Three essays on health economics: Theoretical and experimental evidence on physician behavior

by

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To Emma and César.
In loving memory of Flor María.

Para Emma y César.
En memoria de Flor María.

Curriculum Vitae

The author was born in Medellín, Colombia, on the fifth day of July 1984. She attended Universidad de Antioquia, Medellín, from 2002 to 2007 and graduated with a Bachelor of Arts degree in Economics. She moved in the autumn of 2008 to México City, México, with a scholarship of Consejo Nacional de Ciencia y Tecnología de México (CONACYT), and received a Master of Arts degree in Government and Public Affairs at Facultad Latinoamericana de Ciencias Sociales (FLACSO) in 2010. She came to the Universidad del Rosario in Bogotá, Colombia, in 2015 where she received the Ministerio de Ciencia, Tecnología e Innovación Scholarship from 2015 till 2018. In 2016, she obtained an assistant professor position in the Economics Department at Universidad de Antioquia. Currently, she is on leave during her doctoral studies.

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" Porque si hay un contrincante al que debes vencer
en una carrera de larga distancia, ése no es otro que el tú de ayer"

Haruki Murakami

Resumen

Hace unos años trabajé con un equipo de médicos de diferentes especialidades clínicas en proyectos de evaluación de tecnologías sanitarias. Durante estas interacciones pude conocer particularidades de la toma de decisiones clínica, que, por sus implicaciones económicas, llamaron mi atención. Por ejemplo, no sabía que algunos médicos podían recibir transferencias de dinero de las empresas farmacéuticas para promover la investigación biomédica o incluso recibir financiación para asistir a eventos de formación médica continuada (Genta-Mesa and Flórez, 2019). En efecto, los médicos también persiguen beneficios económicos, y los conflictos de intereses siempre están presentes en la práctica clínica.[1]

Aunque muchos de nosotros hemos sido testigos de la presencia de representantes de ventas de las compañías farmacéuticas (visitadores) en la puerta de un consultorio médico, también sabemos que, en general, los médicos se interesan por el bienestar de sus pacientes. De hecho, esto ha sido especialmente evidente durante la crisis sanitaria impuesta por la pandemia del coronavirus. La enfermedad COVID-19 ha ejercido presión sobre los sistemas sanitarios de todo el mundo, haciendo que los médicos tengan que priorizar el uso de los recursos limitados en las Unidades de Cuidados Intensivos en función de las características y el pronóstico de los pacientes. El personal médico no solo ha tenido que hacer frente a largas y extenuantes jornadas de trabajo, sino que también ha tenido que asumir cargas éticas considerables, pues sus decisiones están determinando en últimas, quién vive y quién muere.

Las decisiones de los médicos son difíciles y complejas, no sólo porque están expuestos a incentivos o restricciones presupuestarias que pueden afectar a su comportamiento, sino también porque tienen motivaciones intrínsecas que a menudo están estrechamente relacionadas con el bienestar de los pacientes. Desempeñan quizá el papel más crucial en la prescripción de tratamientos y medicamentos, y sus decisiones repercuten significativamente en el gasto sanitario. Conscientes de esta situación, los terceros pagadores (aseguradoras privadas o Sistemas Públicos de Salud) también buscan implementar estrategias para contener los costos derivados de la toma de decisiones médicas. Esta

[1] En 2010 en Estados Unidos, se promulgó la Ley de Pagos a Médicos (Physician Payments Sunshine Act) para obligar a los fabricantes de dispositivos médicos a informar de cualquier pago o transferencia realizada a médicos u hospitales para mejorar la transparencia en la relación médico-industria.

tesis es una colección de ensayos en los que estudio el comportamiento de los médicos en entornos en los que o bien están expuestos a diferentes incentivos económicos o existe escasez de recursos para tratar a los pacientes.

En el capítulo 1, proponemos un modelo de principal-agente en el que los contratos óptimos alinean los incentivos de un tercer pagador y un médico en escenarios en donde los médicos pueden recibir transferencias de las compañías farmacéuticas y en donde los pacientes pueden incumplir con la correcta toma de sus medicamentos. Esta falta de cumplimiento se puede solucionar a través del esfuerzo del médico al explicar de manera clara, sencilla y completa al paciente como tomar sus medicamentos, o a través de un medicamento con una tecnología que reemplace dicha la falta de cumplimiento. Argumentamos que el esfuerzo del médico durante el proceso de prescripción y la tecnología son sustitutos. También suponemos que existe una empresa farmacéutica que produce y promueve, a través de una transferencia al médico, la prescripción del medicamento con la tecnología. Demostramos que el tercer pagador podría utilizar una bonificación para alcanzar contratos óptimos en los que el médico prescribe el medicamento sin la tecnología (menos costoso) y ejerce un nivel de esfuerzo positivo. Cuando el esfuerzo y la elección del medicamento no son observables, el tercero debe considerar la transferencia dada por la compañía farmacéutica en el diseño de la bonificación óptima. Examinamos las implicaciones de política de una posible regulación a la transferencia dada por la compañía farmacéutica.

En el capítulo 2, realizamos un experimento con estudiantes de últimos semestres de tres facultades de medicina en Bogotá, Colombia. En la actividad, los participantes enfrentaron a pacientes hipotéticos a los cuales debieron prescribir una versión de marca o una versión genérica de la misma molécula. Evaluamos el efecto de un incentivo de contención de costos para recetar el medicamento genérico en presencia de un regalo para promover la prescripción del medicamento de marca. Utilizando una tecnología de seguimiento ocular, estudiamos cómo estos incentivos económicos afectan los niveles de atención de los participantes, a través de la medición de la dilatación pupilar y del número de fijaciones visuales. Encontramos que recibir el incentivo de contención de costos y el regalo simultáneamente se asocia con mayores prescripciones genéricas y mayores niveles de atención. Vemos que los niveles de atención son mayores cuando los sujetos prescriben genéricos con mayor frecuencia. Además, el regalo afecta negativamente las prescripciones de genéricos y los niveles de atención. Por último,

encontramos que la exposición temprana al regalo sólo afecta a los niveles de atención.

En el capítulo 3, proponemos un experimento de laboratorio para entender ¿si entornos de restricción de recursos e incertidumbre sobre las necesidades relativas de potenciales beneficiarios afectan las decisiones de asignación de los médicos?, y ¿cómo ocurre? Cuando hay incentivos para la sobre provisión, encontramos que un paciente atendido por un médico con restricciones y bajo incertidumbre obtiene mayores beneficios y recibe asignaciones más cercanas a su óptimo que los pacientes vistos por médicos sin restricciones o que deciden sólo bajo incertidumbre. Además, observamos una redistribución de recursos cuando los médicos deciden bajo restricciones de recursos e incertidumbre. En particular, cuando los recursos son escasos, los médicos tienden a asignar los servicios limitados a los pacientes con mejor estado inicial de salud en ausencia de tratamiento, con una mayor capacidad para beneficiarse de recursos adicionales, con baja necesidad de servicios en el óptimo, y a quienes alcanzan el menor beneficio máximo posible. Por último, encontramos que las restricciones, con o sin incertidumbre, llevan a los médicos egoístas a aproximarse a lo que es mejor para el paciente.

Introduction

A few years ago, I worked with physicians from different clinical specialties in health technology assessment studies. During these interactions, I learned about particular aspects of clinical decision-making that attracted my attention because of their economic implications. For instance, I was unaware that some physicians could receive cash transfers from pharmaceutical companies to promote basic biomedical research or even funding to attend continuing medical education events (Genta-Mesa and Flórez, 2019). In fact, physicians also pursue economic benefits, and conflicts of interest are always present in clinical practice.[2]

While many of us have witnessed the presence of medical sales representatives at the door of a doctor's office, we also know that, in general, doctors are interested in the well-being of their patients. Indeed, it has been particularly evident during the global health crisis imposed by the coronavirus pandemic. COVID-19 disease has placed pressures on healthcare systems worldwide, causing physicians to prioritize the use of limited resources in Intensive Care Units based on patient characteristics. Medical staff have had to deal with stressful long working hours and have had to take considerable ethical burdens since their decisions finally affect who lives and who dies.

Physicians' decisions are difficult and complex, not only because they are exposed to incentives or budgetary constraints that may affect their behavior but also because they have intrinsic motivations that are often closely related to the well-being of patients. They play perhaps the most crucial role in prescribing treatments and drugs, and their decisions significantly impact healthcare spending. Aware of this situation, third-party payers (private insurers or Public Health Systems) also seek to implement strategies to contain costs derived from medical decision-making. This thesis is a collection of essays in which I study physicians' behavior in settings where different economic incentives and scarcity of resources to treat patients are present.

In Chapter 1, we analyze how optimal contracts could align the incentives of a physician and a third-party payer in a principal-agent model for drug prescription with

[2]In 2010 in the United States, The Physician Payments Sunshine Act was signed into law to force medical device manufacturers to report any payments or transfers made to physicians or hospitals to improve transparency in the physician-industry relationship.

non-compliant patients. The physician exerts an effort level during the prescription process, which can substitute technology that benefits non-compliant patients. Additionally, a pharmaceutical company promotes the prescription of the drug with said technology by giving a transfer to the physician. We find that the third-party could use a bonus to reach optimal contracts in which the physician prescribes the drug without the technology (less expensive) and exerts a positive effort level. When the effort and the drug choice are not contractible, the third-party must consider the transfer given by the pharmaceutical company in the design of the optimal bonus. We examine the policy implications of a possible regulation of the transfer given by the pharmaceutical company.

In Chapter 2, we run an experiment with students from three medical schools in Bogotá, Colombia, who face hypothetical patients and prescribe a brand or a generic version of the same molecule. We evaluate the effect of a cost-containment incentive to prescribe the generic drug in the presence of a gift to promote the brand drug prescription using eye-tracking technology. We study how these payments affect physicians' attention levels, using pupil dilation and visual fixations performed by the subjects as indices of attention related to cognitive effort. We find that receiving the containment incentive and the gift simultaneously is associated with more generic prescriptions and greater attention levels. We see the attention levels are greater when the subjects prescribe generic more frequently. Furthermore, the gift negatively affects generic prescriptions and attention levels. Last, we find that early exposure to the gift only affects attention levels.

In Chapter 3, we propose a lab experiment to understand if environments of resource restrictions and uncertainty on the relative needs of future beneficiaries affects physician's resource allocation decisions and how. When there are incentives to over-treat, we find that a patient tended by a constrained physician under uncertainty obtains higher benefits and receives allocations closer to her optimum than patients from physicians with no constraints or deciding under uncertainty alone. In addition, we observe a redistribution of resources when physicians decide with resource restrictions and uncertainty. In particular, when resources are scarce, physicians tend to allocate the limited services to patients with higher benefits in the absence of medical services, a higher capacity to benefit from the resources, the scantiest need for service units, and the lowest benefits at the optimum. Finally, we find that constraints, with or without

complete information on patient characteristics, lead selfish physicians to approximate to what is best for the patient.

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Foreword

This thesis is a collection of joint and solo essays on physician economic behavior. Third chapter is a joint work with Amalia Rodríguez-Valencia.

Chapter 1

A model of moral hazard in drug prescription with non-compliant patients

1.1 Introduction

According to the World Health Organization (WHO), at least 50% of all patients fail to take their medication correctly (WHO, 2003). The lack of patient compliance in taking medication is a serious problem for any health system. For instance, due to morbidity and death, the lack of patient compliance costs around $100 billion per year in the USA (Brown and Bussell, 2011). This problem could be due to the patient not having the correct information about how to take the medication, because the patient is reluctant to do so, or because the patient cannot apply the knowledge to take the medication correctly. The instruction phase in the prescription process can have a vital impact on avoiding the lack of patient compliance (WHO, 2012). The effort exerted by the physician, providing appropriate details to the patient about the prescription and using simple and clear language, becomes useful when the patient does not have information about how to take his medication correctly. Even when the lack of patient compliance is due to reluctance, the effort exerted by the physician during the instruction phase would be useful to persuade the patient and to prevent the lack of compliance.[1]

[1]The evidence shows that the patient responds to advise during the treatment. For example, the patient reduces the consumption of cigarettes and alcohol when there is an increase in physician effort, measured as medical treatment or advice (Fichera et al., 2018).

