Chapter 9

Incentives for Individual Compliance with Pandemic Response Measures

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Most governments employ a set of quasi-standard measures to fight COVID-19 including social distancing, wearing masks, and vaccination. However, combining these measures into an efficient holistic pandemic response instrument is even more involved than anticipated. 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 chapter, through simple models, we show the effect of individual incentives on the decisions made with respect to social distancing, mask wearing, and vaccination. We shed light how these may result in sub-optimal outcomes and demonstrate the responsibility of national authorities in designing these games properly regarding data transparency, 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; moreover, there is no one-size-fits-all blueprint when designing an effective solution.

9.1 Introduction

The current coronavirus pandemic is pushing individuals, businesses and governments to the limit. Even with the recently emerged hope of rapidly developed vaccines, people still suffer owing to reduced mobility, social life and income; complete business sectors face an almost 100 per cent 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 deployed is only delayed by around two weeks (the incubation period). From the 24/7 media coverage, all of us have been introduced to a set of quasi-standard measures applied by national and local authorities, including social distancing, wearing masks, vaccination, 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]

We believe that apart from the intuitive (e.g., genetic differences, medical infrastructure availability, hesitancy, etc.), there are two significant 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 their specific *implementation* of response measures, e.g., providing extra unemployment benefits (affecting the likelihood of proper self-imposed social distancing), whether they have been distributing free masks (affecting the efficacy of mask wearing in case of equipment shortage), or regulating the amount of accepted vaccines (affecting the speed of reaching herd-immunity). 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. The objective of this chapter is to show that both individual incentives and the actual design and implementation of the holistic pandemic response mechanism can have a major effect on how (ongoing and future) pandemics are going to play out.

Contribution. In this chapter we model decision situations during a pandemic using game theory where participants are rational, and the proper design of the games could be the difference between life and death. This chapter is a focused version of [1], which is an extension of [2]. Our main contribution is two-fold: we elaborate on several basic decision models of social distancing, mask wearing, and vaccination, and present a pandemic mechanism design viewpoint, in which all of these games are only sub-mechanisms of the bigger picture.

For social distancing, using current COVID-19 statistics we show that going out is only rational when it corresponds to either a huge benefit or staying home results in a significant loss, and we determine the optimal duration (or meeting size) of such an out-of-home activity. We also present a game corresponding to mask wearing and introduce several decision models concerning vaccination, so we can detail pandemic response from a mechanism design perspective. We show that different government policies influence the outcome of these games

[1] Johns Hopkins Coronavirus Resource Center. `https://coronavirus.jhu.edu/map.html`

profoundly, and the standalone response measures of the sub-mechanisms are interdependent.

Organization. The chapter is structured as follows. In the remaining of this section we recap some concepts of game theory we use throughout this chapter. In Section 9.2, we briefly describe related work. In Section 9.3, we develop and analyse the Distancing Game which includes the effects of meeting duration (or size). In Section 9.4, we sketch the two player Mask Game, while in Section 9.5 we introduce several decision models focusing on various aspects of vaccines. In Section 9.6, we frame pandemic response as a mechanism design problem using the introduced models. Finally, in Section 9.7, we outline future work and conclude the chapter.

Preliminaries

Here we shortly elaborate on the main game theoretical notions used in this paper, to facilitate the conceptual understanding of the implications of our results.

Game Theory. Game theory [3] is 'the study of mathematical models of conflict between intelligent, rational decision-makers'. Almost any multi-party interaction can be modeled as a game. In relation to COVID-19, decision-makers could be individuals (e.g., whether to wear a mask), municipalities (e.g., whether to enforce wide-range testing within the city), governments (e.g., whether to apply contact tracing within the country), or companies (e.g., whether to apply social distancing within the workplace). Potential decisions are referred to as strategies; decision-makers (players) choose their strategies rationally so as to maximize their own utility.

Rationality. Note that rational (in a game-theoretical context) does not necessarily mean fully and objectively informed, i.e., individuals will make their decisions based on the *perceived* utility of their actions. Such a decision can even go against scientifically proven best practices, resulting in refusing vaccination or partying carelessly. Naturally, more realistic behavioral modelling (e.g., bounded rationality, unpredictability and a large number of proven behavioral biases [4]) delves deeper into the human decision-making process. However, the simple decision models in this paper serve more of a demonstrative purpose, illustrating i) how (selfish) individual decisions perturb society-level behavior, and ii) how central mechanism design decisions influence the outcome of such models.

Nash Equilibrium. The Nash Equilibrium (NE)—arguably the most famous solution concept—is a set of strategies where each player's strategy is a best response strategy. This means every player makes the best/optimal decision for itself as long as the others' choices remain unchanged. NE provides a way of predicting what will happen if several entities are making decisions at the same time where the outcome also depends on the decisions of the others. The existence of a NE means that no player will gain more by unilaterally changing its strategy at this unique state.

Social Optimum. Another game-theoretic concept is the Social Optimum (SO), which is a set of strategies that maximizes social welfare. Note, that despite the fact that no one can do better by changing strategy, NEs are not necessarily Social Optima (we refer the reader to the famous example of the

Prisoner's Dilemma [3]). In fact, it is well-studied in game theory how much a distributed outcome (e.g., a NE) is worse than a centrally-planned optimum (e.g., SO); this ratio is captured by the Price of Anarchy [5] and by the Price of Stability [6].

