Corona Games: Masks, Social Distance and Mechanism Design

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Abstract
Pandemic response is a complex affair. Most governments employ a set of quasi-standard measures to fight COVID-19 including wearing masks, social distancing, virus testing and contact tracing. We argue that some non-trivial factors behind the varying effectiveness of these measures are selfish decision-making and the differing national implementations of the response mechanism. In this paper, through simple games, we show the effect of individual incentives on the decisions made with respect to wearing masks and social distancing, and how these may result in a sub-optimal outcome. We also demonstrate the responsibility of national authorities in designing these games properly regarding the chosen policies and their influence on the preferred outcome. We promote a mechanism design approach: it is in the best interest of every government to carefully balance social good and response costs when implementing their respective pandemic response mechanism.

1 Introduction
The current coronavirus pandemic is pushing individuals, businesses and governments to the limit. People suffer owing to restricted mobility, social life and income, complete business sectors face an almost 100% drop in revenue, and governments are scrambling to find out when and how to impose and remove restrictions. In fact, COVID-19 has turned the whole planet into a “living lab” for human and social behavior where feedback on response measures employed is only delayed by two weeks (the incubation period). From the 24/7 media coverage, all of us have seen a set of quasi-standard measures introduced by national and local authorities, including wearing masks, social distancing, virus testing, contact tracing and so on. It is also clear that different countries have had different levels of success employing these measures as evidenced by the varying normalized death tolls and confirmed cases[1]

*Although in the same institute, authors have collaborated remotely.
1Johns Hopkins Coronavirus Resource Center. https://coronavirus.jhu.edu/map.html
We believe that apart from the intuitive (e.g., genetic differences, medical infrastructure availability, hesitancy, etc.), there are two factors that have not received enough attention. First, the individual incentives of citizens, e.g., “is it worth more for me to stay home than to meet my friend?”, have a significant say in every decision situation. While some of those incentives can be inherent to personality type, clearly there is a non-negligible rational aspect to it, where individuals are looking to maximize their own utility. Second, countries have differed in the specific implementation of response measures, e.g., whether they have been distributing free masks (affecting the efficacy of mask wearing in case of equipment shortage) or providing extra unemployment benefits (affecting the likelihood of proper self-imposed social distancing). Framing pandemic response as a mechanism design problem, i.e., architecting a complex response mechanism with a preferred outcome in mind, can shed light on these factors; what’s more, it has the potential to help authorities (mechanism designers) fight the pandemic efficiently.

In this paper we model decision situations during a pandemic with game theory where participants are rational, and the proper design of the games could be the difference between life and death. Our main contribution is two-fold. First, regarding decisions on wearing a mask, we show that i) the equilibrium outcome is not socially optimal under full information, ii) when the status of the players are unknown the equilibrium is not to wear a mask for a wide range of parameters, and iii) when facing an infectious player it is almost always optimal to wear a mask even with low protection efficiency. Furthermore, for social distancing, using current COVID-19 statistics we showed that i) going out is only rational when it corresponds to either a huge benefit or staying home results in a significant loss, and ii) we determined the optimal duration and meeting size of such an out-of-home activity. Second, we take a look at pandemic response from a mechanism design perspective, and demonstrate that i) different government policies influence the outcome of these games profoundly, and ii) individual response measures (sub-mechanisms) are interdependent. Specifically, we discuss how contact tracing enables targeted testing which in turn reduces the uncertainty in individual decision making regarding both social distancing and wearing masks. We recommend governments treat pandemic response as a mechanism design problem when weighing response costs vs. the social good.

The remaining of the paper is structured as follows. Section 2 briefly describes related work. Section 3 develops and analyzes the Mask Game adding uncertainty, mask efficiency and multiple players to the basic model. Section 4 develops and analyzes the Distancing Game including the effect of meeting duration and size. Section 5 frames pandemic response as a mechanism design problem using the design of the two games previously introduced as examples. Finally, Section 6 outlines future work and concludes the paper.
2 Related Work

Here we briefly review some related research efforts. For a more complete survey we refer the reader to [3].