On the other hand, a significant group of drugs with drug delivery system (DDS) technologies, has as a function to enhance patient compliance, reducing the frequency of dosing and the interactions with food intake, among others. Thus, a DDS technology and the effort exerted by the physician during the instruction phase are mechanisms to prevent the lack of patient compliance. Moreover, the effort would be a substitute for the technology since, in many cases, persuading or giving the correct information to the patient could replace it. For instance, consider statins or tamsulosin. Some versions of both drugs have a DDS technology (a sustained-release delivery system) which allows the patient to take the doses at any time of the day with or without food. In contrast, an essential instruction for presentations without that technology is to take it after the same meal to increase its plasma concentration. In this case, if the physician exerts some effort that guarantees the patient follows the instruction, he could receive the drug without the technology, and the effect on the lack of compliance would be the same as if he received the drug with the technology. These situations represent a crucial dilemma for a third-party payer, such as a public health system or an insurance company, since drugs with such technologies are more expensive than those without it. Thus, a third-party payer faces a trade-off between financing the drug with the technology and providing the physician with incentives to exert some effort.

Other factors also drive drug prescription. First, the preferences of physicians about brand loyalty, and their habits, can affect prescriptions (Coscelli, 2000; Crawford and Shum, 2005; Dubois and Lasio, 2014; Crea et al., 2019), and physicians may have preferences for generic or brand drugs, depending on who is paying the cost (Lundin, 2000). Second, exposure to pharmaceutical promotions and incentives from the pharmaceutical industry can affect drug choices (Hellerstein, 1998; Kravitz et al., 2005; Avorn et al., 1982; Tringale et al., 2017). Considering these aspects, we develop a non-classical moral hazard model where an external player (a pharmaceutical company) intervenes in the principal-agent relationship via a transfer[2] to the agent (a physician), who is hired by the principal (a third-party payer) for patient care. Moral hazard in drug prescription refers to the situation in which the effort exerted by the physician in drug prescription is not verifiable by the principal, but both the effort and the drug

[2]Although this type of transfer is illegal in many countries, the pharmaceutical industry uses strategies such as biomedical research, advertising, and continuing medical education, among others, to promote the prescription of their brands (Rodwin, 2010). For example, in 2015, 48% of US physicians received $2.4 billion in industry payments (Tringale et al., 2017).

choice do affect the outcomes of the patient; hence, the third-party payer.

In our model, we suppose that the physician can prescribe two versions of the same active ingredient, and one of the versions is more costly as it has a DDS technology which could substitute the patient's non-compliance. The other version of the drug (less expensive) does not have the technology. The effort exerted by the physician during the instruction phase is an important activity when she is uncertain about whether the patient is a complier or not, and it could be a substitute for a DDS technology. We include a parameter that captures the fact that the effort could have different degrees of substitution for the technology. As an additional element, we suppose that the pharmaceutical company that produces the DDS version of the drug also offers a transfer to the physician to promote the prescription of its product. In this context, we analyze how optimal contracts could align the incentives of the principal and the agent. We also examine the policy implications of a possible regulation on the transfer given by the pharmaceutical company.

Our paper falls into the literature of physician agency models (Ellis and McGuire, 1986; Blomqvist, 1991; Jelovac, 2001; Gonzalez, 2004; Jack, 2005; Choné and Ma, 2011)[3]. Ellis and McGuire (1986) and Blomqvist (1991) study how payment schemes affect physicians' level of services to the patients. Contrary to our model, their models do not find results from a principal's maximization problem in which the contract is incentive-compatible and acceptable by the agent. Jack (2005) proposes a model where the government contracts to physicians for patient care. Since the physicians are heterogeneous in delivering quality to the patients, the contribution of Jack (2005) is to find an optimal menu of linear cost-sharing contracts that the health authority can use to induce the physicians to reveal their type. Choné and Ma (2011) study the relationship between an insurer and a physician. The physician possesses private information about how important the patient's benefit into her utility function is and knows the consumer's health benefit (hidden information). Similarly to Jack (2005), Choné and Ma (2011) deal with an adverse selection problem instead of a moral hazard problem. In our approach, there are no different types of physicians. Instead, informational issues arise because the physician can choose an effort level (hidden

[3]Since the literature on the classical physician-patient relationship is extensive, we focus on the papers that study the physician's agency problem when the principal is a third-party player. In these models, the patient is another principal or a passive player receiving medical services.

action) impacting the principal's outcome.

Jelovac (2001) study a model where the physicians' effort during the diagnosis (hidden action) is crucial to receive an informative signal about the patient's health condition (hidden information). Since the diagnosis effort and the patient's health condition are critical variables to choose the patient's treatment, Gonzalez (2004) considers such diagnostic accuracy model to answer how the physician's professional prestige gained in the public practice could affect her private revenues. In both models, the health authorities act as the principal, and the physician is the agent. In our setting, there is no induced moral hazard due to private information since the physician does not know whether the patient is a complier or not. By modeling a non-standard scenario in which a pharmaceutical company intervenes in the principal-agent relationship giving a transfer to the physician, we consider a kind of physician's dual practice in a similar way as in Gonzalez (2004). Both papers show that optimal contracts provide incentives to the physician to prescribe the most appropriate treatment for the patient (Jelovac, 2001 and Gonzalez, 2004). Instead, our optimal contracts offer incentives to the physician to prescribe the more cost-effective drug. Our model is the first to consider moral hazard in drug prescription to the best of our knowledge.

We prove that the third-party payer could implement an optimal contract by using a bonus that induces the physician to exert effort during the prescriptions process and prescribe the less expensive drug. We consider as a benchmark the situation in which the drug choice and the effort level are observable by the third-party (Proposition 1.1). When the drug choice is observable, but the effort is not, the bonus is useful to induce the physician always to exert the maximum effort level when she prescribes the drug without the technology (Proposition 1.2). When the drug choice and the effort level are not observable, the principal can use a bonus that includes the transfer given by the pharmaceutical company to implement a contract in which the physician prescribes the drug without a DDS technology (less expensive) and exerts a positive effort level (Proposition 1.3). Thus, the bonus acts as a pay-for-performance payment (PFP) or a cost-containment incentive (CCI). Next, we suppose there is a prohibition or a limitation of any transfer given by the pharmaceutical company. In that case, the third party could use the bonus to ensure that the physician exerts positive effort levels when she prescribes the drug without the technology.

1.2 The model

We consider a principal-agent model with four players. Only active players take actions in the game, where the third-party payer is a public health system (PS) and is the principal, and the physician is the agent. PS hires the physician for patient care. The treatment of the patient always requires the prescription of a drug, d, and the physician can choose between a drug with a DDS technology, d_t, and a drug without a DDS technology, d_0. We suppose that both drugs have the same active ingredient, but the first version is more expensive than the second. We normalize the cost of the drug without DDS as equal to zero. Then, the additional cost of a drug with technology is $c > 0$. The active players, PS and the physician, are risk-neutral.

The passive players in the game are the patient and the pharmaceutical company. Although the patient receives attention from the physician, he has a passive role because he does not incur the cost of treatment. Additionally, we suppose that the pharmaceutical company that produces the drug with DDS also offers payments to the physician to encourage the prescription of its drug. Then, the physician receives a fixed transfer from the pharmaceutical company when the physician prescribes the drug with DDS. The pharmaceutical company can monitor whether the physician prescribes its drug, but since it does not hire the physician directly, it also has a passive role.[4]

There are two types of patients: compliers and non-compliers. A complier obtains the same benefit from both drugs. If the physician does not exert effort during the prescription, a non-complier obtains more benefit from the drug with DDS than from the drug without DDS. On the other hand, if the non-complier is exposed to the physician's effort during the prescription, she potentially could obtain the same benefit if she receives the drug without DDS than if she receives the drug with the DDS. As we explain later, the effort exerted by the physician could substitute for the technology of the drug.

[4]First, in some countries (Japan, Taiwan, the United Kingdom, Germany, Austria, some states in the US, and some Swiss jurisdictions), physicians prescribe, purchase, and dispense drugs to their patients. Thus, it is reasonable to assume that pharmaceutical companies can know physicians' prescriptions. Moreover, there is anecdotal evidence that pharmacies report the list of physicians and their prescriptions to pharmaceutical companies. Second, as the pharmaceutical company has a passive role, we do not consider that it can have any strategic interaction with another player. Another game between the company and the physician or the health authority is outside the model's scope that we propose and the research question that we want to address in this paper.

Every patient has a healing process which could be successful or not successful. We suppose that the healing process for a complier patient is always successful, while the healing process for a non-complier depends on the drug and the physician's effort. Thus, we suppose that if a patient receives the drug with DDS, regardless of his type, the probability of success is one. If a complier receives the drug without DDS, also the probability of success is one. Finally, the probability of success for a non-complier receiving the drug without DDS is:

$$\mathbb{P}(\text{success}|\text{non-complier}, d_0, e) = \alpha + \beta e \tag{1.1}$$

and the probability of not success for a non-complier receiving the drug without DDS is:

$$\begin{aligned}\mathbb{P}(\text{not success}|\text{non-complier}, d_0, e) &= 1 - \mathbb{P}(\text{success}|\text{non-complier}, d_0, e) \\ &= 1 - (\alpha + \beta e)\end{aligned} \tag{1.2}$$

where e is the effort exerted by the physician during the prescription process, β is the degree of substitution of the effort to a DDS technology, and α is the minimum value that the probability takes when the effort is zero. The parameters, e, α, and $\beta \in [0, 1]$ and $\alpha + \beta \in [0, 1]$.

Usually, to prescribe a drug, the physician diagnoses the patient's health problem, designs an appropriate therapeutic scheme, and provides the patient with information, instructions, and warnings. The effort exerted during the final activity is a relevant variable for a non-complier, who could be cured even if he receives the drug without a DDS technology. In most cases, further and correct explanations given by the physician to the patient could replace the effect of the technology, for example, advising about the exact time of taking medication or its combination with food intake. Note that if the physician exerts the maximum effort level ($e = 1$), the probability of success for a non-complier receiving the drug without DDS would increase compared to the situation in which the physician does not exert any effort ($e = 0$). Exerting effort is costly for the physician, that is, it generates a disutility $v(e) = \frac{ke^2}{2}$, where $k > 0$.

The degree of substitution of the effort to a DDS technology is captured by the parameter β. Depending on the accuracy and specific characteristics of the technology, the effort exerted by the physician could be an imperfect substitute for a DDS technolo-

gy, or even, close to a perfect substitute.[5] The parameter α is the minimum value that the probability takes when the effort is zero. As the active ingredient is the same in both drugs, when a non-complier receives the drug without DDS, he obtains the active ingredient required, but not the technology. Thus, α reflects the fact that the non-complier may have a higher or lower chance of success even when he receives only the active ingredient, and the effort does not affect the probability of success.[6] Note that if β is higher than α, the effort exerted by the physician could be useful to increase the probability of success for a non-complier. On the other hand, the effect of the effort would be less.[7]

If a patient is wrongly treated, that is, a non-complier is not cured by the drug without DDS, then he faces a health loss of $\gamma > 0$. We suppose that the health loss is expressed in monetary units. We also suppose that if a non-complier receiving the drug without DDS is not cured with the first prescription, the physician will order a second prescription in which she will prescribe the drug with DDS.[8] Then, the additional cost related to the wrong treatment of a non-complier is $\rho = c + \gamma$. There is no health loss for a complier receiving the drug with DDS. However, since he could be treated with the drug without DDS, the overrun is equal to the additional cost of the drug with DDS, c.