Mechanism Design. If one knows the NE they prefer as the outcome of a game, e.g., everybody following social distancing guidlines, and they have the power to instantiate the game accordingly, i.e., fixing the structure, game flow and any free parameters, then we talk about mechanism design [7]. In a way, mechanism design is the inverse of game theory; although a significant share of efforts within this field deals with auctions, mechanism design is a much broader term applicable to any multi-stakeholder mechanism, (e.g., optimal organ matching for transplantation, school-student allocation or, in fact, pandemic response), aimed at achieving a preferred steady state result.

9.2 Related Work

In this section we review some well-known and/or recent epidemic response mechanisms and game-theoretic works in relation to social distancing, masks, vaccination, and pandemics in general. A comprehensive systematic literature review on COVID-19 can be found in [8, 9].

Concerning social distancing, [10, 11] aim to provide a comprehensive survey on how emerging technologies, e.g., wireless and networking, artificial intelligence (AI) can enable, encourage, and enforce social distancing practice.

Game-Theoretic Models. In the intersection of epidemics and game theory a comprehensive survey were carried out in [12, 13]. Behavioral changes of people caused by a pandemic and, specifically, COVID-19 were studied in [14, 15], respectively. Others focused on the mobility habits of people travelling between areas affected unevenly by the disease [16]. The authors of [17] took a closer look through the lens of game theory on the effect of self-quarantine on virus spreading. In [18] an optimization problem was formalized by accommodating both isolation and social distancing. Concerning the latter, the authors of [19] considered an approach to schedule the visitors of a facility based on their importance. The impact of social distancing was also studied in [20] in combination with vaccines.

Several other studies also focused on how the availability of vaccines affects human behaviour. For instance in [21] the authors studied personal vaccination preferences and concluded that vaccine delayers relied on herd immunity and vaccine safety information generated by early vaccinators. Another study concerning this vaccination dilemma proposed a model with incentives for individuals to choose the prevention strategy according to risks and expenses in the epidemic campaign [22]. Similarly, researchers in [23] showed the optimal use of anti-viral treatment by individuals when they took into account the direct and indirect costs of treatment.

The Centers for Disease Control and Prevention (CDC) created a policy review of social distancing measures for pandemic influenza in non-healthcare settings [24]. They identified measures to reduce community influenza transmission such as isolating the sick, tracing contacts, quarantining exposed people, closing down schools, changing workplace habits, avoiding crowds, and restricting movement. The impact of several of these (and wearing masks) was studied in [25], where authors used agent-based modelling for the pandemic, simulating actions of people, businesses and the government. Other researchers demonstrated that early school and workplace closures and the restriction of international travel are independently associated with reduced national COVID-19 mortality [26]. On the other hand, lock-down procedures could have a devastating impact on the economy. This was studied in [27] with a modified SIR model and time-dependent infection rate. The authors found that, surprisingly, in spite of the economic cost of the loss of workforce and incurred medical expenses, the optimum point for the entire course of the pandemic is to keep the strict lock-down as long as possible. Finally, the authors in [28] designed and analysed a multi-level game-theoretic model of hierarchical policy making, inspired by policy responses to the COVID-19 pandemic. Taking the step towards making such policies explicit, the same authors have developed a novel class of games and their respective analytic solution framework in [29].

As detailed above, related work has mostly studied narrowly focused specifics of epidemic modelling such as the intricate behaviour of individuals in relation with vaccines, or the preferred actions of mechanism designers such as healthcare system operators. In contrast, our work takes a step back, and focuses on the big picture: we model decision situations during a pandemic as games with rational participants, and promote the proper design of these games. We highlight the responsibility of mechanism designers such as national authorities in constructing these games properly with adequately chosen policies, taking into account their interdependent nature.

9.3 The Distancing Game

One of the most important concepts which got widespread due to the ongoing COVID-19 pandemic is social distancing. By definition it is a set of non-pharmaceutical interventions or measures intended to prevent the spread of a contagious disease, hence it is the first line of defence against SARS-CoV-2. Such measures influence the self-determination of individuals, restricting the freedom of mobility, minimizing social interactions outside ones' household, and potentially, threatening the livelihood of (dominantly) low-income families. Therefore, it is imperative to understand why people do or do not comply with social distancing measures, especially when strict enforcement is a (prohibitively) costly option. We study the incentives underlying the (non-)compliance of individuals via game-theoretical models. To improve readability, we summarize all corresponding parameters and variables in Table 9.1.

Variable	Meaning
C	Cost of staying home
B	Benefit of going out
m	Mortality rate
L	Value of Life
ρ	Probability of infection
t	Time duration

Table 9.1: Parameters of the Distancing Games

9.3.1 Basic Distancing Game

We represent the cost of going out with $\rho \cdot m \cdot L$, i.e., the probability of getting infected (i.e., the infection rate) multiplied with the mortality rate of the disease and with the player's evaluation about her own life.[2] Besides the risk of getting infected, going out and attending a meeting could benefit the player, denoted as B. In parallel to the benefit of a meeting, there is also a cost for staying home or missing a meeting, denoted as C. Of course, there are other alternative ways to capture the benefits and the cost of social distancing [30], but this simple utility function suffices for demonstration purposes.

