# Persuasion in Physician Agency*

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**Abstract**

Overwhelming evidence suggests that there exists a physician's tendency in recommending unnecessary medical treatments to the patients. This paper discusses this issue by providing a theoretical model with one physician and many patients who are uncertain about an underlying state of disease. The physician decides a preliminary test for the patients who need it. We show that the optimal test always reveals the state of disease, but not always the healthy state. The physician's advice may induce people undertaking unnecessary treatment as well as refraining from doing it when is needed. A policy intervention imposing a minimum *information standard* is very effective in reducing overtreatment but does not influence the number of tested people. Moreover, we show unintended consequences of releasing relevant news with or without the policy intervention.

**JEL codes:** D82, D83, I10, I18.

**Keywords:** Overtreatment; Bayesian Persuasion; Medical Tests; Policy Intervention.

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# 1 Introduction

Patients usually need guidance and relevant information to decide whether or not to undergo a health treatment. They have the right to be informed of all risks and benefits of the decisions they are going to make. Due to their expertise, physicians should identify the patient's needs by performing tests like diagnoses, prescriptions, or clinical trials. The patient's decision to accept the medical treatment is ethically acceptable when it is based on *informed consent* as legally required to any healthcare provider. In principle, the consent should be based upon patients fully informed of all material facts and consequences of a therapy. Nevertheless, overwhelming evidence tells us that often doctors do not act in their patients' best interest, inducing them to begin a treatment or medical care, even if is not necessary. Marco et al. (2006) claim that around 10% of medical prescriptions for certain drugs were unnecessary or inappropriate practices.

The tendency of overtreating patients stems from the fact that the doctor-patient relationship encloses an agency problem. The physician for instance can recommend a company treatment due to a financial stake or a commission-based compensation.[1,2] This is typically a problem in the case of vaccines or medicines prescriptions.[3] Moreover, often the patient's treatment becomes part of the research conducted by the physician. Based on randomized control trials for drug administration, Marshall and Aldhous (2006) found that medical centers that have received grants from a pharmaceutical company were less likely than groups with minimal financing to inform about drugs' potential side effects.[4]

Relying on all these evidences, our choice is to model the physician or medical department as an agent interested in maximizing the number of treatments. The physician can induce patients to accept a treatment by designing a preliminary diagnosis for all those who need it. We propose a model with one physician and heterogeneous patients in which medical tests (Bayesian experiments) are simple instruments to inform them about their real conditions. Such tests deliver a result (signal) that recommends the patient whether or not to take the treatment.

We show that the informativeness of the diagnoses through costly medical tests depends on each patient's characteristics. The possibility of providing a signal of health when the patient has a disease - *false negatives* - is ruled out due to the self-interest of the physician. Dif-

[1]Note that this issue arises both when the physician's salary is based on the number of treatments as well as when a medical department is publicly financed according to volumes.

[2]On top of that, Khazzaka (2019) shows that the pharmaceutical industry in Lebanon has yearly paid more than $30 billions to physicians to influence their prescribing patterns in the last decade.

[3]Many studies have concluded that paying physicians for each service creates incentives to increase volumes, see Smith (1992); and Hsiao et al. (1993).

[4]Whenever researchers receive money from the industry, a conflict of interest appears. Tobin (2003) claims that a typical conflict does not mean that researchers are biased or inflict harm. It merely means a risk of bias that can evolve into a wrong prescription of the treatment through a wrong diagnosis.

ferently, a medical test can give a signal of disease when the patient is healthy - *false positives* - entailing a loss for such a wrong choice. In health care, even well-established medical protocols are based on diagnosis which turn out to have a certain probability of mistakes, leading to overtreatment. As an example, consider the needle biopsy checking for the presence of a malign nodule in the thyroid gland which often recommends a thyroidectomy based on some criteria.[5,6] Post-surgery histological studies demonstrate that up to 85% of these nodules are benign, see Vaccarella et al. (2016) and Lim et al. (2017).

In our model, false positives are more likely for people who are more willing to undertake the treatment. Only some patients need the result of the test to opt for the treatment. Some of the latter are excessively difficult to convince, and they are not tested because the physician has no incentives to face the cost. Even simple diagnostic tests carried out for a few dollars everywhere - blood or urine tests - cannot be administered to all patients and thus entail a selection made by doctors. Increasing either the testing cost or the patient loss reduces the persuasive capability of the physician. Unsurprisingly, if the 'disease' state is more likely, the physician finds it easier to convince people to take the treatment.

Our analysis offers a new rationale for thinking about the role of information policy. Scholars wondered whether a public intervention could improve the test informativeness, thus helping patients undertake more conscious actions. Full transparency should begin when a drug, medicine, or general treatment is tested in humans. Detailed protocols of all trials should be registered, providing public access to up-to-date information on clinical trials. In our model, the policymaker objective is to reduce the likelihood of making the wrong decision across states of the world. In particular, the policy challenge is to set rules allowing (i) healthy patients to avoid treatment and (ii) patients with a disease to take it. For the first point, there is a misalignment of incentives between the policymaker and the physician. For the second one, instead, the policymaker's interest is to increase the set of tested people due to the absence of false negatives. Notice that the physician's incentive to persuade leads to a situation in which a test does not change the utility of the single patient but rather changes her probability to make the correct choice. As a consequence, a proper welfare analysis is not in terms of aggregate utilities but it is interpreted as the reduction of the overall informational bias (false positives) in the health care system.

We study the information channel taking two directions. First, the government requires the test to fulfill a minimum *information standard* aiming to reduce false positives. For instance, this would require more details in the process of informed consent. We show that this policy entails a loss for the physician at the benefit of patients who are tested and it is

[5]This is currently the direct experience of one of the authors, Giuseppe.

[6]The results ranking from TIR2 to TIR5 categories require a treatment based on protocols that are heterogeneous across countries. For example, in Japan and USA, a nodule classified as TIR3B requires a second biopsy after a certain period of time, see Kasagi et al. (2009), whereas in Italy, it is sufficient to suggest a resective surgery.

extremely effective. At the limit, if the testing cost is very low, this policy allows to fully eliminate test-induced mistakes. However, this policy does not help the government to increase the pool of tested people as ineffective in changing the physician's incentive. Second, we show the unintended consequences of releasing information able to change the prior of patients. For example, consider recent reports by national regulators who have decided to spread information of blood clottings in adults allegedly induced by the *AstraZeneca* vaccine, leading to the temporary interruption of the vaccination program.[7] In light of our setup, reporting bad (good) news makes the 'disease' (healthy) state more likely for all patients. Bad news induce the physician to administer less informative tests (more false positives) as the patients are *ex-ante* more willing to undertake the treatment. Consequently, people who opt for the treatment are more likely to make the wrong choice if tested and less likely if non-tested. Hence, releasing information influences the number of tested people and can give nontrivial distributional effect in combination with the information standard. Good news have precisely the opposite effect.