Physicians' payments consist of a salary and an extra payment. We adopt the limited liability constraint that the physician always receives a minimum payment m for each patient treated, regardless of the outcome of the healing process, the effort exerted, or the drug choice.[9] Thus, m can be seen as a fixed payment or a fee-for-service (FFS). The physician receives a bonus b if the patient is cured by the drug without DDS

[5]For instance, when β is close to one, the effort could be a perfect substitute. However, when β is close to 0, the technology can not be replaced by any effort.

[6]For example, when $\alpha = \frac{1}{2}$, the non-complier has the same initial probability for both health outcomes.

[7]This could be due to the biological characteristics of the patient or the specificity of a DDS technology that the patient needs.

[8]In practice, third-party payers do not deliver drugs directly to their patients. Instead, it is usual to hire an intermediary for distribution. We suppose that the intermediary is the same for the same patient. Thus, if the patient needs a second prescription, the intermediary knows if the patient already had the first prescription.

[9]Despite having risk neutral players, the limited liability framework permits a relevant moral hazard problem because there is a trade-off between incentives and incomes, as in the classical moral hazard framework.

in the first prescription, that is, when the physician prescribes the drug without DDS and the healing process of the patient is successful. We assume that $b \geq 0$. Finally, the physician receives a transfer $t > 0$ from the pharmaceutical company if she prescribes the drug with DDS in the first prescription.

The expected utility of the physician depends positively on the salary and transfers, and negatively on the effort exerted. We assume that the expected utility function is additively separable in payments and effort. Additionally, it is a linear function of payments and a convex function of effort. If the physician prescribes the drug with DDS, she always receives $m + t$, regardless of the type of patient, and her expected utility is:

$$\mathbb{EU}(e, d_t) = m + t - \frac{ke^2}{2} \tag{1.3}$$

If the physician prescribes the drug without DDS, she obtains $m+b$ or m, depending on whether a non-complier is cured. If the patient is a complier, the physician obtains $m + b$. As the physician does not know the type of patient in advance, given α and β, she must exert some effort in order to obtain a higher utility, according to the following expected utility function:

$$\begin{aligned} \mathbb{EU}(b, e, d_0) &= \frac{1}{2}(m + b) + \frac{1}{2}\left[(\alpha + \beta e)(m + b) + (1 - \alpha - \beta e)m\right] - \frac{ke^2}{2} \\ &= m + \frac{1}{2}\left[(1 + \alpha + \beta e)b\right] - \frac{ke^2}{2} \end{aligned} \tag{1.4}$$

We suppose that the outside option of the physician is $m > 0$. It is common that the physician has more than one job offer, and she could also practice privately. Additionally, we assume that if the expected utility of the physician is at least equal to the outside option m, she always accepts the contract proposed by PS.

PS minimizes the expected cost, which is the total cost of patient care represented by payments to physicians, the cost of drugs prescribed[10], and the health losses for the patient in the case of incorrect prescription. If the physician prescribes the drug with DDS, the expected cost for PS is:

$$\mathbb{EC}(d_t) = m + c \tag{1.5}$$

[10]Although patient care includes other procedures, such as diagnostic tests and hospitalization, we assume that only drugs and outpatient procedures constitute the care process. We consider the wholesale prices as the cost of the drugs.

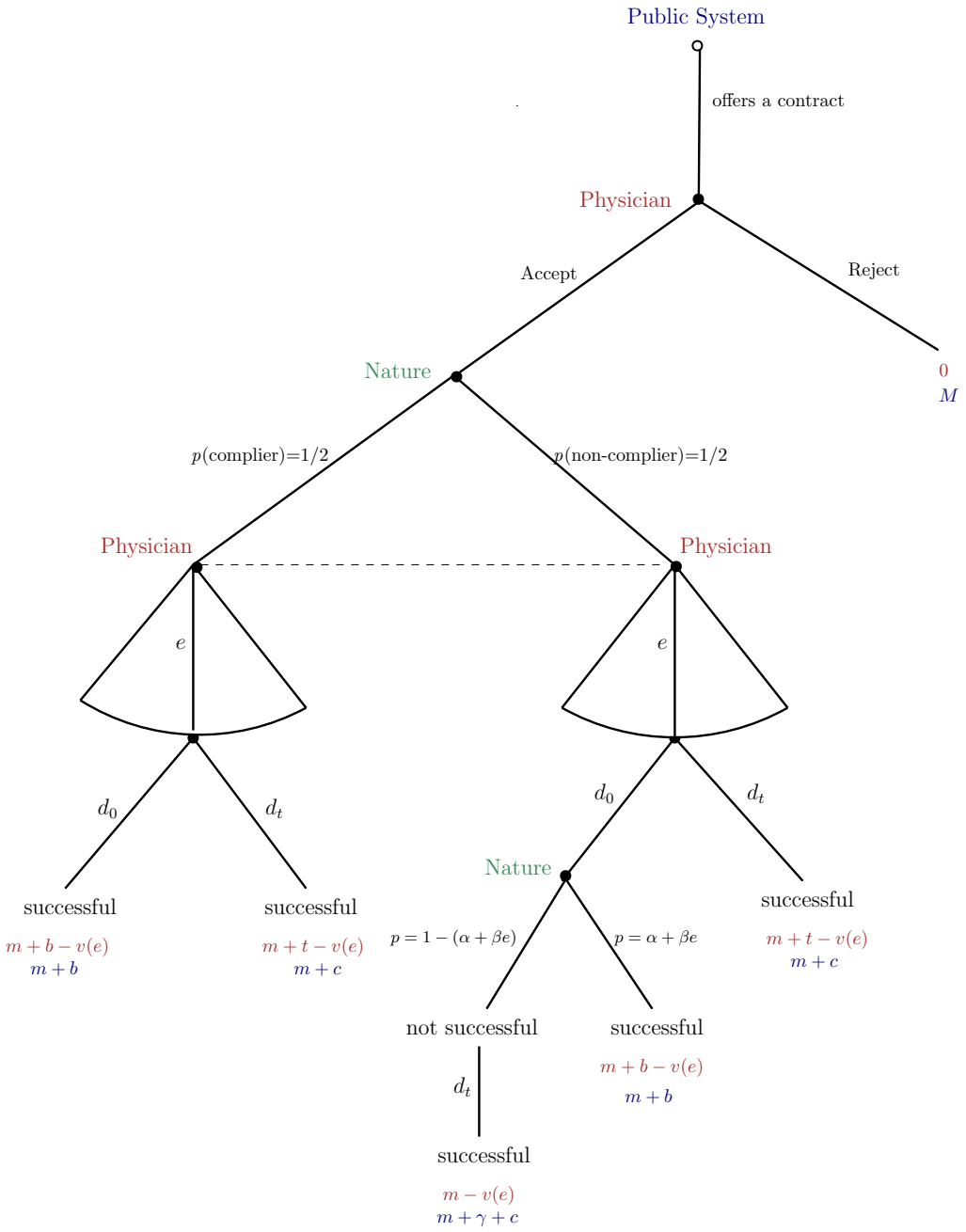
If the physician prescribes the drug without DDS, the expected cost for PS is:

$$\begin{aligned}\mathbb{EC}(b, e, d_0) &= m + \frac{1}{2}\left[(1 + \alpha + \beta e)b + (1 - \alpha - \beta e)(c + \gamma)\right] \\ &= m + \frac{1}{2}\left[(1 + \alpha + \beta e)b + (1 - \alpha - \beta e)\rho\right] \qquad (1.6)\end{aligned}$$

As patient care is mandatory in public health systems, if the physician rejects the contract, the cost for PS is M, which is sufficiently large that PS always offers the physician an acceptable contract. This assumption reflects that the expected cost for PS is always less than M.

We propose an extensive-form game where the time-line is depicted in Figure 1.1. There are five stages of the game. In the first stage, PS offers the physician a contract. In the second stage, the physician either accepts or rejects the contract. If the physician rejects the contract, the game ends. In the third stage, the type of patient is realized with probability 1/2. Then, the physician does not know the type of patient but knows the distribution. We use 1/2 since, as we mentioned in the introduction, at least 50% of all patients do not take their medication accurately. The patient seeks healthcare from the physician, who exerts some effort level in drug prescription (specifically, the instruction phase). In the fourth stage, the physician chooses the type of drug. The physician chooses the effort level before deciding the type of drug, as she is uncertain whether the patient is a complier or not. In the fifth stage, nature chooses the probability of the outcome of the healing process. If the patient is not cured, the physician orders a second prescription. After the second prescription, the patient is always cured and the game ends.

Figure 1.1: Extensive-form of the game.



Public Health System's payments are in blue and physician's payments are in red.

To find the subgame perfect equilibrium of the game, we use backward induction. The set of strategies available to the physician is $S = \{Aed_t, Aed_0, R\}$, where Aed_t is the

strategy when the physician accepts the contract, exerts the effort level, and prescribes the drug with DDS. Aed_0 is the strategy when she accepts the contract, exerts the effort level, and prescribes the drug without DDS. Finally, R is the strategy when she rejects the contract offered by PS. If the physician rejects the contract proposed by PS, she only receives m and PS incurs a cost M. If the physician accepts the contract, after choosing the optimal effort level, she has two alternatives: to prescribe the drug with DDS or the drug without DDS. Thus, the equilibrium of the game is defined as the strategy profile $s^* \in S$ with the property that in no subgame the physician (or PS) can be better off by choosing another strategy, given that PS (or the physician) adheres to its (her) best strategy.

1.3 Physician's decisions and optimal contracts

This section analyzes the physician's decisions regarding drug choice and effort level, considering all possible strategies. We present all the proofs in the Appendix A.

In Lemma 1.1 we show that there is a threshold $\tilde{t}$ of the transfer given by the pharmaceutical company for which it is profitable for the physician to prescribe one of two drugs.

Lemma 1.1. *There exists $\tilde{t} \in \mathbb{R}_+$ such that the physician prescribes the drug without DDS if $t \leq \tilde{t} = \frac{b(1+\alpha+\beta e)}{2}$ and the drug with DDS, otherwise.*

Note that if $e = 0$, then $\tilde{t} = \frac{b(1+\alpha)}{2}$. While $e > 0$, the threshold becomes higher as the effort exerted by the physician is closer to being a perfect substitute for DDS technology until reaching $\tilde{t} = \frac{(1+\alpha+\beta)b}{2}$ if $e = 1$.

The value of the threshold depends mainly on the effort level exerted by the physician and the bonus offered by PS. Then, Lemma 1 illustrates the role of the bonus b to induce the physician choices and its relation with the transfer. Also, the distribution of the type of patients determines the value of the threshold. For instance, keeping the parameters α and β constant, the threshold increases if the proportion of compliers is greater than the non-compliers. This result means that when there are more compliers, the transfer t should be higher to the physician has incentives to choose the generic drug.

In the next lemma, we show the optimal effort level that the physician exerts under two strategies. First, when the physician prescribes the drug with DDS, exerting any effort level is unnecessary. In this case, the effort is costly and irrelevant to obtain a higher payment since the drug with DDS always cures the patient. Second, when the physician prescribes the drug without DDS, she must consider the optimal effort level as the expected payments increase with the effort. In particular, she needs to exert some effort level during the instruction phase to increase the probability that the healing process of a non-complier be successful and achieve a higher expected payment.

Lemma 1.2. *If the physician prescribes the drug with DDS, the optimal effort level is* $e^* = 0$. *If the physician prescribes the drug without DDS, the optimal effort level is* $e^* = min\left\{\frac{\beta b}{2k}, 1\right\}$.