Definition 9.1. *The Distancing Game is a tuple $\langle \mathcal{N}, \Sigma, \mathcal{U} \rangle$, where the set of players is $\mathcal{N} = \{1, 2\}$, and their actions are $\Sigma = \{\textbf{\textit{go}}, \textbf{\textit{stay}}\}$. The utility functions $\mathcal{U} = \{u_1, u_2\}$ are presented as a payoff matrix in Table 9.2.*

	go	**stay**
go	$[B - \rho \cdot m \cdot L, B - \rho \cdot m \cdot L]$	$[-\rho \cdot m \cdot L - C, -C]$
stay	$[-C, -\rho \cdot m \cdot L - C]$	$[-C, -C]$

Table 9.2: Payoff matrix of the Distancing Game

Theorem 9.1. *A trivial Nash Equilibrium of the Distancing Game is (**stay**, **stay**), On the other hand (**go**, **go**) is also a NE if $\rho \cdot m \cdot L < B + C$. If this condition holds than (**go**, **go**) is also the Social Optimum, otherwise it is (**stay**, **stay**).*

Proof. The strategy vector (**stay**, **stay**) is clearly a NE since no player have incentive to deviate from it (because $-C > -\rho \cdot m \cdot L - C$). (**stay**, **stay**) could be a NE as well if the same is true, however, the corresponding condition does not hold trivially except when $-C < B - \rho \cdot m \cdot L$ which is equivalent with $\rho \cdot m \cdot L < B + C$. This inequality (if true) also implies that the total payoff is greatest at (**go**, **go**), but if it is false than (**stay**, **stay**) is the SO. □

Above we focused on analysing the pure-strategy Nash Equilibrium (e.g., either **use** or **no**), however, it is possible that the game also has mixed-strategy Nash Equilibria (i.e., **go** with probability φ and **stay** with probability $(1 - \varphi)$), which may lead to a utility increase [31]. These randomized strategies could also be easily calculated; we leave these calculations to the interested readers. We also defined this game as symmetric, however, one can easily adapt the analysis to an asymmetric payoff structure (i.e., B_1, B_2, C_1 and C_2, instead of B and C).

Example 9.1. *For instance, should a rational American citizen (e.g., Alice) meet Bob based on how much they value their lives? We estimate[3] $m = 0.0225$, because $0.021 \approx \frac{\#\{deceased\}}{\#\{all\ cases\}} < m < \frac{\#\{deceased\}}{\#\{closed\ cases\}} \approx 0.024$ and $\rho = 0.0025$ as $\rho \approx \frac{\#\{active\ cases\}}{\#\{population\}} \approx 0.0025$.*

[2] This is an optimistic approximation, as besides dying, the infection could impose other tolls on a player.

[3] Data from `https://www.worldometers.info/coronavirus/` (accessed 30th April, 2021)

Using these values, Alice should go out only if she values her life less than $17777(=\frac{1}{0.0225\cdot 0.0025})$ *times the sum of the benefit of the meeting and the loss of missing out. According to [32], the value of a statistical life in the US was* 9.2 *million USD in 2013, which is equivalent to* 11.7 *million USD in 2021 (adjusted for inflation with a* 0.3% *rate). This means that Alice should only meet someone if the benefit of the meeting plus the cost of missing it would amount to more than* 658 *USD* $(=\frac{11.7M}{17777})$*.*

9.3.2 Extended Distancing Game

One way to improve the above model is by introducing meeting duration.[4] Leaving our disinfected home during a pandemic is risky, and this risk grows with the time spent in a crowd. In the original model, we captured the infection probability with $\rho = 1-(1-\rho)$. This ratio increases to $1-(1-\rho)^t$ for time t. We leave the interpretation of unit time to the reader. Moreover, the benefit of attending a meeting should depend on this new parameter, as well as the cost of isolation. For instance, staying home for a longer period might cause anxiety, which could get worse over time (i.e., increasing the cost) [33]; on the other hand, spending longer quality time with someone could significantly boost the experience (i.e., increase the benefit).

Definition 9.2. *The Extended Distancing Game is a tuple* $\langle\mathcal{N},\Sigma,\mathcal{U}\rangle$*, where the set of players is* $\mathcal{N}=\{1,2\}$ *and their actions are* $\Sigma=\{\boldsymbol{go},\boldsymbol{stay}\}$*. The utility functions* $\mathcal{U}=\{u_1,u_2\}$ *are presented in Equation (9.1).*

$$
\begin{aligned}
u(\textbf{stay}) &= -\,C(t)\\
u(\textbf{go}) &= \begin{cases} B(t)-(1-(1-\rho)^t)\cdot m\cdot L & \text{if other plays } \textbf{go}\\ -(1-(1-\rho)^t)\cdot m\cdot L - C(t) & \text{if other plays } \textbf{stay}\end{cases}
\end{aligned}
\tag{9.1}
$$

A direct consequence of this extension is that the structure of the Distancing Game remained unchanged, hence, the two games share the same NEs.

Corollary 9.1. *Similarly to the basic Distancing Game, the Extended Distancing Game have the same trivial NEs (**stay**, **stay**) and (**go**, **go**) if* $(1-(1-\rho)^t)\cdot m\cdot L < B(t)+C(t)$*. If this condition holds than (**go**, **go**) is also the Social Optimum, otherwise it is (**stay**, **stay**).*

Example 9.2. *In Figure 9.1, we illustrate the payoffs for several polynomial benefit functions (e.g.,* $B(t)=\{t^2,t^3,t^4\}$*) and a cost function* $C(t)=t^2$*. The rest of the parameters are defined as before, i.e.,* $\rho=0.0025$*,* $m=0.0225$*, and* $L=11,700,000$*. It is visible that the change of the cost is insignificant compared to the benefit, consequently the illustration and the reasoning would be similar if* C *would be linear or constant. It is visible that for small* t *(**stay**, **stay**) is the SO as the utility is higher. On the other hand, as* t *grows (**go**, **go**) becomes the SO. Another clearly visible take-away message is that the threshold of* t *where the SO changes is lower as the benefit is higher.*

[4] We capture the duration of the meeting equivalently to how meeting size can be modelled, hence all our arguments about meeting duration could easily be adapted to optimal meeting size.