The remainder of this paper is organized as follows. Section 2 positions our paper in the literature. We present the model and define the physician's optimal persuasion rule in Section 3. We derive the results on the policy interventions in Section 4. Finally, Section 5 position the paper in the literature and concludes.

## 2 Literature

There is a long literature in health economics discussing overtreament in terms of supply-induced demand by an expert/physician based upon Farley (1986) and Dranove (1988). More recently, De Jaegher and Jegers (2000) build on this setting to provide patients' welfare evaluation. De Jaegher and Jegers (2001) propose an *information economics* interpretation of the supply-induced demand motivating this effect by a combination of cheap-talk game and credence goods.[8] Our approach is different from these two papers both in terms of theoretical approach and welfare analysis. In our case, the physician provides hard information through the diagnosis in a persuasive way by designing the information structure. Accordingly, the optimal test design induces the patient to be indifferent taking the treatment or not with no variations in the expected welfare. This is the reason why we focus on the probability of making mistakes in taking the treatment as a measure of diagnosis-induced patients' loss.

The issue of over- and under-treatment is also discussed in terms of financial incentives (Ellis and McGuire, 1986). They show that overtreatment is typically associated with cost-

[7] https://www.pei.de/EN/newsroom/hp-news/2021/210315-pei-informs-temporary-suspension.html

[8] See Dulleck and Kerschbamer (2006) for a comprehensive perspective of credence goods in health care, and Gottschalk et al. (2020) for a field experiment with dentists in Switzerland.

based reimbursement systems and this effect is reinforced by competition between hospitals.[9] This trend is increasingly observed not only in private healthcare, but also in public systems with limited resources.[10] Garcia Mariñoso and Jelovac (2003) study the physician's behaviour in referring patients to specialists in different health care systems looking at the socially optimal contracts.[11] Similarly, Allard et al. (2011) study how different payment mechanisms affect the referral intensity of the physician. These contributions underline informational problems focusing on providing the right incentives to correct them. More recently, Adida and Dai (2020) theoretically investigate diagnosis under limited outcome visibility, studying the impact of diagnosis-based payment schemes on the assessment of the physician on patients' health conditions. They show that conditioning the payment on the diagnosis entails a higher effort but can induce less precise recommendations.[12] Our contribution is complementary as we study the information design given physician incentives to overtreat, thereby using a "reduced form" of the doctor's payoff function.[13] We abstract from the type of payment schemes, considering the physician's interest in treating as many patients as possible. This allows us to focus only on the informative channel through the accuracy of the diagnosis.

Our model builds upon the literature on Bayesian persuasion and information design pioneered by Kamenica and Gentzkow (2011) and reviewed in Bergemann and Morris (2019) and Kamenica (2019). Recent contributions apply information design approach to healthcare problems as Alizamir et al. (2020) and de Véricourt et al. (2021). We exploit the novelty of this approach to introduce a policy target that changes the information structure of the experiment. The environment we have in mind is the doctor-patient relationship characterized by a commonly unknown state and a conflict of interest, which calls for policy interventions aiming to correct a typical bias that physicians have in administering the tests. The dilemma is now particularly evident, first, in the increasing trend to refer patients to diagnostic or treatment centers and, second, in the rise of expensive in-office ancillary equipment, Pham and Ginsburg (2007). We do so by addressing the physician information strategy in administering the test to the patients. Following Kamenica and Gentzkow (2011), we propose a Bayesian persuasion model where patients have heterogeneous payoffs and a common prior. This creates an interesting setting where the physician decides whether and how to test each patient, explained in the next section.

[9] An interesting case in healthcare is the one of doctors paid more for performing C-sections than vaginal births inducing them to become the most commonly performed operating procedures in the USA in the last decades, see Allin et al. (2015) and Alexander (2017) among others.

[10] Nowadays public hospitals suffer more competition from the private sector and the public healthcare is financed based on volumes.

[11] Along similar lines, hospital evaluation under pay-for-performance or fee-for-service have been studied theoretically and empirically even by Kristensen et al. (2016), Fichera et al. (2018), Lisi et al. (2020).

[12] Interestingly, a recent paper by Dai and Singh (2021) explains the rationale behind the presence of undertesting and overdiagnosis in the case of the recent infectious disease.

[13] Kassirer (2001) claimed that "physicians have been conflicted about their dual roles as professionals and businessmen for millennia".

## 3 The Model

**Intuition.** Imagine two patients who decide whether to take a medical treatment which can be necessary or not. The first patient, conditional on his perception of the benefits, is prone to medical care and decides to opt for the intervention without the need of further information. Differently, the second patient is more reluctant to medical care and needs the advice of his physician to take the treatment.[14] Throughout the paper, we refer to this idiosyncratic perception of benefits as patient *type*. The physician is interested in maximizing the number of treated people and her prescription of blood work, urine or stool test, X-rays or other diagnostic imaging are all part of a diagnosis, that we generically label as *test*. Her decision about which medical scans to require and the details of the medical analysis influence the information the patients have in their decision process. The physician is aware of patient medical needs and knows his relative risk factors and personal characteristics. Hence, the design of the test can be conditioned on patient type. In what follows we study the physician's problem with a large set of patients.

**Setting.** Consider an environment with a persuader $P$ and $N$ decision-makers, indexed $i \in \{1, 2, \dots, N\}$. In our story, she, a persuader is a physician aiming to convince him, a patient, about the advantage of being treated. Hence, decision makers are patients who decide whether or not undergoing a treatment, e.g., taking a drug, receiving a vaccine, starting a medicine, or more in general health care. In our setting, the treatment is defined by an action $a_i$ that each patient may undertake.

Without taking the treatment (action $a_i = 0$), patient $i$ receives zero utility.[15] In contrast, his payoff when undertaking it (action $a_i = 1$) depends on an underlying state of the world $\omega \in (D, H)$, where $D$ stands for the 'disease' state in which the treatment is useful, and the action helps the patient to improve his status. Instead, $H$ stands for the 'healthy' state where the treatment is unnecessary. Taking action $a_i = 1$ gives a positive payoff equal to $\theta_i$ in state $D$. As explained in the previous paragraph, the patient type $\theta_i$ should be interpreted as an idiosyncratic willingness to take a treatment, so that people with a high $\theta_i$ are similar to the first patient and people with a low $\theta_i$ to the second one. Instead, action $a_i = 1$ in state $H$ gives a payoff equal to $-\mu$, with $\mu > 0$, to capture the idea that a healthy patient would suffer from

[14] A recent example of this heterogeneity in patients' preference is the observed behaviour in the voluntary choice to vaccinate.

[15] Assuming zero payoff across states is the most neutral option. Suppose instead the patient incurs a cost in case of no treatment in state $D$, our result should reinforce as it creates more incentives to undertake the treatment aligning to the motivations of the physician.