Last, when the physician prescribes the drug with DDS the proportion of compliers and non-compliers is not relevant. However, when the physician prescribes the drug without DDS, the proportion of the patients is crucial to determine the optimal level of effort. Specifically, when the number of non-compliers is greater than the compliers, the optimal effort must also be greater.

1.3.1 Symmetric information

We present the optimal contract under the assumption that the effort level that the physician exerts in the prescription process and the drug choice are both contractible, and thus, observable. The contract has the form $C^S = (b, e, d)$. There are two types of constraints to be fulfilled. The first is the physician's participation constraint (PC) that ensures the physician accepts the contract. The second is the limited liability constraint (LC) that ensures the bonus b is positive. PS has to solve the following problem:

$$\min_{b,e,d} \mathbb{E}\mathbb{C}(b, e, d)$$

such that

$$\mathbb{E}\mathbb{U}(b, e, d) \geq m, \quad (PC)$$
$$b \geq 0, \quad (LC)$$
$$e \in [0, 1].$$

PS has the same prior information about the type of patient when the contract is signed with the physician. Since PS does not know what type of patient the physician faces, it should offer incentives considering the uncertainty. The type of contract that PS offers should minimize the expected cost.

We first start by characterizing the situation in which both the drug choice and the effort level are observable. Then, we will move to a more realistic situation in which only the drug choice is verifiable. In both cases, PS has to design a contract that ensures the physician accepts. The next proposition presents the optimal contracts under symmetric information when the drug choice and the effort level are contractible.

Proposition 1.1. *When the drug choice and the effort level are contractible:*

- *If PS prefers the physician to prescribe the drug without DDS and to exert the maximum effort level,* $c \geq \frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$*, and* $\beta\rho > 2k$*, the optimal contract is* $C_1^S = \left(\frac{k}{1+\alpha+\beta}, 1, d_0\right)$.
- *If PS prefers the physician to prescribe the drug without DDS and to exert a positive effort level,* $c \geq \frac{2(\sqrt{k^2\alpha^2+2k^2\alpha+k^2+2k\gamma\beta^2}-k(1+\alpha))}{\beta^2} - \gamma$*, and* $\beta\rho \leq 2k$*, the optimal contract is* $C_2^S = \left(\frac{\beta^2\rho^2}{4k(1+\alpha)+2\beta^2\rho}, \frac{\beta\rho}{2k}, d_0\right)$.
- *Otherwise, if PS prefers the physician to prescribe the drug with DDS, it will not offer any bonus since the physician does not have any incentive to exert effort. The optimal contract is* $C_3^S = (0, 0, d_t)$.

Under the strategy Aed_0, PS knows that the effort exerted by the physician during the instruction phase could replace the technology that the drug does not have. Thus, PS uses a positive bonus to reach the optimal contract that ensures that the physician prescribes the drug without DDS and exerts some effort. When the additional cost of a complier treated with the drug with DDS is sufficiently large, PS offers contracts that ensure the physician prescribes the drug without DDS. As a consequence of the positive bonus provided by the principal, the effort level contracted is also positive.

Under the strategy Aed_t, PS prefers the physician choosing the drug with DDS. PS knows that the effort exerted by the physician during the instruction phase would be replaced by the DDS technology of the drug with DDS. Thus, it would be costly to

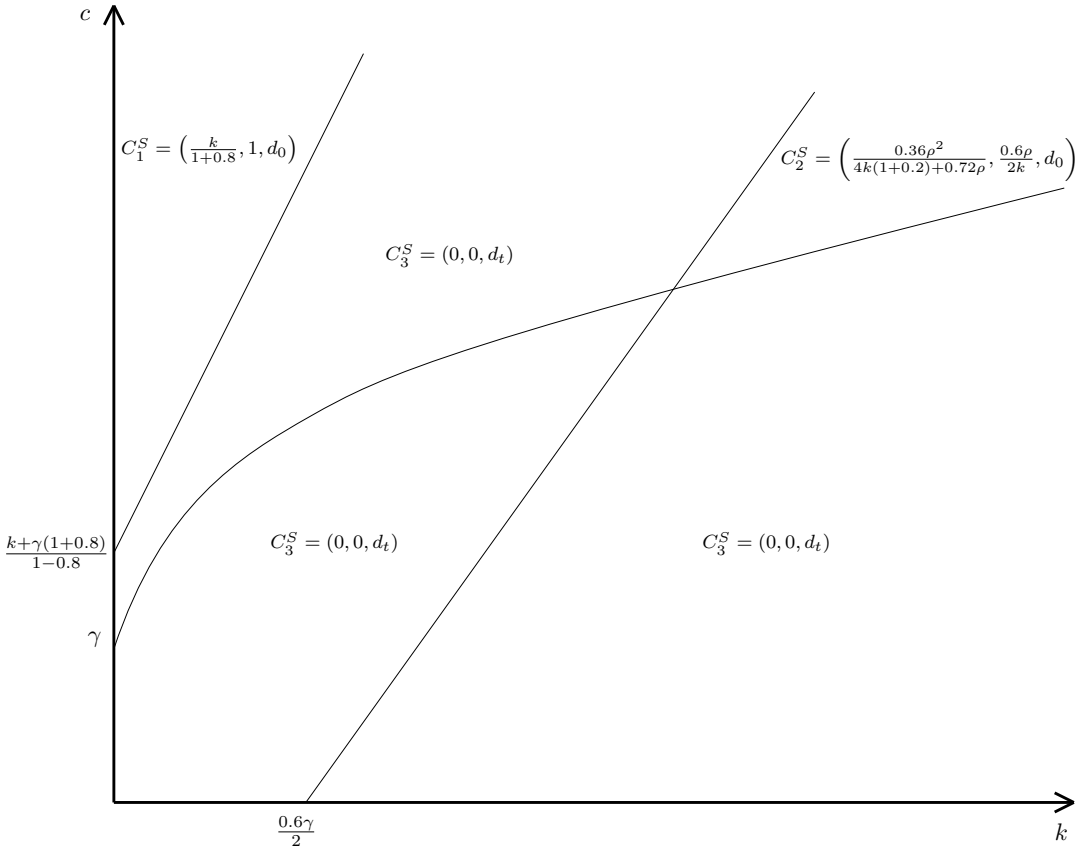
provide incentives for the physician to exert some positive effort level. As a consequence, PS does not have any incentive to offer a positive bonus to the physician. PS has incentives to provide the contract C_3^S only when the additional cost of a complier treated with the drug with DDS c is sufficiently small. In this case, PS never pays a bonus, which is equivalent to a contract with zero effort level, and the physician always prescribes the drug with DDS.

Contracts C_1^S and C_2^S are acceptable and represent to physicians an equal expected utility of zero. On the other hand, with C_3^S, the transfer given by the pharmaceutical company acts as a payment that ensures the physician accepts the contract. Hence, the expected utility of the physician is always strictly positive under that contract.

As drug choice and effort level are both contractible and observable, the transfer given by the pharmaceutical company does not play any relevant role in the optimal contracts under symmetric information. If PS prefers the physician to prescribe the drug without DDS, the bonus depends on the parameters α and β. The conditions in which it is profitable for PS to offer contracts promoting the drug without DDS and positive effort levels, also depend on the parameters α and β.

We show in Figure 1.2 the regions in which each optimal contract could be implemented according to the values of the parameters. For values of $\alpha = 0.2$ and $\beta = 0.6$, we find that the additional cost of the drug with DDS should be sufficiently large for PS to offer contracts in which the physician prescribes a drug without DDS. Moreover, the contract in which the physician exerts the maximum effort level is offered by the PS when k is sufficiently small.

Figure 1.2: Optimal contracts under symmetric information



Optimal contracts $C^S = (b, e, d)$ under symmetric information when drug choice and effort level are contractible for any $\gamma > 0$, $\alpha = 0.2$, and $\beta = 0.6$. Solid lines represent the implementation conditions for each contract according to Proposition 1.2.

In Proposition 1.1 we use a distribution of the patient's type equal to 1/2. However, as a robustness check, we analyze how the results change considering different probability values.[11] We find that keeping the parameters α, β, γ, and k constant, the value of the bonus should increase as the proportion of the non-compliers increases.

Note that under symmetric information, the optimal contracts in Proposition 1.1 represent situations in which all decisions by the physician are contractible. However, it could be possible that PS can enforce the drug choice, or that since the drug choice could be ex-post observable by PS, it could also be contractible. In this case, the problem for PS is very similar to the one described above. Still, now we have an

[11]The analysis is available upon request.

incentive compatibility constraint (IC) that induces the physician to choose the effort level desired by PS. Hence, the problem is:

$$\min_{b,d} \mathbb{EC}(b,e,d)$$

such that

$$\begin{aligned}
&\mathbb{EU}(b,e,d) \geq m, \quad (PC)\\
&b \geq 0, \quad (LC)\\
&e \in \text{argmax}_{e\in[0,1]} \left\{\mathbb{EU}(b,e,d)\right\}, \quad (IC), \text{ and}\\
&e \in [0,1].
\end{aligned}$$

Since PS can include the drug choice in the optimal contract, we consider these contracts are particular cases of symmetric information, and we denote them as $C^F = (b,d)$.

Proposition 1.2. *When the drug choice is contractible, but the effort is not:*

- *If PS prefers the physician to prescribe the drug without DDS and* $c \geq \frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, *the optimal contract is* $C_4^F = \left(\frac{k}{1+\alpha+\beta}, d_0\right)$. *The contract induces* $e = 1$.
- *Otherwise, if PS prefers the physician to prescribe the drug with DDS, the optimal contract is* $C_5^F = (0, d_t)$. *The contract induces* $e = 0$.

When the drug choice is observable, but the effort is not, the bonus is useful to induce the physician always to exert the maximum effort level when she prescribes the drug without the technology. Now, we have only two extreme optimal contracts and a contract similar to C_2^S in Proposition 1.1, in which the effort is positive and different to one, is not present. The characterization of the different optimal contracts is summarized in Table 1.1.

Table 1.1: Effort exerted and drug prescribed according to different optimal contracts

	Contract form	Optimal contracts	Effort exerted and drug prescribed
Symmetric information	$C^S = (b, e, d)$	$C_1^S = \left(\frac{k}{1+\alpha+\beta}, 1, d_0\right)$	Maximum e and drug without DDS
		$C_2^S = \left(\frac{\beta^2\rho^2}{4k(1+\alpha)+2\beta^2\rho}, \frac{\beta\rho}{2k}, d_0\right)$	$e \leq 1$ and drug without DDS
		$C_3^S = (0, 0, d_t)$	Minimum e and drug with DDS
	$C^F = (b, d)$	$C_4^F = \left(\frac{k}{1+\alpha+\beta}, d_0\right)$	Maximum e and drug without DDS
		$C_5^F = (0, d_t)$	Minimum e and drug with DDS
Asymmetric information	$C^A = b$	$C_6^A = \frac{2k}{\beta}$	Maximum e and drug without DDS
		$C_7^A = \frac{2t}{(1+\alpha+\beta)}$	Maximum e and drug without DDS
		$C_8^A = \frac{\sqrt{16\beta^2kt+(2k(1+\alpha))^2}-2k(1+\alpha)}{2\beta^2}$	$e \leq 1$ and drug without DDS
		$C_9^A = 0$	Minimum e and drug with DDS

Contracts C_6^A to C_9^A are introduced in the next section.

1.3.2 Asymmetric information

In this subsection, we present the optimal contract when neither the effort level that the physician exerts nor the drug choice are contractible. Additionally, we analyze the policy implications of possible regulations on the transfer given by the pharmaceutical company. Now, the contract has the form $C^A = b$, consisting only of the bonus, and PS faces an additional incentive compatibility constraint (IC). The IC means that if PS prefers the physician to prescribe one of the two drugs and exerts an effort level, PS must incentivize the physician to choose that strategy.