[13] modeled the behavioral changes of people to a pandemic using evolutionary game theory, and showed that slightly reducing the number of people an individual is in contact with can make a difference to the spread of disease. Moreover, both an earlier warning and when accurate information about the infection is disseminated quickly, people’s responses to the information can limit the spread of disease.

[17] focused on the traveling habits of people between areas affected differently by the disease, and found conflict between the Nash equilibrium (individually optimal strategy) and the Social Optimum (optimal group strategy) only under specific changes in economic and epidemiological conditions.

In line with our mask game, [6] studied how individuals change their behavior during an epidemic in response to whether they and those they interact with are susceptible or infected. The authors show that there is a critical level of concern, i.e., empathy, by the infected individuals above which the disease is eradicated rapidly. Furthermore, risk-averse behavior by susceptible individuals cannot eradicate the disease without the preemptive measures of infected individuals.

In line with our social distancing game, [14] studied how individuals would best use social distancing and related self-protective behaviors during an epidemic. The study found that in the absence of vaccination or other intervention measures, optimal social distancing can delay the epidemic until a vaccine becomes widely available.

[2] studied the vaccination behavior of people. The designed model exhibits a “wait and see” Nash equilibrium strategy, with vaccine delayers relying on herd immunity, and vaccine safety information generated by early vaccinators. As a consequence, the epidemic peak’s timing is strongly conserved across a broad range of plausible transmission rates. Besides, any effect of risk communication at the start of a pandemic outbreak is amplified.

Finally, the game-theoretic model in [15] focuses on the various level of drug stockpiles in different countries, and find controversial results: sometimes there is an optimal solution of a central planner (such as the WHO), which improves the decentralized equilibrium, but other times the central planner’s solution (minimizing the number of infected persons globally) requires some countries to sacrifice part of their population.

Game Notations

To improve readability, we summarize all the parameters and variables used for the Mask and the Distancing Game in Table 1.
### 3 The Mask Game

Probably the most visible consequence of COVID-19 are the masks: before their usage was mostly limited to some Asian countries, hospitals, banks (in case of a robbery), and some other places. Due to the coronavirus pandemic, an unprecedented spreading of mask-wearing can be seen around the globe. Policies have been implemented to enforce their usage in some places, but in general, it has been up to the individuals to decide whether to wear a mask or not based on their own risk assessment. In this section, we model this via game theory. We assume there are several mask types, giving different level of protection:

- **No Mask**: This corresponds to the behavior of using no masks during the COVID-19 (or any) pandemic. Its cost is consequently 0; however, it does not offer any protection against the virus.

- **Out Mask**: This is the most widely used mask (e.g., cloth mask or surgical mask). They are meant to protect the environment of the individual using it. They work by filtering out droplets when coughing, sneezing or simply talking, therefore hinders the spreading of the virus. They do not protect the wearer itself against an airborne virus. The cost corresponding to this protection type is noted as \( C_{\text{out}} > 0 \).

- **In Mask**: This is the most protective prevention gear designed for medical professionals (e.g., FFP2 or FFP3 mask with valves). Valves make it easier to wear the mask for a sustained period of time and prevent condensation inside the mask. They filter out airborne viruses while breathing in, however the valved design means it does not filter air breathed out. Note that CDC guidelines\(^2\) recommend using a cloth/surgical mask for the general public, while valved masks are only

\[\begin{array}{|c|c|}
\hline
\text{Variable} & \text{Mask Game} & \text{Distancing Game} \\
\hline
C_{\text{out}} & \text{Cost of playing out} & C & \text{Cost of staying home} \\
C_{\text{in}} & \text{Cost of playing in} & B & \text{Benefit of going out} \\
C_{\text{i}} & \text{Cost of being infected} & m & \text{Mortality rate} \\
C_{\text{use}} & \text{Cost of playing use} & L & \text{Value of Life} \\
\rho & \text{Prob. of being infected} & \rho & \text{Probability of infection} \\
p & \text{Prob. of using a mask} & p & \text{Probability of meeting} \\
a & \text{Protection Efficiency} & t & \text{Time duration of meeting} \\
b & \text{Spreading Efficiency} & g & \text{Group size of meeting} \\
\hline
\end{array}\]

Table 1: The parameters of the games.