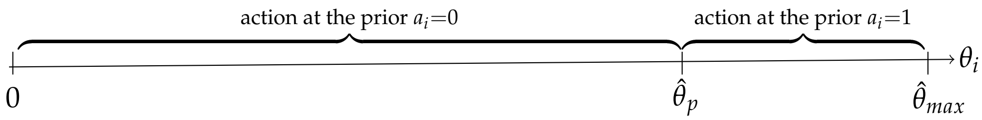


**Figure 1:** Patients who undergo or not medical treatment based on the prior

a treatment. Summarizing, the payoff of patient $i$ is

$$U^i(a|\omega) = \begin{cases} \theta_i & \text{if } a_i = 1 \text{ and } \omega = D, \\ -\mu & \text{if } a_i = 1 \text{ and } \omega = H, \\ 0 & \text{if } a_i = 0 \text{ and } \omega \in \{D, H\}. \end{cases} \tag{1}$$

The payoff of each patient is common knowledge, whereas the true state is unknown to all players. Ex-ante, there is a probability $\alpha$ of the 'disease' state and, consistently with the probability of each state to occur, $\alpha$ is the common prior of all patients, so that $Prob(\omega = D) = \alpha$ and $Prob(\omega = H) = 1 - \alpha$. We assume that the idiosyncratic $\theta_i$ is randomly drawn from a distribution with cumulative $F(\cdot)$ and density $f(\cdot)$ on the support $[0, \theta_{max}]$.

The physician aims to induce as many patients as possible to accept the treatment. Note that commission-based compensations such as individual performance, bonuses, pay-for-service or percentage methods may explain why the incentive of the physician does not align with those of patients.[16] Accordingly, let us define the physician's payoff as follows:

$$\Pi^P(a_1, a_2, \ldots, a_N) = \sum_{1}^{N} a_i.$$

Without any other information, patients with $\theta_i \geq \frac{(1-\alpha)\mu}{\alpha} \equiv \hat{\theta}_p$ undertake the treatment, i.e, action $a_i = 1$. They necessitate the treatment and get so many benefits in the disease state $D$ to compensate for the possible loss in the healthy state $H$ where the treatment is unnecessary. Differently, patients with $\theta_i < \hat{\theta}_p$ opt for no treatment – action zero. Their advantage in going for medical care in the disease state does not counterbalance the expected loss in the healthy state, see Figure 1.

It is in the physician's interest to inform patients with a relatively low $\theta_i$ through a test. Otherwise, based on the prior, these people would not have undertaken the treatment. The test recommends taking action 1 when it is positive. Having a test is in the interest of the patient as he receives information helping to make a more conscious choice. As in the real world, we assume that the physician observes each patient $\theta_i$ pointing out the central importance of *doctor-patient confidentiality*. Anamnesis and clinical examination are the key functions of

[16]Such a contract describes the work conditions of a single doctor as well as whole departments in private or public hospitals often financed on the basis of volumes.

medical doctors to reveal health problems. Hence, she can decide to conduct the examination through a *personalized* medical test on each patient $i$.[17]

Each test costs $c < 1$ per patient[18] and delivers a signal $s \in \{d, h\}$, which recommends either to undertake the treatment (signal is $d$) or not (signal is $h$). The physician designs the test by setting conditional probabilities $\phi_D^i \equiv \Pr(s = d|\omega = D)$ and $\phi_H^i \equiv \Pr(s = h|\omega = H)$ and this induces some posterior beliefs about the state of the world, so that the patient $i$ should find it convenient to follow the medical prescription and undergo the treatment ($a_i = 1$) when the signal is $d$. Exploiting the fact that $\mathbb{E}U^i(a = 0|s = \cdot) = 0$ and using Bayesian rule, it follows:

$$\mathbb{E}U^i(a = 1|s = d) = \frac{\alpha\phi_D^i}{\alpha\phi_D^i + (1-\alpha)(1-\phi_H^i)}\theta_i - \mu\frac{(1-\alpha)(1-\phi_H^i)}{(1-\alpha)(1-\phi_H^i) + \alpha\phi_D^i} \geq 0 \qquad (2)$$

Similarly, patient $i$ should prefer not to undertake the treatment ($a_i = 0$) when the signal is $h$ so that:

$$\mathbb{E}U^i(a = 1|s = h) = -\mu\frac{(1-\alpha)\phi_H^i}{(1-\alpha)\phi_H^i + \alpha(1-\phi_D^i)} + \theta_i\frac{\alpha(1-\phi_D^i)}{\alpha(1-\phi_D^i) + (1-\alpha)\phi_H^i} < 0 \qquad (3)$$

In the physician's eyes, conditions (2) and (3) are the only constraints. In particular, the physician has to decide which is the optimal test for patient $i$ and whether or not testing him. Remind that the physician's payoff depends on how many patients decide to take the medical treatment. Given that an informative test cannot deliver always signal $d$, patient $i$ takes it in probabilistic terms, so that $Prob(a_i = 1) = Prob_i(s = d) = \alpha\phi_D^i + (1-\alpha)(1-\phi_H^i)$. The following proposition reports the optimal test for patient $i$.

**Proposition 1.** *The optimal test to patient i is given by:*

$$\phi_H^i(\theta_i) \equiv \max\left\{1 - \frac{\alpha\theta_i}{(1-\alpha)\mu}, 0\right\}; \quad \phi_D^i(\theta_i) = 1.$$

*Proof.* The problem of the physician is to maximize $Prob_i(s = d)$ subject to conditions (2) and (3). Condition (3) is trivially satisfied by setting $\phi_D^i = 1$. Plugging into condition (2) and solving for $\phi_H^i$, we find the optimal test for patient $i$ that is positive when $\theta < \hat{\theta}_p$. □

The intuition is as follows. Independently of $\theta_i$, the physician always wants to treat the patient in the state of disease $D$. Hence, the test fully discloses information about this state.

[17] In case of chronic pathological diseases, for instance, the doctor should transfer information to the patients' medical records.

[18] Note that the cost faced by the physician has to be interpreted as an *opportunity cost*. Such cost adds to the monetary one, which we normalize to 0 without loss of generality, also to capture the idea that is often publicly financed.

Differently, information delivered in the healthy state $H$ depends on the patient type. Patients with a lower $\theta_i$ are less willing to undertake the treatment and thus need a more informative test to opt for it. This is why $\phi_H^i$ is a decreasing function of $\theta_i$.