The problem that PS has to solve is the following:

$$\min_b \mathbb{EC}(b, e, d)$$

such that

$$\begin{aligned}
&\mathbb{EU}(b, e, d) \geq m, \quad (PC)\\
&b \geq 0, \quad (LC)\\
&\{d, e\} \in \operatorname{argmax}_{d\in\{d_t,d_0\},e\in[0,1]} \{\mathbb{EU}(b, e, d)\}, \quad (IC), \text{ and}\\
&e \in [0, 1].
\end{aligned}$$

In Proposition 1.3, we present the optimal contracts under asymmetric information.

Proposition 1.3. *When the drug choice and the effort level are not contractible:*

- *If PS induces the physician to prescribe the drug without DDS and to exert the*

maximum effort level,

- $c \geq \frac{2k}{\beta} + \frac{\gamma(1-\alpha-\beta)}{(1+\alpha+\beta)}$, *and* $t > \frac{k}{\beta}(1+\alpha+\beta)$, *the optimal contract is* $C_6^A = \frac{2k}{\beta}$, *or*
- $c \geq \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, *and* $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)\right]$, *the optimal contract is* $C_7^A = \frac{2t}{(1+\alpha+\beta)}$.

- *If PS induces the physician to prescribe the drug without DDS and to exert a positive effort level,* $c \geq \frac{\gamma(1-\alpha)2\sqrt{k}}{\sqrt{k}(1+\alpha)+\sqrt{4\beta^2 t+k(\alpha+1)^2}}$, *and* $t \leq \frac{k}{2}$, *the optimal contract is* $C_8^A = \frac{\sqrt{16\beta^2 kt+(2k(1+\alpha))^2}-2k(1+\alpha)}{2\beta^2}$, *with* $e = \frac{\sqrt{16\beta^2 kt+(2k(1+\alpha))^2}}{4\beta k} - \frac{(1+\alpha)}{2\beta} > 0$.
- *Otherwise, if PS induces the physician to prescribe the drug with DDS and, as a consequence, to exert no effort, the optimal contract is* $C_9^A = 0$.

If PS prefers the physician to prescribe the drug without DDS and to exert some positive effort level, that is the Aed_0 strategy, it has to offer a positive bonus. The bonus depends on the transfer given by the pharmaceutical company t, the degree of substitution of the effort to a DDS technology β, and the parameters k and α. On the other hand, under the strategy Aed_t, PS does not have any incentive to offer the physician a strictly positive bonus. In this case, the physician prescribes the drug with DDS and chooses an effort level equal to zero, according to Lemma 1.2. In this case, the expected utility of the physician is always strictly positive.

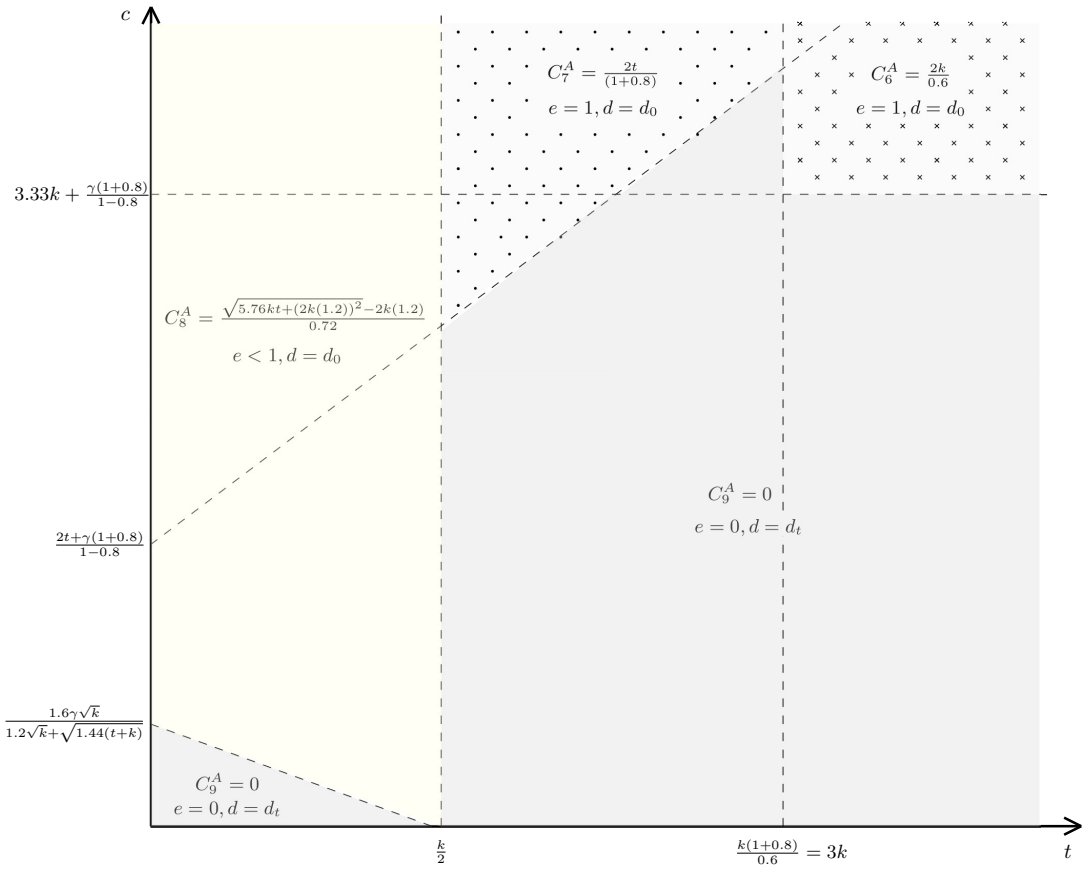
We find four incentive-compatible and acceptable contracts. Again, when the additional cost of a complier treated with the drug with DDS is sufficiently small, and regardless of the value of the transfer given by the pharmaceutical company, the contract induces zero effort because PS does not offer any bonus.

When the additional cost of a complier treated with the drug with DDS, c, is sufficiently large, PS could offer three different positive bonuses depending on the parameters α, β, k, and the value of the transfer given by the pharmaceutical company. These contracts provide the physician with incentives to prescribe the drug without DDS. Consequently, they induce positive effort levels. Interestingly, PS could offer different contracts for different transfer levels, and they would all induce prescription of the drug without DDS. Moreover, if c is sufficiently large and the transfer is higher,

PS could offer a contract that induces the physician to exert the maximum effort level.

We show in Figure 1.3 the regions in which each optimal contract could be implemented according to the values of the parameters. For values of $\alpha = 0.2$ and $\beta = 0.6$, we find that when the transfer and the cost of the drug with DDS are sufficiently large, PS could offer contracts that induce the physician to exert the maximum effort level and to prescribe the drug without DDS.

Figure 1.3: Optimal contracts under asymmetric information



Optimal contracts $C^A = b$ under asymmetric information when drug choice and effort level are not contractible for any $\gamma > 0$, $\alpha = 0.2$, and $\beta = 0.6$. Dashed lines represent the implementation conditions for each contract according to Proposition 1.3.

Next, we analyze the implications of a limited or complete prohibition of the transfer given by the pharmaceutical company. A radical regulation would be the prohibition

of any transfer by the pharmaceutical industry. In our model, this would be equivalent to the transfer given by the pharmaceutical company being zero, that is, $t = 0$. Then, Proposition 1.3 becomes as follows:

Corollary 1.1. *When the transfer is prohibited:*

- *If PS induces the physician to prescribe the drug without DDS and* $c \geq \frac{2k}{\beta} + \frac{\gamma(1-\alpha-\beta)}{(1+\alpha+\beta)}$*, the optimal contract is* $C_6^A = \frac{2k}{\beta}$*, with* $e = 1$
- *Otherwise, if PS induces the physician to prescribe the drug with DDS, the optimal contract is* $C_9^A = 0$*, with* $e = 0$*.*

In corollary 1.1, we have a unique solution inducing the prescription of the drug without DDS. In this case, the positive bonus ensures a contract in which the effort level is one when the physician prescribes the drug without DDS. PS offers the incentive when the cost of a complier treated with the drug with DDS is $\frac{k}{\beta}(1+\alpha+\beta)+\frac{\rho}{2}(1-\alpha-\beta)$. An important implication of this result is that only when the cost of the drug with DDS is sufficiently large will PS provide the physician with incentives to exert effort during the prescription.

In Proposition 1.3, the bonus is higher under the contract C_6^A than under C_7^A and C_8^A. The effort level induced is greater under C_6^A and C_7^A. Therefore, PS faces a trade-off between a contract that induces a perfect effort level and a contract in which it must pay a lower incentive (see Table 1.1). When the transfer is banned, the trade-off disappears, and the only contract that PS could offer the physician is the one that induces an effort level equal to one.

Another regulation could be a limitation on the transfer given by the pharmaceutical company. We define a minimum level of $t = \frac{k}{2}$ since it reflects how the physician's marginal disutility increases with the effort exerted by the physician. The following corollary presents the optimal contract under this restriction.

Corollary 1.2. *When the transfer is limited to* $t < \frac{k}{2}$*:*

- *If PS induces the physician to prescribe the drug without DDS and* $c \geq \frac{\gamma(1-\alpha)2\sqrt{k}}{\sqrt{k}(1+\alpha)+\sqrt{4\beta^2 t+k(\alpha+1)^2}}$, *the optimal contract is* $C_8^A = \frac{\sqrt{16\beta^2 kt+(2k(1+\alpha))^2}-2k(1+\alpha)}{2\beta^2}$, *with* $e = \frac{\sqrt{16\beta^2 kt+(2k(1+\alpha))^2}}{4\beta k} - \frac{(1+\alpha)}{2\beta} > 0$.
- *Otherwise, if PS induces the physician to prescribe the drug with DDS, the optimal contract is* $C_9^A = 0$, *with* $e = 0$.

The restriction implies that only contracts in which the effort level is positive but not necessarily equal to one would be implemented. In this case, the contract also induces the physician to prescribe the drug without DDS. Again, the contract would be profitable for PS if the cost of a complier treated with the drug with DDS is $\frac{\rho}{2}(1-\alpha)$. Otherwise, PS does not offer any bonus, and the effort during the instruction phase would be zero.

Finally, a convenient regulation could be aimed at reducing the cost for the physician during the instruction phase of the prescription process. In particular, if k decreases, the bonuses in optimal contracts of Proposition 1.3 would fall, and PS could offer lower incentives to the physician to ensure the prescription of the drug without DDS. As C_6^A and C_8^A depend on k, it is easy to see that the bonuses fall if k decreases. Note that PS offers C_7^A if the transfer given by the pharmaceutical company belongs to an interval, $\left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)\right]$, that is now smaller because of the reduction of k. As a result, the bonus in C_7^A would decrease.

Regarding the proportion of the patient's type and keeping the parameters α, β, γ, and k constant, we find the bonus offered in contracts C_7^A and C_8^A in Proposition 1.3 should increase as the proportion of non-compliers does. Oppositely, for contract C_6^A PS could offer a smaller bonus when the proportion of the non-compliers is greater than the compliers. The particular conditions to implement contract C_6^A explained the last result, as shown in Figure C.2 when both the cost of the drug with DDS and the transfer are large.