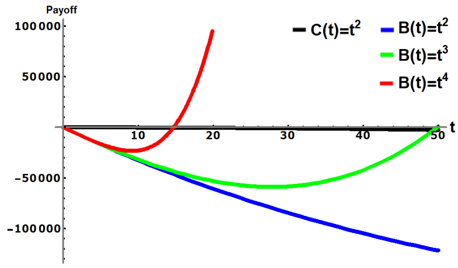


Figure 9.1: Illustrating the payoffs of the NEs (**stay**, **stay**) and (**go**, **go**) for the Extended Distancing Game with parameters $B = \{t^2, t^3, t^4\}$, $C(t) = t^2$, $m = 0.0225$, $\rho = 0.0025$, and $L = 11,700,000$

9.4 The Mask Game

Another visible effect most people has experienced during the current COVID-19 pandemic is masks: before, their usage was mostly limited to some Asian countries, hospitals, constructions, and banks (in case of a robbery). Nowadays 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 decision situation via game theory: we introduce a simple[5] Mask Game to be played in sequence with the previously introduced Distancing Game: once a player decided to meet up with friends she can decide whether to wear a mask for the meeting by playing the Mask Game. We assume that there are several types of masks, providing different levels of protection.

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

- **Out** 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 they limit the spreading of the virus. They do not protect the wearer itself against an airborne virus. The cost of deciding for this protection type is noted as $C_{out} > 0$.

- **In** 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 they do not filter the while air breathing out. The cost of this protection type is $C_{in} > C_{out}$.

Besides which mask they use (i.e., the available strategies), the players are either susceptible or infected, i.e., we are using a basic SI model. Being infected has some undesired effects; hence, we model it by adding a cost C_i to these

[5]The interested reader can follow up on the various extensions of this basic game in [1].

Variable	Meaning
C_{out}	Cost of playing **out**
C_{in}	Cost of playing **in**
C_i	Cost of being infected
C_{use}	Cost of playing **use**

Table 9.3: Parameters of the various Mask Games

players' utility (which is magnitudes higher than cost of wearing any mask, i.e., $C_i \gg C_{in} > C_{out}$). Consequently, in the Mask Game we minimized the costs instead of maximize the payoff as with the Distancing Game. We summarize all the parameters and variables used for the Mask Game in Table 9.3. Using these states and masks, we can present the basic game's payoffs where two players with known health status meet, and decide which mask to use.

Definition 9.3. *The basic Mask Game is a tuple $\langle \mathcal{N}, \Sigma, \mathcal{U} \rangle$, where the set of players is $\mathcal{N} = \{1, 2\}$ and their actions are $\Sigma = \{$**no**, **in**, **out**$\}$. The utility functions $\mathcal{U} = \{u_1, u_2\}$ are presented as a cost matrix in Table 9.4. In details, Table 9.4a corresponds to the case when both players are susceptible, while Table 9.4b corresponds to the case when one player is infected while the other is susceptible. Note that when both players are infected, the payoff matrix would be as when both are susceptible, with an additive constant cost C_i.*

	no	**out**	**in**
no	$[0, 0]$	$[0, C_{out}]$	$[0, C_{in}]$
out	$[C_{out}, 0]$	$[C_{out}, C_{out}]$	$[C_{out}, C_{in}]$
in	$[C_{in}, 0]$	$[C_{in}, C_{out}]$	$[C_{in}, C_{in}]$

(a) Payoff matrix when both players are susceptible

	no	**out**	**in**
no	$[C_i, C_i]$	$[0, C_{out} + C_i]$	$[C_i, C_{in} + C_i]$
out	$[C_{out} + C_i, C_i]$	$[C_{out}, C_{out} + C_i]$	$[C_{out} + C_i, C_{in} + C_i]$
in	$[C_{in}, C_i]$	$[C_{in}, C_{out} + C_i]$	$[C_{in}, C_{in} + C_i]$

(b) Payoff matrix when exactly one player is susceptible

Table 9.4: Payoff matrices of the Mask Game

Theorem 9.2. *When perfect knowledge is available about the states of the players, then if both players are of the same type, both the pure strategy Nash Equilibrium and the Social Optimum of the Mask Game are (**no**, **no**); while if exactly one is susceptible (e.g., player 1) then the NE is (**in**, **no**) and the SO is (**no**, **out**).*

Proof. From Table 9.4a it is trivial 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 (**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.

When only one of the players is susceptible as represented in Table 9.4b, using no mask is a dominant strategy for the infected player[6], since it is a best response, independently of the susceptible player's action. Consequently, the best option for the susceptible player is **in**, i.e., the NE is (**in**, **no**). On the other hand, the social optimum is different: (**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 defence against Distributed Denial of Service Attacks (DDoS) attacks [34]: although it would be much more efficient to filter malicious traffic at the source (i.e., **out**), Internet Service Providers rather filter at the target (i.e., **in**) owing to a rational fear of free-riding by others.