As a consequence, we can state the following:

**Proposition 2.** *Patient $i$ is tested only if $\theta_i \in [\tilde{\theta}, \hat{\theta}_p]$.*

*Proof.* Given the optimal test in (1), the maximal expected payoff that the physician can obtain by testing patient $i$ is $Prob_i(s = d) = \alpha + \frac{\alpha\theta_i}{\mu}$. This payoff is larger than the testing cost only if $\theta_i \geq \tilde{\theta} \equiv \max\left\{\frac{(c-\alpha)\mu}{\alpha}, 0\right\}$. Thus, provided that $c < 1$, patients with $\theta_i \in [\tilde{\theta}, \hat{\theta}_p]$ are tested. Notice also that if $c < \alpha$, $\tilde{\theta}$ becomes zero. Differently, all patients with $\theta_i > \hat{\theta}_p$ undergo the treatment even if not tested. Thus, it is not worth for the physician to face the cost of testing them. □

Proposition 2 rationalizes why from the physician's viewpoint not all patients should be tested. On the right of $\hat{\theta}_p$, a patient would ask for the treatment based on the preliminary information - prior - without being tested. On the left of $\tilde{\theta}$, it is not worth to face the cost as these patients are excessively difficult to persuade to take the treatment, see Figure 2. This is true in any case of medical rationing which necessarily implies withholding informative tests from some patients.

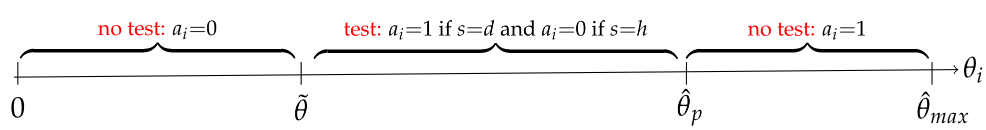


**Figure 2:** Tested and non tested patients at the optimal physician choice.

The range of tested types $[\tilde{\theta}, \hat{\theta}_p]$ depends on the variations of $c$, $\mu$ and $\alpha$. This is summarized in the next lemma:

**Corollary 1.** *Consider the thresholds $\tilde{\theta}$ and $\hat{\theta}_p$ in Proposition 2. The following holds:*

*(i) Decreasing the testing cost $c$ widens the interval of tested patients.*

*(ii) Increasing the prior $\alpha$ and decreasing the loss $\mu$ narrow the interval of tested patients.*

*Proof.* The testing cost enters only in $\tilde{\theta}$ and $\frac{\partial\tilde{\theta}}{\partial c} = \frac{\mu}{\alpha} > 0$. In this case, $\tilde{\theta}$ moves left when $c$ decreases, thus enlarging the space in which it is convenient for the physician to administer a test to the patients. Further, the prior belief $\alpha$ and the loss $\mu$ influence both $\tilde{\theta}$ and $\hat{\theta}_p$. In particular, we observe that these thresholds move right if the prior $\alpha$ decreases or the loss $\mu$ increases.

$$\frac{\partial \tilde{\theta}}{\partial \alpha} = c\frac{\partial \hat{\theta}_p}{\partial \alpha} = -\frac{c}{\alpha^2} < 0, \qquad \frac{\partial \tilde{\theta}}{\partial \mu} = \frac{c-\alpha}{\alpha} > 0, \qquad \frac{\partial \hat{\theta}_p}{\partial \mu} = \frac{1-\alpha}{\alpha} > 0.$$

As $c < 1$, $\frac{\partial \hat{\theta}_p}{\partial \alpha} > \frac{\partial \tilde{\theta}}{\partial \alpha}$ and $\frac{\partial \hat{\theta}_p}{\partial \mu} > \frac{\partial \tilde{\theta}}{\partial \mu}$, the area of testing patients reduces as $\tilde{\theta}$ decreases more slowly than $\hat{\theta}_p$. □

To interpret the comparative statics in Corollary 1, we highlight the incentives of the physician and the patients. The threshold $\tilde{\theta}$ reveals when the physician's expected payoff is insufficient to compensate for the testing cost. Consequently, if the cost decreases, the physician is willing to test more people moving the cutoff value towards the left. At the limit, if the cost is zero, $\tilde{\theta} = 0$ enlarging the range of tested people. Moreover, as depicted in Figure 3, decreasing the prior belief (or increasing the loss in the state $H$) renders a test necessary for some patients, while reducing the physician's incentives to test some other patients – $\hat{\theta}_p$ and $\tilde{\theta}$ move right, respectively. Note that $\tilde{\theta}$ moves towards the right slower than $\hat{\theta}_p$ expanding the whole interval of tests.[19]

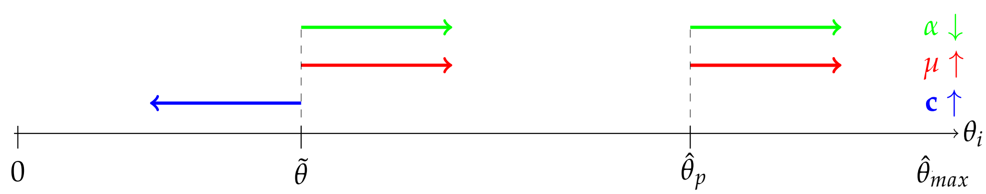


**Figure 3:** Tested and non tested patients in response to changes of $c$, $\mu$, and $\alpha$.

Varying $c$, $\mu$, and $\alpha$ impacts the physician's payoff as follows:

**Lemma 1.** *The payoff of the physician at the optimal level:*

*(i) increases with the prior $\alpha$;*

*(ii) decreases with the testing cost $c$ and the loss $\mu$.*

[19] The overall number of tested patients - frequency - depends on the distribution $F(\theta)$ on the support $[0, \theta_{max}]$. As a simple example, if $\theta \sim U[0, \theta_{max}]$, the number of tested patients increases when the prior value rises or the loss reduces, respectively.

*Proof.* Given the optimal persuasion rule, the maximal payoff of the physician is:

$$\begin{aligned}
\Pi^P &= \sum_1^N a_i = \sum_1^N (\alpha + (1-\alpha)\left[\Pr(\theta_i \geq \hat{\theta}_p) + \frac{\alpha\theta_i}{(1-\alpha)\mu}\Pr(\tilde{\theta} \leq \theta_i \leq \hat{\theta}_p)\right] \\
&= \sum_1^N (\alpha + (1-\alpha)\left[1 - F\left(\hat{\theta}_p\right) + \frac{\alpha\theta_i}{(1-\alpha)\mu}F\left(\hat{\theta}_p\right) - F\left(\tilde{\theta}\right)\right] = \\
&= N\left(\alpha + (1-\alpha)F\left(\hat{\theta}_p\right)\left[\frac{\alpha}{\mu}\bar{\theta} - (1-\alpha)\right] - \frac{\alpha}{\mu}\bar{\theta}F\left(\tilde{\theta}\right) = \\
&= N\left[1 + \frac{F\left(\hat{\theta}_p\right)\left(\alpha\bar{\theta} - (1-\alpha)\mu\right) - \alpha\bar{\theta}F\left(\tilde{\theta}\right)}{\mu}\right],
\end{aligned}$$