\(^2\)https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html
recommended for medical personnel in direct contact with infected individuals. The cost of this protection is $C_{in} >> C_{out}$.

Besides which mask they use (i.e., the available strategies), the players are either susceptible or infected\(^3\). The latter has some undesired consequence; hence, we model it by adding a cost $C_i$ to these players’ utility (which is magnitudes higher than $C_{in}$ and $C_{out}$). Using these states and masks, we can present the basic game’s payoffs where two players with known status meet and decide which mask to use. On the left of Table 2, the payoff matrix corresponds to the case when both players are susceptible. Note, that in case both players are infected, the payoff matrix would be the same with an additional constant $C_i$. On the right of Table 2 corresponds to the case when one player is infected while the other is susceptible.

Table 2: Payoff matrices for the cases when only one (right) and both (left) player is susceptible.

| susceptible / susceptible | susceptible / infected |
|---------------------------|------------------------|
| no | out | in | no | out | out | in |
| (0, 0) | (0, $C_{out}$) | (0, $C_{in}$) | $(C_i, C_i)$ | (0, $C_{out} + C_i$) | $(C_i, C_{in} + C_i)$ |
| $(C_{out}, 0)$ | $(C_{out}, C_{out})$ | $(C_{out}, C_{in})$ | $(C_{out} + C_i, C_i)$ | $(C_{out}, C_{out} + C_i)$ | $(C_{out} + C_i, C_{in} + C_i)$ |
| $(C_{in}, 0)$ | $(C_{in}, C_{out})$ | $(C_{in}, C_{in})$ | $(C_{in}, C_i)$ | $(C_{in}, C_{out} + C_i)$ | $(C_{in}, C_{in} + C_i)$ |

On the left side of Table 2 it is visible that both players’ cost is minimal when they do not use any masks, i.e., the Nash Equilibrium of the game when both players are susceptible is $(\text{no, no})$. This is also the social optimum, meaning that the players’ aggregated cost is minimal. The same holds in case both players are infected, as this only adds a constant $C_i$ to the payoff matrix. This changes when only one of the players is susceptible (i.e., right side of Table 2): the infected player using no mask is a dominant strategy for her\(^4\), since it is her best response, independently of the susceptible player’s action. Consequently, the best option for the susceptible player is $\text{in}$, i.e., the NE is $(\text{in, no})$. On the other hand, the social optimum is different: $(\text{no, out})$ would incur the least burden on the society since $C_{out} << C_{in}$.

In social optimum, susceptible players would benefit, through a positive externality, from an action that would impose a cost on infected players; therefore it is not a likely outcome. In fact, such a setting is common in man-made distributed systems, especially in the context of cybersecurity. A well-fitting parallel is defense against DDoS attacks\(^5\): although it would be much more efficient to filter malicious traffic at the source (i.e., $\text{out}$), Internet Service Providers rather filter at the target (i.e., $\text{in}$) owing to a rational fear of free-riding by others.

\(^3\)We simplify the well-known SIR model\(^6, 5\) since in case of COVID-19 it is currently unknown how the human body behaves after recovery when exposed again to the virus.

\(^4\)Note that the payoffs does not take into account the legal consequences of a deliberate infection such as in [https://www.theverge.com/2020/4/7/21211992/coughing-coronavirus-arrest-hiv-public-health-safety-crime-spread](https://www.theverge.com/2020/4/7/21211992/coughing-coronavirus-arrest-hiv-public-health-safety-crime-spread).

\(^5\)Note that the payoffs does not take into account the legal consequences of a deliberate infection such as in [https://www.theverge.com/2020/4/7/21211992/coughing-coronavirus-arrest-hiv-public-health-safety-crime-spread](https://www.theverge.com/2020/4/7/21211992/coughing-coronavirus-arrest-hiv-public-health-safety-crime-spread).
3.1 Bayesian Game

Since in the basic game no player plays out, we simplify the choice of the players to either use a mask or no (hence, we note the cost of a mask with $C_{use}$). To represent the situation better, we introduce ambiguity about the status of the players: we denote the probability of being infected as $\rho$. We know from the basic game that if both players are infected (with probability $\rho^2$) or susceptible (with probability $(1-\rho)^2$) they play (no, no), while if only one of them is infected (with probability $2 \cdot \rho \cdot (1-\rho)$) the infected player plays no while the susceptible plays use.