1.4 Extension: The physician internalizes the patient's losses.

In this section, we propose an extension to contrast the results of our base model.[12] We introduce in the model the idea that the physician also bears the cost of the health losses of the patient. In our model, we do not consider a health benefit function for the patient into the physician's utility, as is usual in the literature dealing with the altruism of the physician (Ellis and McGuire, 1986; Jack, 2005; Biglaiser and Ma, 2007; Allard et al., 2011; Choné and Ma, 2011). Instead, we take into account only the health losses derived from the wrong treatment. Thus, we suppose the physician internalizes the health losses introducing γ as a negative payment in her expected utility when the patient is not cured.

The literature has considered that the physician also includes the patient's health benefit in her utility function. In these models, the physician's utility depends on her profit and also on the benefits of the patient. Usually, the weight attached to the patient's benefit is called the altruism parameter. Thus, in a strict sense, we are not modeling an altruistic physician, but we are considering a physician who faces a disutility when her patient is not cured.

The expected utility of the physician when prescribing the drug without DDS is the following:

$$\mathbb{EU}(b, e, d_0|h) = \frac{1}{2}\left[(1+\alpha+\beta e)(m+b) + (1-\alpha-\beta e)(m-\gamma)\right] - \frac{ke^2}{2} \tag{1.7}$$

Since the physician now bears the patient's health losses, the incentives to choose one of the two drugs or exert some effort also change. In particular, in Lemma 1.3, we show that the threshold $\tilde{t}$ of the transfer for which it is profitable for the physician to prescribe one of two drugs is smaller than in Lemma 1.1 of the base model for a given effort level and the parameters α and β. This result means that the pharmaceutical company could offer a smaller transfer to the physician to promote the prescription of the drug with DDS.

[12]The proofs in this section are available upon request, and formal presentations of the propositions are in the Appendix A

Lemma 1.3. *There exists* $\tilde{t} \in \mathbb{R}_+$ *such that the physician prescribes the drug without DDS if* $t \leq \tilde{t} = \frac{b(1+\alpha+\beta e)-\gamma(1-\alpha-\beta e)}{2}$ *and the drug with DDS, otherwise.*

On the other hand, keeping e, α, and β constant, if the physician prescribes the drug without DDS, the effort is now greater than when she does not bear the health losses for the patients, as shown in Lemma 1.4 compared with Lemma 1.2 in the base model.

Lemma 1.4. *If the physician prescribes the drug with DDS, the optimal effort level is* $e^* = 0$. *If the physician prescribes the drug without DDS, the optimal effort level is* $e^* = min\left\{\frac{\beta(b+\gamma)}{2k}, 1\right\}$.

Again, we first start by characterizing the optimal contracts when the drug choice and the effort level are observable. Then we present the contracts when both are not observable. We suppose that the expected cost for PS remains the same as in the base model, that is, PS faces an additional charge of $\rho = c + \gamma$ corresponding to the wrong treatment of a non-complier.

The results in Proposition 1.4 are very similar to the ones in Proposition 1.3 under symmetric information problem. However, an interesting analysis compares the incentives that PS has to offer now to reach the implementation of the same optimal contracts. If PS prefers the physician to prescribe the drug without DDS and exerts the maximum effort level, it should offer the same bonus as in the base model if $(1 - \alpha - \beta) = 0$. If $(1 - \alpha - \beta) > 0$, the bonus now always is higher than in the base model (see details in the appendix). Note that when the physician internalizes the patient's losses and the effort required from PS is the maximum, the bonus never could be lesser than the bonus in the base model. Then, in the better scenario for PS, it faces at least the same cost as the base model. On the other hand, if PS wants a positive effort level from the physician, it should offer an incentive that is less costly than in the base model if $4k(1 - \alpha) \leq \beta^2\gamma^2$. If $4k(1 - \alpha) > \beta^2\gamma^2$ and depending on the parameters, the bonus could be higher or lower than in the base model. These results show that if PS is willing to obtain some effort different from the maximum, it could save some money by offering a lesser bonus than when the physician does not internalize the patient's losses. Finally, if PS prefers the physician to prescribe the drug with DDS, it does not offer any bonus.

Proposition 1.4. *When the drug choice and the effort level are contractible:*

- *If PS prefers the physician to prescribe the drug without DDS and to exert the maximum effort level, the bonus is always higher than in the base model if* $(1-\alpha-\beta) \neq 0$.
- *If PS prefers the physician to prescribe the drug without DDS and to exert a positive effort level, the bonus is lower than in the base model if* $4k(1-\alpha) \leq \beta^2\gamma^2$.
- *Otherwise, as in the base model, if PS prefers the physician to prescribe the drug with DDS, it will not offer any bonus since the physician does not have any incentive to exert effort.*

Under asymmetric information, we find that if PS prefers the physician to exert the maximum effort level and, simultaneously, to prescribe the drug without DDS, it can use one of two contracts as we detailed in the appendix. In one of those contracts, the bonus is always lower than in the base model, while the other is higher or equal. In both cases, the bonus has to include the transfer given by the pharmaceutical company, the parameters α, β, and the cost of the wrong treatment γ. If PS wants to induce the physician to exert a positive effort, then the bonus is lower than in the base model under some condition. As in Proposition 1.3, the bonus is zero if PS wants the physician to prescribe the drug with DDS.

Proposition 1.5. *When the drug choice and the effort level are not contractible:*

- *If PS induces the physician to prescribe the drug without DDS and to exert the maximum effort level,*
  - $c \geq \frac{2k(1+\alpha+\beta)-2\beta\gamma(\beta+\alpha)}{\beta(1+\alpha+\beta)}$, *and* $t > \frac{k}{\beta}(1+\alpha+\beta)-\gamma$, *the bonus is always lower than in the base model, or*
  - $c \geq \frac{2t+2\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, *and* $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)-\gamma\right]$, *the bonus is always higher than in the base model if* $(1-\alpha-\beta) \neq 0$.
- *If PS induces the physician to prescribe the drug without DDS and to exert a positive effort level, the bonus is lower than in the base model if* $16k\beta^2\gamma = 12\beta^2kt + 3(k+k\alpha)^2$.

- *Otherwise, as in the base model, if PS induces the physician to prescribe the drug with DDS, the effort level is equal to zero.*

1.5 Concluding remarks

We developed a model in which the effort exerted by the physician during the prescription process can be a substitute for a technology that benefits non-compliant patients and represents an additional cost for the public health system. As a notable aspect, the pharmaceutical company produces and promotes the prescription of the drug with such technology. We represent in the model the promotion of that drug by a transfer from the pharmaceutical company to the physician.

Since the effort is a substitute of the drug with the technology, the physician has incentives to exert some positive effort while prescribing the drug without the technology. Oppositely, when she chooses the drug with the technology, the effort is costly for the physician. The degree to which the effort substitutes the drug's technology affects the incentives that the health authority offers to the physician to follow its guidelines on prescription decisions. Additionally, the transfer from the pharmaceutical company also acts as an important incentive for the physician when they face the decision of what drug she should choose.

In the base model, we show that the public health system could offer the physician a bonus to prescribe the drug without the technology (less expensive) and exert a strictly positive effort to enhance patient compliance. Some of these contracts can induce the physician to exert the maximum effort level during the prescription process. Particularly, when the drug choice and the effort level are not contractible, to avoid the moral hazard problem, the public health system has to design the optimal bonus, considering the transfer given by the pharmaceutical company.

The idea of a health authority offering bonifications to the physicians to counteract gifts' effects from the pharmaceutical companies can appear challenging to implement. However, an important step to improve the use of the resources in the Heath Systems is to understand how these different incentives affect physician prescriptions. Furthermore, initiatives such as Open Payments in the United States and the Transparency Register in Europe have focused on the gift's effect on drug choices.

A radical regulation is the prohibition of any transfer from the pharmaceutical industry. We show that only when the additional cost of the drug with the technology is sufficiently large does the public health system provide the physician incentives to exert effort during the prescription process. In that way, the non-compliers patients could perceive better outcomes even when they receive the drug without the technology. When the cost of the effort and the transfer are both sufficiently high, the third-party payer could not offer an incentive that induces a maximum effort level from the physician. Thus, regulation could instead be a limitation on the transfer given by the pharmaceutical company. This restriction implies that only contracts in which the effort level is less than one would be implemented.

We present an extension of the base model and introduced the possibility that the physician internalizes the patient's losses. Since the physician bears the cost of wrong treatment for non-compliers, the third-party payer could sometimes face a bonus higher or lower than that of the base model, depending on the parameters and the effort level that the public health system is willing to induce from the physician.

Our model can be helpful to study other scenarios or agency research questions. For example, in education, the effort exerted by a teacher (agent) can, combined with technology (didactic resources), make students in state schools obtain better educational achievements, which are the outcomes the government (principal) wants. Additionally, following this topic of patient compliance, it could be interesting to explore the physicians' role in avoiding antibiotics' inappropriate use.

Chapter 2

Monetary incentives, drug prescription, and attention: Experimental evidence using eye-tracking technology

2.1 Introduction

Given the physician's role in pharmaceutical spending, health authorities have been implementing policies that seek to contain cost in drug prescription.[1] For instance, France has been executing policies to replace brand drugs with generic drugs, and Spain has incentives to improve prescribing practices (WHO, 2010 and Moreno-Torres et al., 2011). Although some of these policies include incentives to promote the generic prescription, the pharmaceutical industry's incentives could limit the cost-containment policies' effect. On the other hand, prescription decisions could be demanding, requiring a significant level of cognitive effort or attention by the physician. Notably, the physician should choose the drug's presentation considering its possible effects and, in public health systems, even its cost-effectiveness. To investigate the effect of monetary payments on prescriptions and physician's attention, we conduct an experiment in which subjects perform clinical tasks facing different incentives.

[1]Estimations suggest that unnecessary expenses, irrational use, and poor quality control of drugs are responsible for losses equal to 5% of total health expenditure (WHO, 2010).

In our experimental setting, medical students from three different schools in Bogotá, Colombia, prescribe a brand drug or a generic version of the same molecule to six hypothetical patients.[2] We randomly assign the participants to two alternative payment schemes. In the control group, they receive a fixed fee per patient, and in the treatment group, they also received a containment incentive to prescribe the generic drug. Additionally, each physician receives, in random order, a transfer to promote a brand drug prescription for three patients. Unlike the containment incentive, the transfer acts as a gift since it was not mandatory to choose the brand drug to receive it. We use monetary payments since, in real life, the physicians receive this type of incentive,[3] and these payoffs are standard in experimental settings to incentivize the subjects.

The subjects receive information on health conditions and diagnosis for each hypothetical patient, and they know the indication and cost of both drugs. We present that information to permit the physicians to focus their attention on the two drugs' decision to treat the patients instead of diagnosing them. Thus, we aim to capture the subject's attention on the patient's health status and two drugs' information. Remarkably, the physician could make a simple calculation and know the cost-effective-ness of each drug. We build all six hypothetical clinical cases using real clinical information. Last, we use eye-tracking technology to capture pupil dilation and visual fixations to measure attention.

Health economics literature studying how economic incentives affect drug prescription decisions is considerable.[4] Using the fact that the physicians can self-dispense drugs through on-site pharmacies,[5] Liu et al. (2009), Iizuka (2012), and Rischatsch et al. (2013) find, in general, that physicians change their prescription decisions when they receive profits from the sale of drugs. Meanwhile, Kaiser and Schmid (2016) and Burkhard et al. (2019) find that dispensing increases drug cost. However, Ahammer and Zilic (2017) report not necessarily higher drug expenses from physicians operating

[2]We argue that both versions have the same effectiveness. However, we control in the analyses for quality perceptions on both drugs using an incentivized task that we included.

[3]At least half of the US physicians received $2.4 billion in industry payments in 2015.

[4]Literature studying the determinants of the prescription decision between a brand and a generic drug includes variables such as drug prices, habits, and advertising, among others, to understand the factors driving prescription decisions. We focus on the papers that explicitly mention an economic incentive as a monetary payment, income, or profit explaining the prescription process.