where $\bar{\theta} = \sum_{i=1}^N \theta_i / N$. It is easy to note that,

$$\begin{aligned}
\frac{\partial \Pi^P}{\partial c} &= \frac{N}{\mu}\left[-\alpha\bar{\theta}f(\tilde{\theta})\frac{\partial\tilde{\theta}}{\partial c}\right] < 0, \\
\frac{\partial \Pi^P}{\partial \mu} &= \frac{N}{\mu}\left[f(\hat{\theta}_p)\frac{\partial\hat{\theta}_p}{\partial \mu}\Phi - (1-\alpha)F(\hat{\theta}_p) - \alpha\bar{\theta}f(\tilde{\theta})\frac{\partial\tilde{\theta}}{\partial \mu}\right] < 0, \\
\frac{\partial \Pi^P}{\partial \alpha} &= \frac{N}{\mu}\left[f(\hat{\theta}_p)\frac{\partial\hat{\theta}_p}{\partial \alpha}\Phi + F(\hat{\theta}_p)(\bar{\theta} + \mu) - \bar{\theta}F(\bar{\theta}) - \alpha\bar{\theta}f(\tilde{\theta})\frac{\partial\tilde{\theta}}{\partial \alpha}\right] > 0.
\end{aligned}$$

where $\Phi = \alpha\bar{\theta} - (1-\alpha)\mu$ is the average expected payoff. □

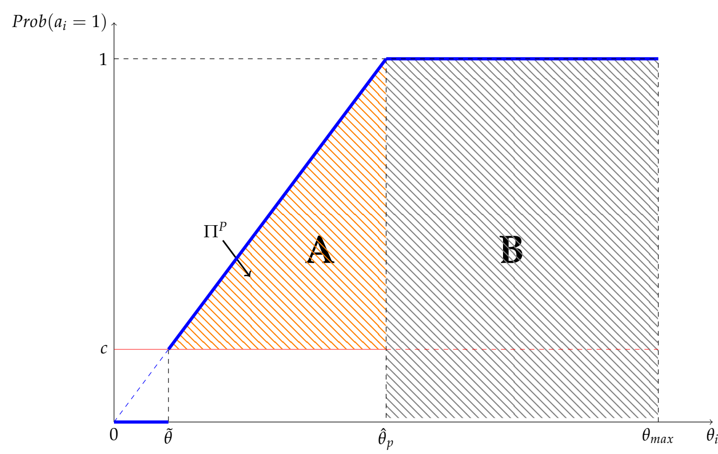


**Figure 4:** The physician's expected payoff $\Pi^P$ (area A+B) at the optimal persuasion rule. Area A: tested patients, Area B: non-tested patients.

Lemma 1 suggests that whenever the prior $\alpha$ increases, patients have more incentives to accept the treatment so that the physician gets a larger payoff. Suppose instead the cost of testing patients increases. As a reaction, the physician administers fewer tests, particularly for people close to $\tilde{\theta}$ as they are more difficult to convince due to their lower $\theta_i$. A similar effect exists when the loss $\mu$ is larger as unnecessary treatments become more harmful.

In Figure 4, the areas below the blue lines (concave closure) identify the physician 's payoff $\Pi^P$ (A+B). Area A represents the payoff for convincing some patients to take the medical treatment through the test. In contrast, area B corresponds to the payoff coming from the patients accepting the medical treatment without being tested. People who are not tested below $\tilde{\theta}$ result in zero payoff.

We can observe how in the $[\tilde{\theta}, \hat{\theta}_p]$ range, administering tests is more convenient for the physician as it increases the probability to convince patients to take the treatment, $a_i = 1$ and benefits systematically more. Without administering tests, the physician's expected payoff would be null as all patients with $\theta_i$ below $\hat{\theta}_p$ would not accept the treatment based on the prior $\alpha$.

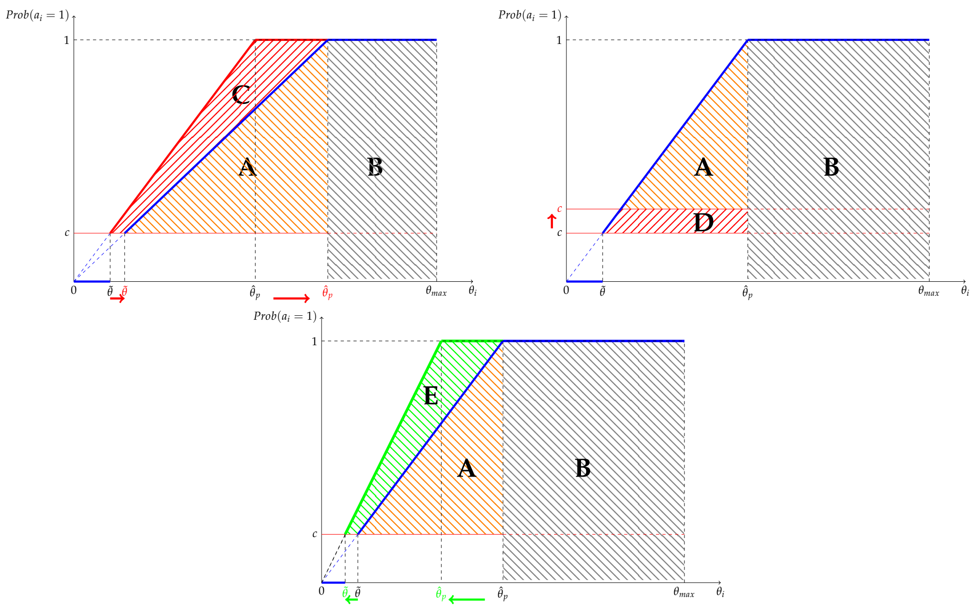


**Figure 5:** Variation of the physician payoff. *Top-Left Panel:* effect of an increase of the loss $\mu$. *Top-Right Panel:* effect of an increase of the cost of administering tests. *Bottom Panel:* effect of an increase of the prior $\alpha$.

Figure 5 depicts the results stated in Lemma 1. Starting from the Top-Left Panel, an increase in the loss $\mu$ moves both $\tilde{\theta}$ and $\hat{\theta}_p$ towards the right. Such a variation reshapes area A compared to the original one in Figure 4 and reduces area B. The net effect is a clear-cut reduction in the payoff identified by area C. Similarly, a higher $c$ in the Top-Right Panel reduces the area A of $\Pi^P$ as people previously tested do not receive the test anymore. Area D defines the net (negative) effect of an increase in the cost. We observe an opposite effect looking at the Bottom Panel, where an increase in $\alpha$ moves both $\tilde{\theta}$ and $\hat{\theta}_p$ towards the left, inducing a positive variation in the payoff of the physician (area E).