In this Bayesian game the players play no most of the cases (e.g., with probability $1 - (\rho \cdot (1-\rho))$). This chain of thought is too simplistic, as we assumed case-wise that the players know their status. Consequently, with uncertainty we must minimize the costs of the players: if both players are infected with equal probability, the payoff for Player 2 is Equation (1) where $p_n$ is the probability that Player n plays use (otherwise she plays no). The payoff for the other player is similar since the game is symmetric. In more detail, the first two lines correspond to the case when Player 2 is not infected (hence the multiplication with $1-\rho$ at the beginning), while the last line captures when she is infected. Either way, she plays use with probability $p_2$, which costs $C_{use}$. Otherwise she plays no, which has no cost except when Player 1 is infected and she plays no as well (end of the second line).

\[
U_2 = (1-\rho) \cdot (1-\rho) \cdot p_2 \cdot C_{use} + (1-\rho) \cdot (1-p_2) \cdot p_2 \cdot C_{use} + \rho \cdot p_2 \cdot (1-\rho) \cdot (1-p_1 \cdot C_i + p_1 \cdot 0)] \quad (1)
\]

Since this formula is linear in $p_2$, its extreme point within $[0,1]$ is at the edge. We take its derivative to uncover the function steepness: the condition for the function to be decreasing (i.e., higher probability for using a mask corresponds to lower cost) is seen below. Consequently, the only scenario which might admit wearing a mask with non-zero probability corresponds to the availability of sufficiently cheap masks.

\[
\frac{\partial U_2}{\partial p_2} < 0 \iff \frac{C_{use}}{C_i} < \rho \cdot (1-\rho) \cdot (1-p_1) \leq 1 \quad (2)
\]

3.2 Efficiency Game

In the basic game we assumed in provides perfect protection from infected players, while out protects the other player fully. However, in real life these strategies only mitigate the virus by decreasing the infection probability (i.e., $\rho$) to some extent. For this reason, we define $a, b \in [0,1]$ in a way that the smaller value of the parameter corresponds to better protection; $a$ measures the protection efficiency of the protection strategy, while $b$ captures the efficiency of eliminating the further spread of the disease. Consequently,
a and b was set in the previous cases to $a_{out} = 0, a_{in} = 1$ (both in prevents further spread fully, while out does not prevent it at all), $b_{out} = 1$ (out has no effect on protecting the player) $b_{in} = 0$ (in fully protects the player).

We simplify the action space of the players as we did in the Bayesian game: in and out is merged into use, with efficiency parameters $a$ and $b$. We set $b = \frac{2}{3}$, as surgical masks on the infectious person reduce cold & flu viruses in aerosols by 70% according to [12], while a home-made mask achieves $\frac{2}{3}$ of this efficiency [4]. Parameter $a$ is much harder to measure. It should be $a \leq b$ since any mask keeps the virus inside the players more efficiently than stopping the wearer from getting infected. For the sake of the analysis we set $a = b^2 = \frac{1}{3}$.

We are interested in the mask-wearing probability of a susceptible player when the other player is infected. The utility in such a situation is shown in Equation (3), where for simplification we defined $p = p_1 = p_2$, i.e., both players play a specific strategy with the same probability. With such a constraint, we restrict ourselves from finding all the solutions; however, since the game is symmetric, an equilibrium of this reduced game is also an equilibrium when the players could use a different strategy distribution.

$$U = p^2 \cdot (C_{use} + C_i \cdot a \cdot b) + p \cdot (1 - p) \cdot (C_{use} + C_i \cdot a) + (1 - p) \cdot p \cdot (C_i \cdot b) + (1 - p)^2 \cdot C_i$$

From this we easily deduce that use corresponds to a smaller cost that no if $\frac{C_{use}}{C_i} < \frac{7}{9}$, which holds by default as $C_{use} \ll C_i$ (even for more inefficient masks). Moreover, use (i.e., $p = 1$) is the best response most of the time because of the following.