9.5 Vaccination Models

The most recent virus spreading prevention mechanism against the COVID-19 is vaccination. Since researching and developing a vaccine takes time, it could not be utilized as rapidly as the rest of the techniques detailed in this work (e.g., social distancing and masks). On the other hand, this protection mechanism is considered to be the most efficient and has proven its strength several times in the past [35]. Concerning the rapidly developed COVID-19 vaccines, most governments and international organizations agree that all vaccines are safe to use and protect (to an extent) against COVID-19 for the general population. Yet, there are various aspects in which these vaccines differ, so individuals could have preferences.

Here, we introduce several optimization models, where—in contrast to multiplayer games—the utility of an individual does not depend on other players' actions.[7] The decision we model originates from the choice among multiple specific vaccines. Instead of focusing on whether to be vaccinated or not, as several previous works [21, 22, 23] did, we compare two hypothetical vaccines, differing along 6 different dimensions as summarized in Table 9.5. *Technology* refers to the working mechanism of the vaccine (e.g., using dead/weakened virus, mRNS, etc) [36]. *Availability* means the point in time when the vaccines are at the actual disposal of individual decision-makers. It is reasonably expected that vaccines based on traditional technologies could be mass manufactured

[6]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`.

[7]The interested reader can see a game-theoretic extension of these basic decision models in [1].

	Tech	Availability	Side-Effect	Efficiency	Duration	Usability
α	old	now	no	low	long	limited
β	new	soon	maybe	high	short	wide

Table 9.5: The two vaccines and their properties: Technology, Availability, Side-Effect, Efficiency, Duration, and Usability

and transported with ease, while vaccines based on new technologies could be delayed for many reasons [37]. A similar difference corresponds to the potential *side-effect*: vaccines based on older technologies were utilized in the past around the globe, hence the rare side-effects are either known or non-existing. On the other hand, side-effects concerning modern vaccines are only based on tests with a limited number of participants [38]. The *efficiency* and *duration* of the vaccines (e.g., the probability of mitigating the severe consequences of an infection and the length of the response of the body triggered by the vaccine, respectively) also differ, favouring the newer technology [39]. Finally, the *usability* of a vaccine refers to the portion of individuals who could/should get it, e.g., there are vaccines which were associated with severe side effects which effects various demographic groups differently [40]. These differences between the two vaccines considered by the individuals are formalized in Table 9.6 with the corresponding cost and benefit variables.

In the following optimization models we select 2-3 of the dimensions above, and present the utility/objective function for which the individuals optimize by selecting the vaccine with the higher payoff. We do not provide formal theorems and proofs as the results are trivial corollaries of the exact definitions.

Duration-Efficiency Decision. As defined in Table 9.6a we assume vaccine α provides protection for duration d_α with protection level e_α. On the other hand, we assume that Vaccine β protects for a shorter duration d_β but with a stronger protection level e_β. This is also illustrated in Figure 9.2a.

Definition 9.4. *The Duration-Efficiency decision problem is a tuple $\langle \Sigma, \mathcal{U} \rangle$, where the actions are $\Sigma = \{\alpha, \beta\}$ and the corresponding utility functions $\mathcal{U} = \{U(\alpha), U(\beta)\}$ are presented in Equation (9.2):*

$$U(\alpha) = \int_0^{d_\alpha} e_\alpha \, \mathrm{d}t = e_\alpha \cdot d_\alpha \qquad\qquad U(\beta) = \int_0^{d_\beta} e_\beta \, \mathrm{d}t = e_\beta \cdot d_\beta \tag{9.2}$$

It is clear that the optimal decision depends on the exact values of e_α, e_β, d_α, and d_β: if $e_\alpha \cdot d_\alpha > e_\beta \cdot d_\beta$ then Vaccine α is the optimal choice, otherwise it is Vaccine β. For instance if we set $e_\alpha = 0.76$, $e_\beta = 0.95$, $d_\alpha = 49$ and $d_\beta = 35$ then $U(\alpha) \approx 37 > 33 \approx U(\beta)$.[8]

[8] The values used through all our examples within this section are serving only illustrative purposes and do not correspond to any existing vaccines.

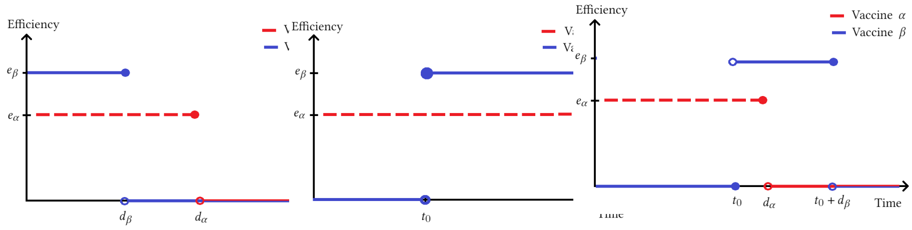
Vaccine	α	β
Protection Efficiency	e_α	e_β
Effect Duration (time)	d_α	d_β
Availability (from time)	0	t_0
Side-effect Probability	0	ϵ
Benefit of being vaccinated	B_α	B_β

(a) Vaccine specific variables

Variable	Meaning
C_i	Cost of being infected
C_s	Cost of the side-effect
p	Vaccine preference

(b) Costs & Benefits of the Vaccination Models

Table 9.6: The parameters concerning the Vaccines and the Vaccination Models



(a) Duration and efficiency of the vaccines (b) Availability and efficiency of the vaccines (c) Availability, duration, and efficiency of the vaccines

Figure 9.2: Illustration of vaccine properties

Availability-Efficiency Decision. Following Table 9.6a we assume Vaccine α is available now (i.e., at $t = 0$), but it only provides protection level e_α. On the other hand, Vaccine β will only become available at t_0, but with a stronger protection level e_β. This is also illustrated in Figure 9.2b. Even without taking the duration into account, we have to introduce time-based discounting for the utility via the factor δ, as generally treated in the economics literature [41].