On the patients' side, it is important to highlight the number of mistakes - wrong decision conditional on the state - in choosing or not the medical treatment. In particular, a healthy patient might decide to be treated – when it is not necessary to do so – while the opposite holds for a patient suffering from a disease. Namely, if the state is $D$, the correct action would be to take the treatment, whereas the correct decision in state $H$ is not to undertake it. However, a wrong decision in state $H$ can occur due to the false positives that the medical test could induce at the advantage of the physician, see Left Panel, Figure 6. Instead, given the test is always informative in state $D$, the false negatives do not exist and the wrong choice can only derive from the lack of test when needed (Right Panel, Figure 6).

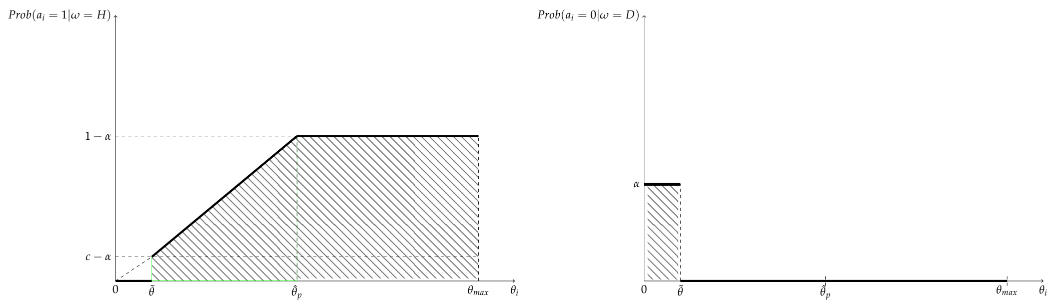


**Figure 6:** *Left Panel:* Expected mistakes when taking action $a_i = 1$ at the optimal persuasion choice. *Right Panel:* Expected mistakes when taking action $a_i = 0$ at the optimal persuasion choice.

Formally, at the optimal test for the physician, the probability of patient $i$ taking $a_i = 1$ in state $H$ is:

$$Prob(a_i = 1|\omega = H) = \begin{cases} 0 & \text{if } \theta < \tilde{\theta}, \\ (1-\alpha)(1-\phi_H^i) & \text{if } \theta \in [\tilde{\theta}, \hat{\theta}_p], \\ (1-\alpha) & \text{if } \theta > \hat{\theta}_p, \end{cases}$$

and, alternatively, the probability of patient $i$ taking $a_i = 0$ in state $D$ is:

$$Prob(a_i = 0|\omega = D) = \begin{cases} \alpha & \text{if } \theta < \tilde{\theta} \\ 0 & \text{if } \theta > \tilde{\theta} \end{cases}$$

Aggregating across patients, we have

$$\sum_{i=1}^{N} Prob(a_i = 1|\omega = H) = N(1-\alpha)(1-F(\hat{\theta}_p)) + \left(\sum_{i=1}^{N}(1-\alpha)(1-\phi_H^i)\right)(F(\hat{\theta}_p) - F(\tilde{\theta})) \quad (4)$$

and

$$\sum_{i=1}^{N} Prob(a_i = 0|\omega = D) = \alpha F(\tilde{\theta}). \quad (5)$$

## 4 Policy Discussion

In our analysis, patients do not always make the correct decision and this is true even when they are tested. Moreover, some patients who need the test do not receive it. This calls for a policy intervention to reduce wrong decisions in undertaking or not the treatment. The necessity of more precise information emerges in patient satisfaction questionnaires. The 2019 Consumer Health Insights Survey made by McKinsey & Company[20] claims that more than 60 percent of patients report they want to be more informed when deciding where to get care. Almost 49 percent of respondents stated that they have followed the recommendation for care from their doctor or clinician although remaining disappointed soon after their choice.[21]

Public interventions for informational transparency could be helpful as patients should access to relevant information when making a health care decision. They will choose an option that best meets their needs. In this section, our aim is understanding whether or not there exists informative interventions that can reduce wrong decisions by patients. Namely, the policymaker's purpose is to treat only people who have the disease. In a model in which the physician has a conflict of interests, the policymaker faces a tradeoff when asking for a more informative content of tests. Indeed, forcing the physician to reduce false positives can induce her to make less tests – augmenting the number of people who have a disease and are not treated.

Accordingly, the purpose of the policymaker is to minimize equations (4) and (5). To this goal, we consider the possibility to impose a minimum information standards for tests - medical protocols or more stringent rules on informed consent. Moreover, we study how releasing information able to change the prior beliefs of patients about the state of the world before the test influences the number of mistakes. As examples, consider the recent *World Health Organization*'s report on pandemic trends[22] or the *European Medicines Agency*'s guidelines on vaccine approval.[23]

**Information standard.** Imposing an informational standard requires lower bounds, $\underline{\phi}_D$ and $\underline{\phi}_H$, on the conditional probabilities $\phi^i_D$ and $\phi^i_H$, respectively. If both probabilities are set equal to 1, all tests are fully informative. However, such a choice would reduce the incentive of the physician to test patients. Letting the physician set her optimal $\phi^i_D = 1$ minimizes the probability that ill patients do not opt for the treatment. However, there exists a misalignment of interests in the 'healthy' state where some tested patients are going to take the treatment following signal $s = d$ even if state is $H$ (false positives).

The effect of a minimum information standard is to insure a more informative test for each

[20] https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights

[21] https://healthcare.mckinsey.com/the-role-of-information-transparency

[22] https://www.who.int/data/data-collection-tools/score/dashboard/

[23] https://www.ema.europa.eu/en/human-regulatory/vaccines-covid-19/covid-19-vaccines-key-facts

patient $i$, $\underline{\phi}_H \geq \phi^i_H(\theta_i)$. The only constraint is that $\underline{\phi}_H$ must be incentive compatible for the physician, i.e., $Prob(a_i = 1) \geq c$. As a consequence, we conclude the following:

**Proposition 3.** *The optimal choice is to set the largest minimum information standard compatible with the incentive of the physician to make a test. This choice reduces $Prob(a_i = 1|\omega = H) = c - \alpha$ for all tested people.*

*Proof.* For the minimum information standard to be compatible for the physician, we need:

$$Prob(a_i = 1) = \alpha + (1 - \alpha)(1 - \underline{\phi}_H) \geq c \Leftrightarrow \underline{\phi}_H \equiv 1 - \frac{c - \alpha}{1 - \alpha}.$$

Notice that $\underline{\phi}_H$ insures the level of information of all tested people increases. This is equivalent to:

$$\phi^i_H(\tilde{\theta}) = 1 - \frac{\alpha\tilde{\theta}}{(1 - \alpha)\mu} = 1 - \frac{c - \alpha}{1 - \alpha}.$$

Therefore, all tested people receive the same level of information and this level is higher than that provided by the physician without the minimum information standard. Plugging $\underline{\phi}_H$ into equation (4), we get $Prob(a_i = 1|\omega = H) = c - \alpha$ for all tested people, without changing for non-tested patients. □

The result in Proposition 3 suggests that the minimum information standard is able to nullify the physician's advantage in testing patients. Indeed, as it can be observed in Left Panel, Figure 7, the expected payoff that the physician makes by tests is precisely equal to the testing cost. This entails a loss of the physician depicted in area A. The intervention goes at the benefit of tested people, who make fewer mistakes, as depicted in area F, Right Panel, Figure 7.[24]

Suppose that $c$ is relatively low (close to the prior $\alpha$), the intervention would be extremely effective in reducing false positives. Indeed, many patients would be tested such that $\tilde{\theta}$ tends to zero and the policymaker can ask for fully informative tests, i.e., $\underline{\phi}_H = 1$. However, there is no possibility to reduce mistakes among non-tested people.