[5]In Japan, Taiwan, the United Kingdom, Germany, Austria, some states in the US, and some Swiss jurisdictions, physicians can prescribe and dispense drugs simultaneously.

on-site pharmacies than other physicians.

There is very little evidence of how the pharmaceutical industry's incentives can affect other incentives' performance to influence prescription decisions. Epstein and Ketcham (2014) evaluate information technology provision (patient's formulary coverage) as mechanisms to influence prescription. Combining a randomized experiment with a survey, they find that exposure to pharmaceutical promotion affects prescription less than information. Our contributions are in the same line as Epstein and Ketcham (2014) and the experimental health economics literature studying how payment schemes affect physician's provision behavior (Hennig-Schmidt et al., 2011; Brosig-Koch et al., 2013, 2016, 2017, 2019; Green, 2014; Keser et al., 2014, 2020; Lagarde and Blaauw, 2017; Bejarano et al., 2017).[6] In particular, we are the first to estimate the impact of a cost-containment incentive to prescribe a generic drug in the presence of a gift given by a pharmaceutical company.

Our second contribution is to measure the effect of the incentives on physicians' visual attention using a novel technology in a medical setting non studied before. Mostly, to understand consumer decisions, researchers have used eye-tracking technology. For instance, Van der Lans et al. (2008) analyze how consumers locate brands within a display without choice. While Chandon et al. (2006) analyze natural product decisions without time pressure, Reutskaja et al. (2011) incorporate time pressure and option overload of snack food. Besides, Krabijch (2012) evaluated the attentional drift-diffusion model for understanding the computational process employed in purchasing decisions. In more recent years, academics have used this technology to understand the agents' behavior in games: learning (Knoepfle et al., 2009), truth-telling and deception (Wang and Camerer, 2010), dynamic patterns to identify strategic sophistication and attention (Polonio et al., 2015), and decision rules neglecting the other players' incentives and beliefs (Devetag et al., 2016). In addition, procedures to choose between two lotteries (Arieli et al., 2011), empirical contrast of intertemporal choice models (Amasino et al., 2019), and evaluations of healthy food behavior (Sullivan et al., 2019; Rramani et al., 2020) are research questions also approached using such technology.[7]

[6]The payment schemes evaluated in this literature comprise fee-for-service, capitation, pay-for-performance, and mixed payments. These papers aim to contribute to understanding, using experimental settings, how monetary incentives affect medical services provision.

[7]In these papers, subjects usually receive food from one of the choices they made instead of monetary incentives, as we consider. Literature on food choice using process-tracing methods is

We find that the containment incentive and the gift only do not affect subjects' decisions substantially. However, we find evidence of more generic prescriptions and greater visual attention levels when the subjects receive both incentives simultaneously. Notably, we see the attention levels are greater in the part of the experiment in which the generic prescriptions are more frequent. Additionally, we find that within-subjects, the presence of a gift affects generic prescriptions and attention levels negatively. Finally, early exposure to the gift affects the attention levels but not the prescriptions.

2.2 Design and procedures

We invited students in their last three years of study from three different medical schools in Bogotá, Colombia, to participate in a medical context experiment.[8] Subjects received a set of six clinical cases, each with information about the health condition and the diagnosis for a hypothetical patient. Also, they received information about the indications and cost of a brand and a generic version of the same molecule (active ingredient) to treat such disease. They had to prescribe one of the two drug presentations for every patient that is assumed as fully insured.

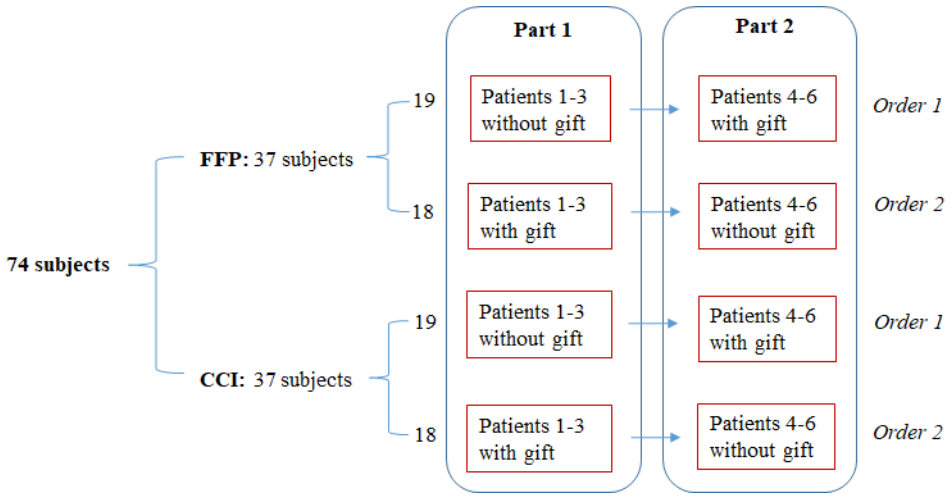
We built the clinical cases using real clinical information and inspired by a learning strategy used in some medical schools, called "problem-based learning". We provided a precise diagnosis (made by a specialist) in each case for two reasons. First, we are interested in capturing the subject's attention on the two drugs' information instead of diagnosing the patient. Second, in modern clinical practice, physicians have evidence-based medicine tools that synthesize clinical research findings and include algorithms to determine the patient's diagnosis and the possible interventions (including drugs). We argue that our task is useful to measure the physician's attention while prescribing since the subjects only have to focus on the drug's decision. Notably, since both drug presentations have the same effectiveness, the physician could make a simple calculation and know each drug presentation's cost-effectiveness. The clinical cases used in the experiment are available in Figures B.1-B.6 in the Appendix.

extensive, and we do not pretend to cover all available material.

[8]Usually, in Colombia, medical students spend at least six years before becoming a general practitioner. During the first three years, they receive theoretical education, and then they acquire practical knowledge in hospitals and health care centers. In their last year, they do a medical internship.

We randomly assigned the participants to two alternative payments. They received a fixed fee per patient w in the control group (FFP group).[9] In contrast, subjects in the treatment group also received a cost-containment incentive δ to prescribe the generic drug (CCI group). Additionally, we apply a within-subject design, where each subject received a gift τ to promote a brand drug prescription in three of the six patients.[10] We organized patients one to three and four to six in two blocks and randomized the order in which the subjects receive the gift according to these groups. With 50% probability, the subjects received the gift during the first block (patients 1-3) in the first part of the experiment, and with 50% probability, they received the gift during the second block (patients 4-6) in the second part (Figure 2.1). We design both blocks considering balancing the number of words used to describe the patient's clinical problem, the hypothetical diagnosis, and the cost difference between the drugs.[11] The randomization took place at the session-level.

Figure 2.1: Between and within-subjects distribution.



The figure shows our participants' distribution in both treatments: Fixed fee per patient (FFP) and cost-containment incentive (CCI). Also, we present the number of participants according to the order and the block of patients they receive the gift.

[9]This payment scheme differs from capitation. In the latter, the physician usually receives a fixed payment for each patient, regardless of the number of medical services dispensed; that is, the physicians assume the cost of the services provided.

[10]This extra transfer aims to introduce an incentive similar to the one pharmaceutical companies offer to physicians. Usually, the companies give "gifts" to physicians to promote the prescription of their brand but cannot force them to prescribe it.

[11]For example, both blocks had a pediatric case and two internal medicine cases.

Contrary to the cost-containment incentive, the gift does not depend on the drug choice. Table 2.1 presents the payoffs according to the subjects' decisions in each group. These payments simplify mixed schemes that physicians could face in their clinical practice. To set the payments, we considered that $w > \tau > \delta$, and that δ and τ was 10% and 30% of w, respectively; where w is equal to COP 10.000 (around $2.7) per case. This parametrization aims to approximate a more realistic situation where the FFP is greater than the CCI, and also, the pharmaceutical company's gift is higher than the CCI.

Table 2.1: Subject's payments according to the treatment group and the prescription decision.

		Without gift		**With gift**	
		Prescription decision		*Prescription decision*	
		Generic	Brand	Generic	Brand
Group	FFP	$w = 10.000$	$w = 10.000$	$w + \tau = 13.000$	$w + \tau = 13.000$
	CCI	$w + \delta = 11.000$	$w = 10.000$	$w + \delta + \tau = 14.000$	$w + \tau = 13.000$

Payments in COP depending on the subject's prescription decisions by treatment group. FFP: fixed fee per patient, w; CCI: cost-containment incentive, δ; τ represents the gift.

We used pupil dilation in millimetres (mm) and the number of fixations performed by the subjects during the experiment as attention measurements. Pupil dilation is sympathetic arousal that often accompanies cognitive effort (Wang and Camerer, 2010; Van Steenbergen and Band, 2013; Westbrook and Braver, 2015), and visual fixations are patterns in eye movements that support inferences about the cognitive process while the subjects are reading (Raney et al., 2014). Visual fixations are highly related to attention, a superior cognitive function closely associated with cognitive effort. To capture both metrics, we used eye-tracking technology, a sensor that allows us to know where a person is looking.

We included an incentivized task where the participants faced a list of brand and generic versions of 10 molecules to account for baseline preferences on the type of drug the subjects tended to choose.[12] They answered which of the two versions of the list

[12]The list of molecules corresponds to the pharmacological treatments for diseases associated with

they thought was the most frequently prescribed in the country last year, and then, they were asked about which of the two versions of the same list they would prescribe (see Figures B.7 and B.8, in the Appendix). We classified subjects as "generic type" when prescribing at least 6 generic molecules of the list. The subjects received payoffs corresponding to the total of molecules they correctly thought were the most prescribed in the first question.

Additionally, we included a task to capture risk preferences where the subjects made eleven choices between a lottery and an amount of money with certainty (see Table B.1, in the Appendix).[13] For payments, we selected, at random, one of the eleven choices in the lottery. We also ask the physicians to answer the Jackson Personality Inventory modified risk-taking scale used in medical decision-making studies and a socio-economic questionnaire.

The experiments were carried out at Universidad del Rosario between May 10th and August 31st in 2018. We contacted medical schools to invite students enrolled in their last years. The subjects who expressed their willingness to participate in the experiment were registered in the Online Recruitment System for Economic Experiments (ORSEE) from Rosario Experimental and Behavioral Economics Lab (REBEL). We invited two participants per session to an activity that could last for 1 hour. All the instructions were available on the same screen, and the subjects answered control questions to ensure they understood the tasks. We conducted all the sessions in the same room under identical lighting conditions, using an eye-tracking headset device with a front and an eye camera (see details in Figure B.9, in the Appendix). The participants used the device during the whole experiment. We programmed and conducted the experiment with z-Tree (Fischbacher, 2007), and we used the open-source platform Pupil to star the eye-tracking device and collect the data (Kassner et al., 2014). The participants spent between 20 and 30 minutes on average. At the end of the experiment, they received an average payment equal to COP 76.365 with a standard deviation of COP 3.258,6 (about $20 and $0,8, respectively).

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the ten main reasons for consultation in Colombia. We verified that a generic and a brand version were available and registered for each active ingredient.

[13] Since subjects may feel monitored by the eye-tracking device, their risk preferences may affect their decisions.

2.3 Hypotheses

In this section, we present our hypotheses about the physician's prescription and attention behavior. As is expected, when δ incentivizes the decision, a selfish subject will choose the generic drug rather than the brand drug. Then, we should have the following:

Hypothesis 1: The number of generic prescriptions is higher in CCI than in FFP. Even in the presence of a gift, the effect remains.