Definition 9.5. *The Availability-Efficiency decision problem is a tuple $\langle \Sigma, \mathcal{U} \rangle$, where the actions are $\Sigma = \{\alpha, \beta\}$, and the corresponding utility functions $\mathcal{U} = \{U(\alpha), U(\beta)\}$ are presented in Equation (9.3):*

$$U(\alpha) = \int_0^\infty e_\alpha \cdot \delta^t \,\mathrm{d}t = \frac{-e_\alpha}{\log \delta} \qquad U(\beta) = \int_{t_0}^\infty e_\beta \cdot \delta^t \,\mathrm{d}t = \frac{-e_\beta}{\log \delta}\delta^{t_0} \tag{9.3}$$

Again, the optimal decision trivially depends on the exact values of e_α, e_β, t_0, and δ: if $e_\alpha < e_\beta \cdot \delta^{t_0}$ then Vaccine α is the optimal choice, otherwise it is Vaccine β. For instance, with $e_\alpha = 0.76$, $e_\beta = 0.95$, $t_0 = 28$, and $\delta = 0.999$, the utilities are $U(\alpha) \approx 1749$ and $U(\beta) \approx 2126$, respectively.

Duration-Efficiency-Availability Decision. It is possible to combine the previous two decision models as illustrated in Figure 9.2c.

Definition 9.6. *The Duration-Efficiency-Availability decision problem is a tuple $\langle \Sigma, \mathcal{U} \rangle$, where the actions are $\Sigma = \{\alpha, \beta\}$, and the corresponding utility functions $\mathcal{U} = \{U(\alpha), U(\beta)\}$ are presented in Equation (9.4):*

$$\begin{aligned} U(\alpha) &= \int_0^{d_\alpha} e_\alpha \cdot \delta^t \,\mathrm{d}t = (\delta^{d_\alpha} - 1) \cdot \frac{e_\alpha}{\log(\delta)} \\ U(\beta) &= \int_{t_0}^{t_0+d_\beta} e_\beta \cdot \delta^t \,\mathrm{d}t = (\delta^{d_\beta} - 1) \cdot \delta^{t_0} \cdot \frac{e_\beta}{\log(\delta)} \end{aligned} \tag{9.4}$$

The optimal decision depends on the exact values of e_α, e_β, d_α, d_β, t_0, and δ: if $\frac{e_\alpha}{e_\beta} \cdot \delta^{t_0} > \frac{\delta^{d_\alpha}-1}{\delta^{d_\beta}-1}$ then Vaccine α is the optimal choice, otherwise it is Vaccine β. For instance, with $e_\alpha = 0.76$, $e_\beta = 0.95$, $d_\alpha = 49$, $d_\beta = 35$, $t_0 = 28$, and $\delta = 0.999$, the utilities are $U(\alpha) \approx 84$ and $U(\beta) \approx 73$, respectively.

Side-Effect Decision. Suppose Vaccine α is based on a traditional vaccination technology, hence, it provides protection level e_α with a negligible risk of any undesired side-effect. On the other hand, Vaccine β is a product of the most advanced technological improvements, consequently, it offers a stronger protection level e_β but with a small likelihood ϵ of serious undesired consequences. In the following, instead of defining the utility purely based on the vaccine parameters as previously, we utilize explicit costs and benefits variables. B_α and B_β are the benefits of the corresponding vaccines. These might differ due to regional diversity of acceptance: one could be accepted worldwide, while the other may be accepted by only specific national authorities. Concerning the costs we capture the cost of infection with C_i while C_s corresponds to the cost of the side-effect wich occures with probability ϵ. We assume the individual is exposed to the virus, hence non-efficient protection correspond to infection.

Definition 9.7. *The Side-Effect decision problem is a tuple $\langle \Sigma, \mathcal{U} \rangle$, where the actions are $\Sigma = \{\alpha, \beta\}$, and the corresponding utility functions $\mathcal{U} = \{U(\alpha), U(\beta)\}$ are presented in Equation (9.5):*

$$U(\alpha) = B_\alpha - (1 - e_\alpha) \cdot C_i \qquad U(\beta) = B_\beta - (1 - e_\beta) \cdot C_i - \epsilon \cdot C_s \tag{9.5}$$

The optimal decision depends on the exact values of e_α, e_β, B_α, B_β, C_i, and C_s: if $B_\beta - B_\alpha > \epsilon \cdot C_s - (e_\beta - e_\alpha) \cdot C_i$ then Vaccine α is the optimal choice, otherwise it is Vaccine β. For instance, with $e_\alpha = 0.76$, $e_\beta = 0.95$, $b_\alpha = b_\beta = 100$, $C_i = C_s = 1000$, and $\epsilon = 0.001$, the utilities are $U(\alpha) \approx -140$ and $U(\beta) \approx 49$, respectively.