1. The utility is a second order polynomial, hence it has one extreme point.
2. This extreme point is a minimum due to $U'' = \frac{4}{9} \cdot C_i > 0$.
3. The utility (i.e., cost) is decreasing on the left and increasing on the right of this minimum point.
4. The utility’s minimum point is at $p = \frac{9}{4} \cdot \frac{C_i - C_{use}}{C_i}$ due to $U' = C_{use} - C_i + \frac{4}{3} \cdot C_i \cdot p$.
5. The minimum point is expected to be above 1 due to $C_{use} \ll C_i$.
6. $p \in [0,1]$ is on the left of the minimum point, hence, a higher $p$ corresponds to a smaller cost.

\*\*The Bayesian game combined with efficiency is left for future work due to the lack of space.\*\*
3.3 Multi Player Game

This game can be further extended by allowing more players to participate. In this extension, if there exists an infected player (who plays no as we showed already), all the susceptible players should play in. This NE is the SO as well if the ratio of the infected (which is identical to the probability $\rho$ of being infected) is sufficiently high: the accumulated cost when the susceptible players play in (and the infected play no) is less than the accumulated cost when the infected players play out (and the susceptible play no) if $\frac{C_{IN}}{C_{OUT}} < \frac{\rho}{1-\rho}$. Although it is mathematically possible that the infected plays no in the SO, but it is doubtful: both the cost of in is significantly higher than out, and the infection ratio $\rho$ is low (at least at the beginning of the pandemic).

4 The Distancing Game

Another thing most people has experienced during the current COVID-19 pandemic is social distancing. Here we introduce a simple Distancing Game; it is to be played in sequence with the previously introduced Mask Game: once a player decided to meet up with friends via the Distancing Game, she can decide whether to wear a mask for the meeting using the mask game.

A summary of the used parameters are enlisted in Table 1: we represent the cost of getting infected with $m \cdot L$, i.e., the mortality rate of the disease multiplied with the player’s evaluation about her own life.\footnote{All statistics in the paper from https://www.worldometers.info/coronavirus/ (accessed May 20th, 2020)} We set $m = 0.1$, as this value is approximately in the middle of the possible interval \footnote{This is an optimistic approximation, as besides dying the infection could bear other tolls on a player.} $0.06 \approx \frac{\#\{\text{dead}\}}{\#\{\text{all cases}\}} < m < \frac{\#\{\text{dead}\}}{\#\{\text{closed cases}\}} \approx 0.14$.

Besides the risk of getting infected, going out or attending a meeting could benefit the player, denoted as $B$. On the other hand, staying home or missing a meeting could have some additional costs, denoted as $C$. The probability of getting infected is denoted as $\rho$. With these notations, the utility of the Distancing Game is captured on the left of Equation (4), where $p$ is the probability of going out. Since this is linear in $p$, its maximum is either at $p = 0$ (stay home) or $p = 1$ (go out). Precisely, the player prefers to stay home if the right side of Equation (4) holds.

$$U = p \cdot (B - \rho \cdot m \cdot L) - (1 - p) \cdot C$$

$$\frac{B + C}{\rho \cdot m} < L \quad \text{(4)}$$

Example.

For instance, a rational American citizen should go out only if she values her life less than $2941(= \frac{1}{0.0034 \cdot 0.1})$ times the benefit (of going out) and the loss (of staying home) together if we approximate the infection ratio with
\[
\frac{\text{#(active cases)}}{\text{#(population)}} = 0.0034 \text{ as of 20th of May, 2020. According to [10], the value of a statistical life in the US was 9.2 million USD in 2013, which is equivalent to 11.3 million USD in 2020 (with 0.3% interest rate). This means a rational average American should only meet someone if the benefit of the meeting and the cost of missing it would amount to more than 3842 USD (= \frac{11.3M}{2941}).}
\]

4.1 Number of Participants & Duration

One way to improve the above model is by introducing meeting duration and size. Leaving our disinfected home during a pandemic is risky, and this risk grows with the time we spend outside. Similarly, a meeting is riskier when there are multiple participants involved. In the original model, we captured the infection probability with \( \rho = 1 - (1 - \rho) \). This ratio increases to \( 1 - (1 - \rho)^{g \cdot t} \) when there are \( g \) possible infectious sources for \( t \) time. Since \( g \) and \( t \) are interchangeable, we merge this two together under a common notation: \( z = g \cdot t \).

