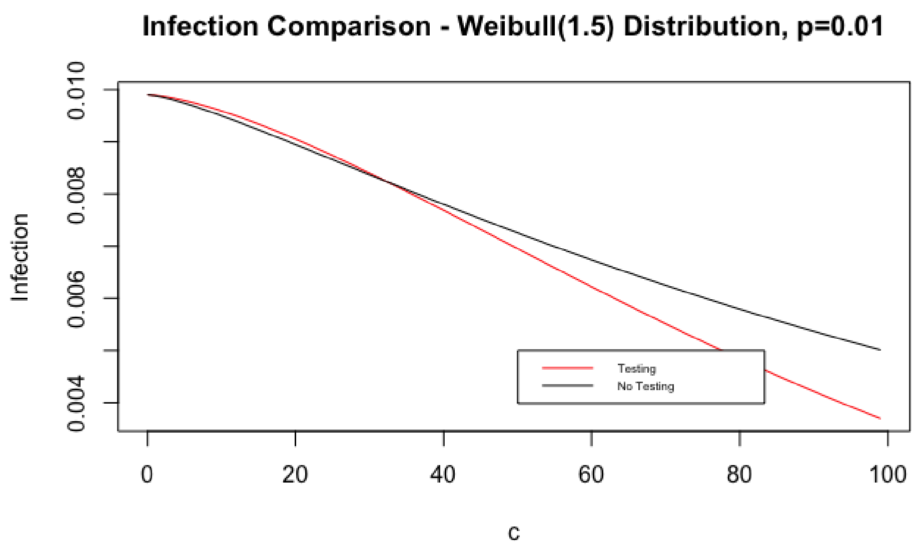

Figure 4: Weibull Simulation