9.6 Pandemic Mechanism Design

The three counter-COVID mechanisms (social distancing, mask wearing, vaccination)modeled above are only parts of the bigger picture. Here we analyse the impact of specific policies on data transparency, social distancing, mask wearing, testing and contact tracing, and vaccination.

9.6.1 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* [7]. 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 maximising a different objective function of the designer.

In the context of the coronavirus pandemic, the immediate response mechanism is composed of, e.g., social distancing, wearing a mask, testing and contact tracing, among others, followed by vaccination. 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. 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 three games, and adding testing and contact tracing to the mix.

9.6.2 Data Quality and Transparency

It is well-known that inaccurate reporting of epidemic data can potentially decrease the efficacy of forecasting, and thus, response measures [42]. A less understood aspect of the data quality problem is the deliberate distortion of such reports. While not specific to handling the COVID-19 situation, a government's decision to be fully transparent or to partially conceal information from its citizens could have a profound impact on the success of pandemic response. It is fairly straightforward to see that if people make their individual decisions based on deliberately manipulated, coarse-grained or gappy data, the results will be sub-optimal and, potentially even more detrimental, unpredictable. If there is no unanimously trusted source of information available, people's beliefs will be heterogeneous, as if they were playing different games altogether. As a simple example, take the Distancing game in Section 9.3: individuals will make their assessments whether to meet based on ρ, the probability of getting infected. If media reports on this parameter are altered or varying across different channels, people may a) meet up when it is not in their best interest, or b) stick to staying home even if it is no longer sensible. While the detrimental effect of data concealment seems rather indirect and hard to piece together, there exist quantitative reports aiming to shed light on such issues, e.g., on data concealment and COVID-19 mortality [43].

9.6.3 Social Distancing

Within the Extended Distancing Game in Section 9.3.2, the time parameter t captures the duration of a meeting. This could have another interpretation as well, as meeting size could be captured the same way as time. Consequently, if the government imposes an upper limit T for the size of congregations, this will put a strict upper bound on the 'optimal meeting size' t^*, and the resulting group size will be $\min(T, t^*)$, instantiating a decreased benefit, and, therefore, promoting staying at home.

Social distancing can be a strong measure in good hands. However, the need for individual (dis)incentives for adhering to distancing policy is clear; especially, after the novelty of the pandemic has worn out. Governments and municipalities could encourage home office, compensate workers whose jobs would demand physical presence, promote open-air cultural activities, and educate citizens on the benefits of social distancing. Schools and universities could enforce a hybrid system, where only half of the students are present physically at the same time, with weekly (or daily) shifts. Furthermore, indoor venues, such as restaurants, movie theaters, museums, etc., could restrict their capacity to, e.g., 50% to enable proper distancing. Each of these policies, when enforced, has an effect on the outcome of distancing games presented in Section 9.3.

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.

9.6.4 Mask Wearing

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.

9.6.5 Vaccination

By far, vaccination policy is the most complicated and scrutinized among all sub-mechanisms, owing to its direct relation to control over one's own body, a pillar of human rights.

The availability of multiple, high efficacy vaccines enables governments to contain and suppress the pandemic. It is clear that, even if herd immunity is never reached, the more people are vaccinated, the less problem COVID-19 will cause in the near future. As mandatory vaccination is not feasible even in semi-democracies, the design of an efficient carrot-and-stick system is sensible. Therefore, countries have started to introduce vaccination passports [44], which give to its holders benefits over their non-vaccinated countrymen, such as attending indoor venues, mass events like concerts or football matches, and traveling internationally without continuous testing. Sensibility notwithstanding, even the vaccine passport concept is under heavy legal and ethical scrutiny. Note, that some EU countries have used many types of vaccines, including ones developed in China and/or Russia, currently not recognized by the European Medicines Agency (EMA); citizens who had received such a vaccine are not entitled to a vaccine passport[9].

As vaccines have so far been a scarce resource, government decision on which vaccines to purchase in what quantities can be crucial. Exacerbated by incomplete trial documentation, the lack of trust between countries, being in different stages of the pandemic, and having greatly varying financial and healthcare means available, national governments have followed different strategies. In a country, where the pandemic is fairly well-contained with mild restrictive measures, playing it safe makes perfect sense.[10] However, it is in the best interest of a country with high mortality and collapsing healthcare to grab any available, perhaps under-documented or lower efficacy vaccine in significant quantities. In the latter scenario, there might be 5-6 different types of vaccines in a national vaccination program.[11]

Adding to the set of available vaccines, the proposed order of vaccination is another important control lever. Most implemented policies agree on prioritising medical staff and emergency first responders, but can differ on prioritising the elderly (demographic segment with the highest risk of death/severe symptoms) or the actively working people (segment with the highest risk of transmission) [45]. Combining this aspect with the individual preference for a certain type of vaccine, the part of the population that does not want to be vaccinated, and the uncertainty of to which extent vaccines prevent transmission, realistically, the mechanism designer can only aim for an approximately optimal policy design.

[9] https://www.schengenvisainfo.com/news/all-details-on-eu-covid-19-passport-revealed-heres-what-you-need-to-know/

[10] https://www.fhi.no/en/id/vaccines/coronavirus-immunisation-programme/

[11] https://abouthungary.hu/news-in-brief/coronavirus-heres-the-latest

Adding to this, the right policy for relaxing restrictive measures as the vaccination progresses constitutes an issue of its own [45], and has an effect on all the sub-mechanisms and games mentioned above.