This extended model can be used to determine the optimal duration and size of a meeting, once the player decided to go out according to the basic distancing game. We define \( 0 < z < 100 \), as no player has infinite time or meeting partners. Moreover, the benefit and the loss of attending and missing a meeting should depend on this new parameter. For instance, staying home in isolation for a longer period might cause anxiety, which could get worst over time (i.e., increasing the cost), or attending a meeting with many friends at the same time could significantly boost the experience (i.e., increase the benefit). Consequently, a rational person should leave her home only if Equation (5) holds which is the extension of the right side of Equation (4).

\[
\max_{0<z<100} \left( \frac{B(z) + C(z)}{(1 - (1 - \rho)^z) \cdot m} \right) < L 
\]

In Figure 1, we present three use-cases of the formula inside the maximization above: the left one represents the case when both the benefit and the cost are constant, the right one corresponds to the case when both of them are linear. In the middle is a mixture of these two. Note that we needed to restrict \( z \) to be under a certain amount; otherwise, the formula goes to infinity as \( z \to \infty \) in some cases.

Example.

Let us assume, a bus’ tank is leaking; the owner is loosing 1 USD of petrol every \( t \) time, i.e., \( C(z) = 1 \cdot t \) (as the owner must visit a mechanic and meet one person). In the meantime, the benefit of leaving the house is constant, e.g., \( B(z) = 1 \). The middle of Figure 1 corresponds to this setting. It is visible, that going out for a short or long period (e.g., \( z = 5 \) and \( z = 100 \)) is only rational for someone who values her life below 3553 and 3499 USD, respectively.
Figure 1: A few examples for various benefit and cost functions of the lower limit on the life value which would ensure that a rational American would stay home (i.e., the formula inside max in Equation (5)). $x$ axis represents $z$, while $y$ axis represents the utility.

5 Pandemic Mechanism Design

Pandemic response is a complex affair. The two games described above model only parts of the bigger picture.

5.1 The government as mechanism designer

We refer to the collection (and interplay) of measures implemented by a specific government fighting the epidemic in their respective country as mechanism. Consequently, decisions made with regard to this mechanism constitutes mechanism design. In its broader interpretation, mechanism design theory seeks to study mechanisms achieving a particular preferred outcome. Desirable outcomes are usually optimal either from a social aspect or maximizing a different objective function of the designer.

In the context of the corona pandemic, the immediate response mechanism is composed of e.g., wearing a mask, social distancing, testing and contact tracing, among others. Note that this is not an exhaustive list: financial aid, creating extra jobs to accommodate people who have just lost their jobs, declaring a national emergency and many other conceptual vessels can be utilized as sub-mechanisms by the mechanism designer, i.e., usually, the government; we do not discuss all of these in detail due to the lack of space. Instead, we shed light on how government policy can affect the sub-mechanisms, how sub-mechanisms can affect each other and, finally, the outcome of the mechanism itself. We illustrate the importance of mechanism design applying different policies to our two games, and adding testing and contact tracing to the mix.

5.2 Policy impact on sub-mechanisms and the final mechanism

Here we analyze the impact of commonly seen policies: compulsory mask wearing, distributing free masks, limiting the amount of people gathering and total lock-down.
**Compulsory mask wearing and free masks.** If the government declares that wearing a simple mask is mandatory in public spaces (such as shops, mass transit, etc.), it can enforce an outcome (out, out) that is indeed socially better than the NE. The resulting strategy profile is still not SO, but it i) allocates costs equally among citizens; ii) works well under the uncertainty of one’s health status; and iii) may decrease the first-order need for large-scale testing, which in turn reduces the response cost of the government. By distributing free masks, the government can reduce the effect of selfishness and, potentially, help citizens who cannot buy or afford masks owing to supply shortage or unemployment.

**Limiting the amount of people gathering and total lock-down.** If the government imposes an upper limit $l$ for the size of congregations, this will put a strict upper bound on the “optimal meeting size” $g^*$, and the resulting group size will be $\min(l, g^*)$. Note that if $l < g^*$ then it creates an “opportunity” for longer meetings (larger $t$), as Equation (5) maximizes for $z = gt$. On the other hand, if the chosen restrictive measure is a total lock-down, both the Distancing Game and the Mask Game are rendered moot, as people are not allowed to leave their households.