**Unintended consequences of information release.** Here the policymaker releases information changing the prior beliefs from $\alpha$ to $\tilde{\alpha}$. In particular, if the policymaker receives news that the state $D$ is more likely, then $\tilde{\alpha} > \alpha$. Receiving this information is considered *bad news*. On

[24]Notice that we report the effect of the policy only on patients under the medical treatment as the policy is fully ineffective for people who take zero action.

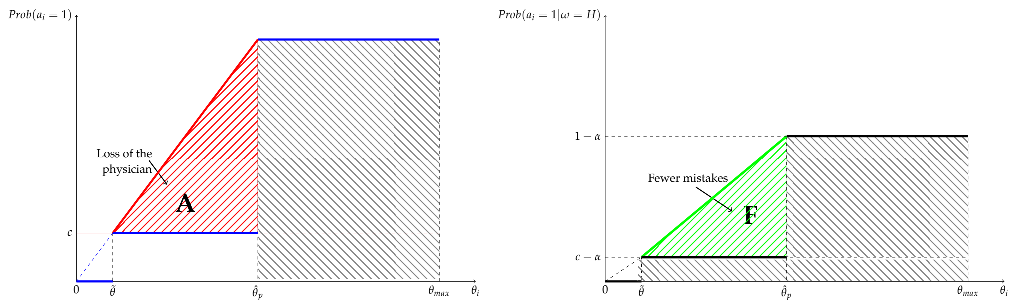


**Figure 7:** *Left Panel:* Effect of minimum information standard on expected payoff of the physician. *Right Panel:* Effect of minimum information standard on the number of mistakes when $a_i = 1$.

the opposite side, news that state $H$ is more likely (*good news*) will give $\tilde{\alpha} < \alpha$. We first notice the following:

**Proposition 4.** *The tests provided by the physician are less (more) informative if bad (good) news are released.*

*Proof.* Remember the optimal $\phi^i_H$ from Proposition 1

$$\phi^i_H(\alpha) = 1 - \frac{\alpha\theta_i}{(1-\alpha)\mu}$$

Deriving with respect to the prior we get:

$$\frac{\partial\phi^i_H(\alpha)}{\partial\alpha} = -\frac{(1-\alpha+\alpha^2)\theta_i}{(1-\alpha)^2} < 0$$

As a consequence:

- good news, i.e., $\tilde{\alpha} < \alpha$ implies that $\phi^i_H(\tilde{\alpha}) > \phi^i_H(\alpha)$;
- bad news, i.e., $\tilde{\alpha} > \alpha$ implies that $\phi^i_H(\tilde{\alpha}) < \phi^i_H(\alpha)$.

□

The information provided by the tests impacts the physician's payoff as well as the patients' utilities. For exposition purposes, we focus on $\tilde{\alpha} > \alpha$.[25] Bad news induce the physician to provide less information and the probability of sending signal $h$ decreases. Both thresholds $\hat{\theta}_p$ and $\tilde{\theta}$ move left. Indeed, bad news increase the prior about state $H$ so that more people are willing to undertake the treatment even if not tested. Moreover, the testing cost is compensated for patients with lower $\theta_i$. As a consequence, the new threshold value $\tilde{\theta}(\tilde{\alpha})$ is lower than

[25] The case in which $\tilde{\alpha} < \alpha$ gives the opposite insight and is available upon request.

$\tilde{\theta}(\alpha)$. Given that $\frac{\partial\tilde{\theta}}{\partial\alpha} = c\frac{\partial\hat{\theta}_p}{\partial\alpha} = -\frac{c}{\alpha^2} < 0$ and $c < 1$, the interval of tested patients is narrowed, further reducing the social value of information.


**Figure 8:** Effect of releasing bad news $\tilde{\alpha} > \alpha$.

In principle, we could imagine that having a higher prior would induce more precise information. Interestingly, moving the interval towards the left may reduce the number of tests (see Figure 8) as well as provide less information. This also entails an ambiguous effect on the probability of making the wrong choice, as shown in Right Panel of Figure 9. On the one side, having a higher prior reduces the probability of making mistakes for people who are not tested. On the other side, tested people are less informed by the physician, and the experiment has more false positives, i.e., lower $\phi^i_H$ by Proposition 4.

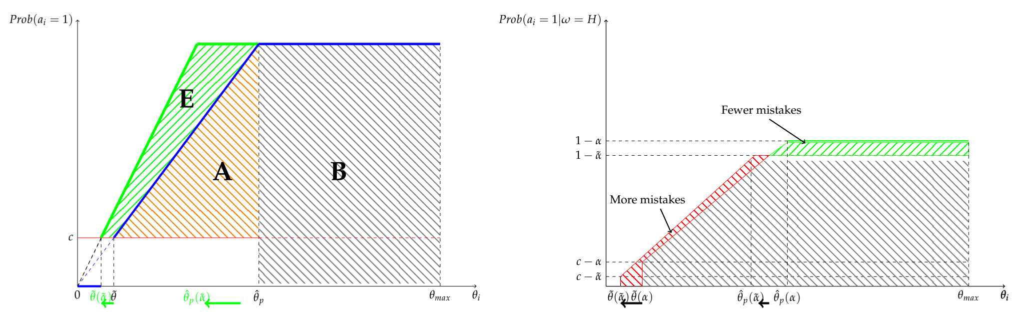


**Figure 9:** *Left Panel:* Effect of releasing information $\tilde{\alpha} > \alpha$ on expected payoff $\Pi^P$ of the physician (A+B+E). *Right Panel:* Effect of releasing information $\tilde{\alpha} > \alpha$ on the number of mistakes when $a_i = 1$. For the effect of of releasing information $\tilde{\alpha} > \alpha$ on the number of mistakes when $a_i = 0$, see Figure 10 (*Top Panel*).

Thus, releasing the information benefits the physician as depicted in Left Panel of Figure 9. Indeed, the news improves the patient's prior beliefs about the state in which the treatment is needed. The benefit is that, at the new prior, some people undergo for the treatment even though not tested and some people are now tested taking the treatment with positive probability.