9.6.6 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 reduces the uncertainty, enables the government to impose mandatory quarantine thereby removing infected players, and identifies individuals who are temporarily immune, and thus, can be vaccinated at a later stage without imposing greater risk on them.

Even more impactful, mandatory testing (as in Wuhan[12]) render 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 the Distancing and Mask Games as well as to the Vaccination Decision Models.

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.[13] (Similarly, from the concerned individual's perspective, a single test might be unaffordable.) Contact tracing, whether traditional or mobile app-based, serves as an important input sub-mechanism to testing [46]. It identifies the individuals who are *likely* affected based on spatial proximity, 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. Another potential cost of contact tracing for individuals could be the loss of privacy. Note that mobile OS manufacturers are working on integrating privacy-preserving contact tracing into their platform to eliminate adoption costs for installing an app.[14]

9.6.7 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. It is vital to observe and profit from

[12] New York Times. `https://www.nytimes.com/2020/05/26/world/asia/coronavirus-wuhan-tests.html`

[13] But not without precedence, e.g., in Slovakia (`https://edition.cnn.com/world/live-news/coronavirus-pandemic-10-18-20-intl/h_beb93495fe9b83701023eafd5f28e39d`)

[14] Apple. `https://covid19.apple.com/contacttracing`

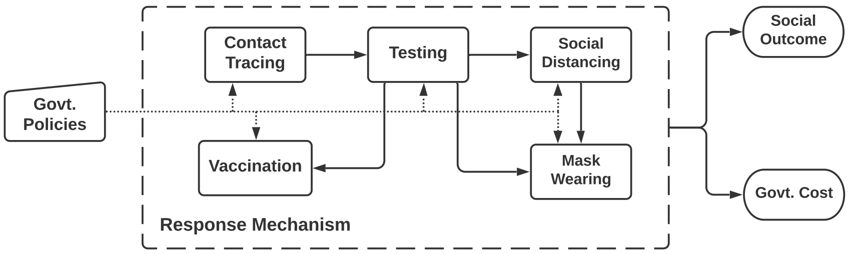


Figure 9.3: Pandemic response mechanism as influenced by government policy (dotted lines) and the interplay of sub-mechanisms (solid lines)

the interdependence of the sub-mechanisms; not even a strong weapon such as social distancing can stand against the pandemic on its own. If done properly, sub-mechanisms can strengthen each others' effectiveness, e.g., selective testing based on contract tracing can change the framing for social distancing. If done poorly or without acknowledging the interdependence, the sub-mechanisms may undermine each other, resulting in sub-optimal pandemic response with potentially catastrophic consequences.

After i) games have been designed and parameterized, ii) games have been played by selfish individuals, and iii) outcomes have been determined, iv) the cost for the mechanism designer itself is realized (see Figure 9.3). The corresponding cost function is very complex incorporating factors from ICU beds through civil unrest and affected future election results to a drop in GDP over multiple time scales [47]. Therefore, governments have to carefully balance the—very directly interpreted—social optimum and their own costs; this indeed requires a mechanism design mindset.

9.7 Conclusion

In this chapter we have made a case for treating pandemic response as a mechanism design problem. Through simple games and decision models modeling interacting selfish individuals we have shown that it is necessary to take individual incentives into account during a pandemic. First, we have shown how individual decisions (and, therefore, social impact) concerning social distancing depend on the perceived benefits of meeting up and the cost of missing out. Second, we have shown how individual incentives impact mask wearing and illustrated how individuals could optimize when selecting between two hypothetical vaccines taking into account availability, efficacy and duration of immunity.

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. Furthermore, we have discussed the notoriously complex nature of the vaccination policy; designing such in an even approximately optimal way has to take into account medical, behavioral, economic and legal factors. We have also argued that sharing high quality and truthful pandemic data with the public promotes better individual decision-making, and thus, more efficient handling of the pandemic. Governments have significantly more power than traditional mechanism designers in distributed systems; therefore, it is even more crucial for them to carefully study the trade-off between social good and the cost of the designer when implementing their pandemic response mechanism.

Limitations. The work presented here has several limitations from a policy-making standpoint. First, although the mechanism designer can directly influence the payoff functions and thus the outcome of the games presented (e.g., by imposing fines on non-compliant citizens or giving benefits to the vaccinated), and the factors currently used in the payoffs —without doubt—do play a part in individual decisions making, the utility functions themselves are—of course—simplified: behavioral decision-making aspects are out of scope for this paper. Second, at this level of abstraction, the games and their respective designs cannot form a practical guidebook for governments. In fact, complex simulation studies and the analysis of already existing real historical data have to be undertaken in order to make real-world decisions affecting human lives. The objective of this study is to *illustrate the impact of individual decision-making* on social distancing and other common pandemic measures, and *advocate for a mechanism design mindset* for policy-makers.

Future Work. We have barely scratched the surface of pandemic mechanism design. The models presented are simple and mostly used for demonstrative purposes. In turn, this gives us plenty of opportunity for future work. A potential avenue is extending our models to capture the temporal aspect, combining them with epidemic models as games played by many agents on social graphs, and parameterizing 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. Moreover, 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. Finally, special attention should be given to sustainable pandemic response measures, such as milder forms of social distancing, which could be used for prolonged times as COVID-19 seems to be staying with us for years to come. 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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