**Testing and contact tracing.** It is clear that the Distancing and the Mask Games are not played in isolation: people deciding to meet up invoke the decision situation on mask wearing. On the other hand, so far we have largely ignored two other widespread pandemic response measures: testing and contact tracing.

With appropriately designed and administered coronavirus tests, medical personnel can determine two distinct features of the tested individual: i) whether she is actively infected spreading the virus and ii) whether she has already had the virus, even if there were no or weak symptoms. (Note that detecting these two features require different types of tests, able to show the presence of either the virus RNA or specific antibodies, respectively.) In general, testing enables both the tested person and the authorities to make more informed decisions. Putting this into the context of our games, testing i) reduces the uncertainty in Bayesian decision making, and ii) enables the government to impose mandatory quarantine thereby removing infected players. Even more impactful, mandatory testing as in Wuhan completely eliminates the Bayesian aspect rendering the situation to a full information game: it serves as an exogenous “health oracle” imposing no monetary cost on the players. To sum it up, the testing sub-mechanism outputs results that serve as inputs to both the Distancing and the Mask Game.

Naturally, a “health oracle” does not exist: someone has to bear the costs of testing. From the government’s perspective, mandatory mass testing is extremely expensive. (Similarly, from the concerned individual’s perspective, a single test could be unaffordable.) Contact tracing, whether traditional or mobile app-based, serves as an important input sub-mechanism to testing [7]. It identifies the individuals who are likely affected and inform both
them and the authorities about this fact. In game-theoretic terms, for such players, the benefit of testing outweigh the cost (per capita) with high probability. From the mechanism designer’s point of view, contact tracing reduces the overall testing cost by enabling targeted testing, potentially by orders of magnitude, without sacrificing proper control of the pandemic. Note that mobile OS manufacturers are working on integrating contact tracing into their platform to eliminate adoption costs for installing an app [1].

**The big picture.** As far as pandemic response goes, the mechanism designer has the power to design and parametrize the games that citizens are playing, taking into account that sub-mechanisms affect each other. After games have been played and outcomes have been determined, the cost for the mechanism designer itself are realized (see Figure 2). This cost function is very complex incorporating factors from ICU beds through civil unrest to a drop in GDP over multiple time scales [11]. Therefore, governments have to carefully balance the – very directly interpreted – social optimum and their own costs; this requires a mechanism design mindset.

## 6 Conclusion

In this paper we have made a case for treating pandemic response as a mechanism design problem. Through simple games modeling interacting selfish individuals we have shown that it is necessary to take incentives into account during a pandemic. We have also demonstrated that specific government policies significantly influence the outcome of these games, and how different response measures (sub-mechanisms) are interdependent. As an example we have discussed how contact tracing enables targeted testing which in turn reduces the uncertainty from individual decision making regarding social distancing and wearing masks. Governments have significantly more power than traditional mechanism designers in distributed systems; therefore it is crucial for them to carefully study the tradeoff between social optimality and the cost of the designer when implementing their pandemic response mechanism.

**Limitations and future work.** Clearly, we have just scratched the sur-
face of pandemic mechanism design. The models presented are simple and are mostly used for demonstrative purposes. Also, the mechanism design considerations are only quasi-quantitative without proper formal mathematical treatment. In turn, this gives us plenty of opportunity for future work. A potential avenue is extending our models to capture the temporal aspect, combine them with epidemic models as games played on social graphs, and parametrize them with real data from the ongoing pandemic (policy changes, mobility data, price fluctuations, etc.). Relaxing the rational decision-making aspect is another prominent direction: behavioral modeling with respect to obedience, other-regarding preferences and risk-taking could be incorporated into the games. Finally, a formal treatment of the mechanism design problem constitutes important future work, incorporating hierarchical designers (WHO, EU, nations, municipality, household), an elaborate cost model, and analyzing optimal policies for different time horizons. If done with care, these steps would help create an extensible mechanism design framework that can aid decision makers in pandemic response.

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