**Consequences of information release under information standard.** In many cases, the two above-mentioned instruments can be used together to further improve the informativeness and the diffusion of tests. Indeed, the logic behind this mix is twofold. On the one hand, releasing bad news reduces the mistaken choices of patients when taking action $a_i = 1$. On the other hand, imposing an information standard reduces false positives. As a consequence, it is natural to expect less mistaken actions.

However, compared to the information standard alone, the combination with information release entails more mistakes for some patients and less mistakes for some others. This can be

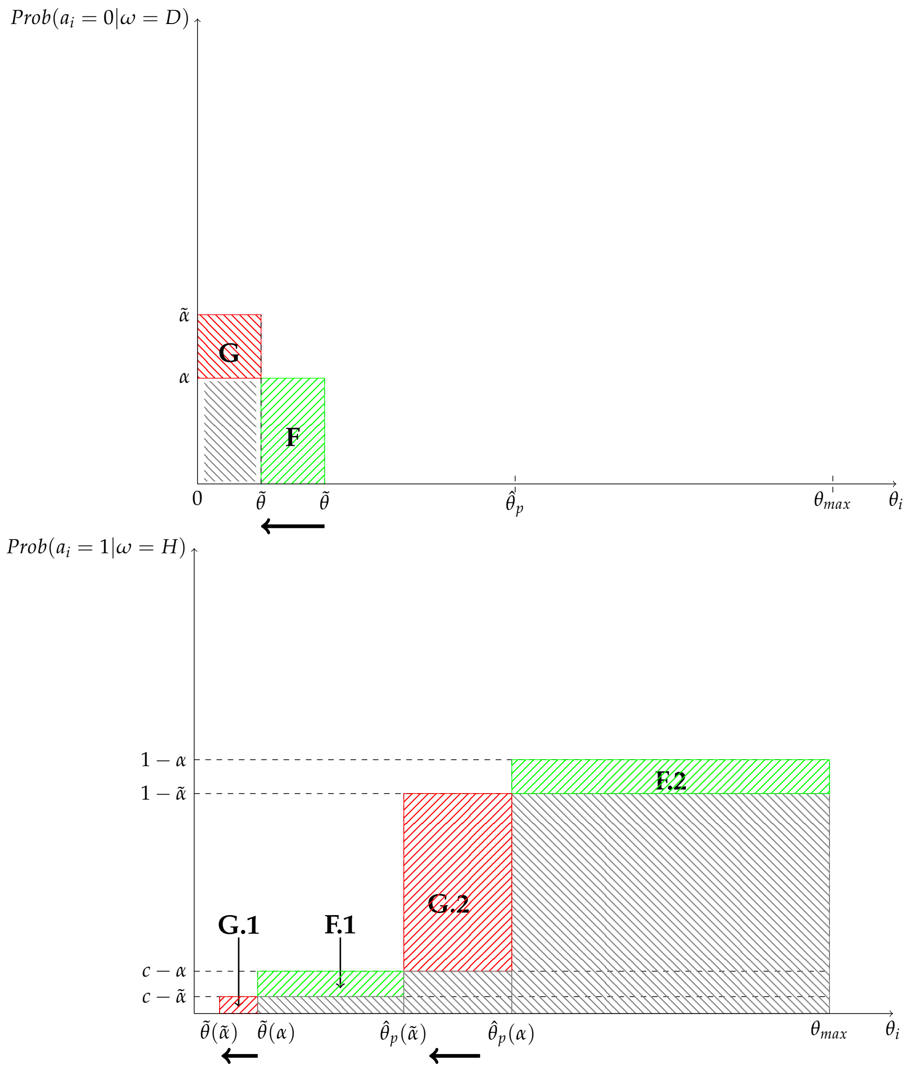


**Figure 10:** Effect of a policy mix. *Top Panel:* Impact of releasing information on the probability of mistakes when taking action $a_i = 0$ when there is a minimal *information standard*. *Bottom Panel:* Impact on the probability of mistakes when taking action $a_i = 1$.

easily grasped by looking at Figure 10 where the gray area represents the benchmark in which only the information standard is imposed.

In state $D$, patients who opt for no treatment make a mistake and this is only possible if they are not tested and have a low $\theta_i$. The cutoff $\tilde{\theta}$ moves left. All people who would not have been tested under the prior $\alpha$, but are now tested at $\tilde{\alpha}$, are better off. This positive effect is captured by region F in the Top Panel of Figure 10. Differently, non-tested people are more likely to take a wrong action ($a_i = 0$ as $\tilde{\alpha}$ is larger than $\alpha$) – area G in the same figure.

Similarly, in state $H$ (Bottom Panel), there are losers and winners. Starting from low levels of $\theta_i$, area G.1 describes people who are tested and they wrongly decide to take the treatment. Before, without the information release, the latter would not have opted for the treatment. Moving towards the right of $\tilde{\theta}(\alpha)$, region F.1 captures an improvement for people who are tested and decide to take the treatment with a lower probability. Agents with $\theta_i \in \left[\theta_p(\tilde{\alpha}), \theta_p(\alpha)\right]$ are now worse off as they are not tested when information is released as it increases the likelihood to take an unnecessary treatment (area G.2). Finally, agents on the right of $\theta_p(\alpha)$, who always take the treatment, benefit because state $D$ is more likely (area F.2).

## 5 Concluding Remarks

This paper has explained overtreatment based on the informational channel in the doctor-patient relationship. Namely, we propose a setup where a physician can induce more treatments upon designing the information structure of medical tests through diagnosis. We show that the optimal persuasion rule of the physician is to set medical tests that always inform about the disease (there are no false negatives) whereas imperfectly inform about a 'healthy' state (false positives). The number of tested people depends on personal characteristics and testing costs.

As Loewenstein et al. (2007) suggested, information revelation is the traditional way to ensure transparency in the market. An informative setup is considered as an efficient means of instituting such protections, given the practical limits of even well-designed disclosures. In this context, we look at some policy interventions aiming at improving the number of correct choices when undergoing a medical treatment.

We consider how an information standard imposed to the physician can reduce the number of wrong medical choices. We show that this policy is extremely effective in terms of reducing false positives, whereas it is silent on the number of tested people. Furthermore, we highlight the unintended consequences of releasing information on the state of nature sharing bad or good news. We show that bad news increase the physician's payoff as more people undergo for the medical treatment. On the patient side, people who are tested are more likely to take unnecessary treatment, whereas people who take it without the test are better off. Note that there are also people who refrain from undertaking a needed treatment. The likelihood of these mistakes reduces for tested people. Good news have instead the opposite effect.

When releasing information is combined with information standard, it is natural to expect that releasing bad (good) news reduces (increases) the probability of making mistakes. However, compared to the information standard alone, this combination has non-trivial effects on the patient side. Hence, our analysis suggests to pay attention on the possible unintended consequences that releasing information may entail for patients. In particular, the extent to which the informative policies affect the behavior of general practitioners in the hospitalization process constitutes the fertile ground in this field of research.

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