On the other hand, since τ is a fixed and unconditioned payoff, we should not expect the gift to affect the subjects' prescription decisions. However, subjects could make decisions moved by behavioral biases or reciprocity. In the case of physicians, although they do not consider receiving gifts from the pharmaceutical industry as inappropriate behavior, it could provoke unconscious complacency bias affecting physicians' judgments. As it could appear as a controversial issue and even as an open question, we expect a selfish subject to be indifferent between the two types of drugs from a rational point of view. Moreover, a physician receiving both incentives at the same time will choose generic rather than brand if they want to reach a higher payoff.

Hypothesis 2: The number of generic prescriptions should be similar in the presence of a gift than in its absence, regardless of the treatment group.

In moral hazard problems, the asymmetry of information is related to the fact that the agent's actions are not observable o verifiable for the principal. Contract theory suggests that the principal should offer incentives to lead the agents to exert more effort and, as a result, the principal will obtain better outcomes (Macho-Stadler and Pérez-Castrillo, 2018). Therefore, bonuses or other contractible incentives, instead of fixed payments, are helpful to achieve these purposes.

Let a_δ and a_w be the indices of attention during the task when the subjects receive the cost-containment incentive and the fixed payment per patient, respectively. Let a_δ^τ be the indices of attention when the subject receives the containment incentive and gift τ simultaneously, and a_w^τ when receives the fixed payment and the gift at the same time. Then, according to the theory, we expect that:

$$a_w < a_\delta, \text{ and } a_w^\tau < a_\delta^\tau.$$

Hypothesis 3: Physician's attention levels are higher when the subjects receive a CCI than when obtaining only FFP. Even in the presence of a gift, the effect remains.

Since τ is a fixed payment, we expect the attention levels to be similar for subjects in the CCI group when they receive the gift and the containment incentive simultaneously to when they only receive the cost-containment incentive. Then, we should observe that:

$$a_\delta = a_\delta^\tau.$$

We expect similar results for subjects in the FFP group. Thus:

$$a_w = a_w^\tau.$$

Hypothesis 4: Physician's attention levels are similar in the presence of a gift than in its absence. We should observe that result within each treatment group.

However, experimental literature has provided evidence that large stakes do not necessarily improve performance as the theory predicts (Slonim and Roth, 1998; Ariely et al., 2009)[14]. Even though our cost-containment incentive is not precisely a big stake, the gift is significant compared to the incentive. Then, the presence of a gift combined with the incentive could explain possible deviations from our hypotheses. Moreover, we consider that the moment in which subjects receive the gift could be critical regarding of the level of attention they decide to exert during all the clinical tasks. We argue that the subjects who receive the gift first can exhibit higher attention levels for the whole experiment since they receive the arousal for executing tasks from an initial point.

Hypothesis 5: Early exposure to the gift is related to higher attention levels throughout the experiment than a later exposition.

In the same way, the experimental design allows us to test how early exposure to the gift affects generic prescriptions. We expect that subjects who receive the gift early

[14]For a review of the the experimental literature on the effect of incentives see Camerer and Hogarth (1999).

should choose the generic drugs less frequently. There is empirical evidence indicating that physicians without contact with the pharmaceutical industry reduce their brand prescriptions (Larkin et al., 2017). Even more, some clinicians propose that medical students should not receive any gift from the pharmaceutical industry (Wayne et al., 2017).

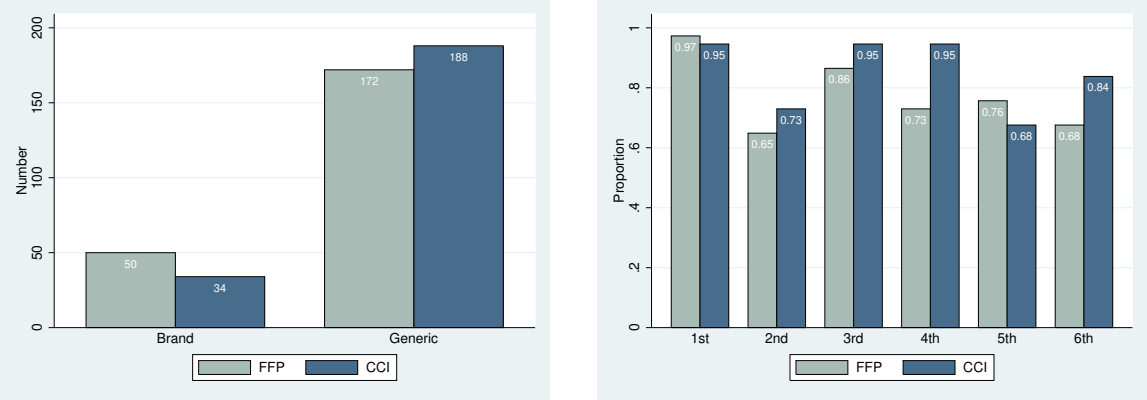
Hypothesis 6: Early exposure to the gift is related to greater brand prescriptions than later exposition.

2.4 Results

We have 74 subjects making six choices for six hypothetical patients (a total of 444 decisions). We present in Figure 2.2(a) the distribution of the number of generic and brand prescriptions across treatments. As expected, physicians in the CCI group do more generic prescriptions than subjects in the FFP group. Also, in Figure 2.2(b), we present the proportion of the subjects in each treatment group choosing the generic drug by every patient. On average, the second and fifth patients are those receiving the lower proportions of generic prescriptions. For all patients but the first and the fifth, more physicians in the CCI group than in the FFP group prescribe a generic drug; and the most significant differences between CCI and FFP are those for patients fourth and sixth.

Figure 2.2: Prescriptions decisions by treatment group.

(a) Prescriptions by treatment. (b) Generic prescriptions by patient.



Panel (a) shows the number of generic and brand prescriptions (y-axis) by treatment; Panel (b) presents the proportion of subjects in each treatment group (y-axis) choosing the generic drug by patient (x-axis). FFP: fixed fee per patient and CCI: cost-containment incentive.

Regarding the attention measurements, we have 378 observations corresponding to the average pupil diameter for each of the six patients treated by 63 subjects and 312 registers of the number of visual fixations for each of the six patients for 52 participants.[15] The average pupil diameter for all subjects during the time they treated all six patients was 3.62 mm (standard deviation of 0.71 mm), and the average number of fixations was equal to 89.73 (standard deviation of 74.89).[16] Panels (a) and (c) in Figure 2.3 show the distributions of pupil diameter and visual fixations for all subjects by treatment group. In general, we observe that pupil diameter distributions are more symmetric than the distributions for visual fixations, which are left-skewed. In particular, kernel density for pupil diameter in the FFP group concentrates more observations around the median than the CCI group's density. The opposite happens for visual fixations, where the CCI curve concentrates more information around the average. Additionally, from panels (b) and (d) in Figure 2.3, we conclude that pupil

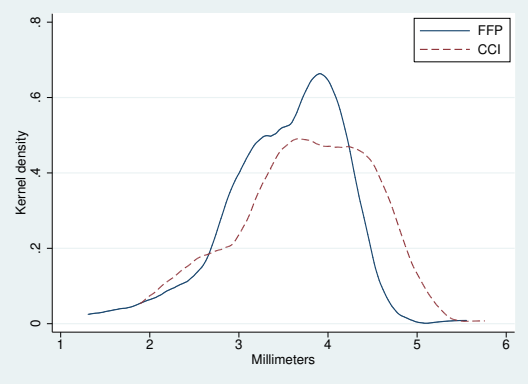
[15] Although the subjects used the eye-tracker device during the whole experiment, we analyze the attention measures only when they were looking at the screens with the clinical case's information corresponding to each patient. We used timestamps to be as accurate as possible. Although we calibrated the device correctly for all participants, we couldn't retrieve the data for some of them. Then, we had a loss of sample equivalent to 11 subjects for the pupil diameter and 22 participants for the number of fixations.

[16] We have a considerable level of arousal during the task since the average normal size of the pupil in adults under light conditions fluctuates from 2 to 4 mm. The average number of visual fixations could vary depending on the task the subjects face.

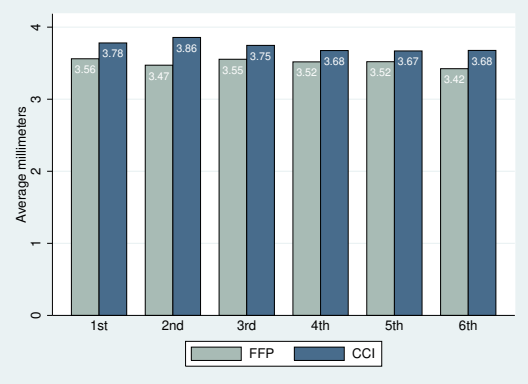
diameter and the number of fixations are higher for subjects in the CCI group than for participants in the FFP group for all six patients. There are larger differences between CCI and FFP in visual fixations than in pupil diameter. Three particular patients drive this result: the second, the fifth, and the sixth patient.

Figure 2.3: Attention measures by treatment group

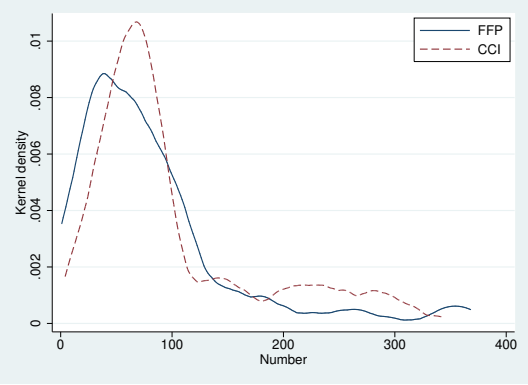
(a) Diameter of the pupil.



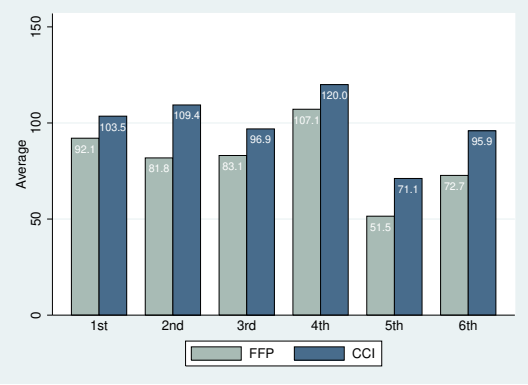
(b) Diameter of the pupil by patient.



(c) Visual fixations.



(d) Visual fixations by patient.



Panels (a) and (c) show the kernel density of the average diameter of the pupil and the average visual fixations performed by the subjects during the clinical tasks by treatment group; Panels (b) and (d) represent the same information by patient. FFP: fixed fee per patient and CCI: cost-containment incentive.

Finally, we perform mean tests and Kolmogorov-Smirnov (KS) test to evaluate the pre-treatment variables' balance, considering the treatment group and the order in which the subject received the gift (order-block). Overall, we find that the samples are well balanced within treatments and order-block (see Table B.2, in the Appendix).

Using t-test, we do not find balance for the socioeconomic level[17] and mother's educational level when comparing FFP and CCI. However, the KS test suggests that such variables have equal distribution in the FFP group as in the CCI group. We obtain the same conclusion for the order-block (see Table B.3, in the Appendix).

2.4.1 Non-parametric analysis

To evaluate the effect of monetary payments, we classify the subjects according to the treatment group and the moment in which they receive the gift:

1. *FFP:* includes the decisions of the subjects in the fixed fee per patient group when they did not receive the gift, that is, Order 1 in Part 1 and Order 2 in Part 2 (see Figure 2.1).

2. *FFP+gift:* includes the decisions of the subjects in the fixed fee per patient group when they received the gift, that is, Order 2 in Part 1 and Order 1 in Part 2.

3. *CCI:* includes the decisions of the subjects in the cost-containment incentive group when they did not receive the gift, that is, Order 1 in Part 1 and Order 2 in Part 2.

4. *CCI+gift:* includes the decisions of the subjects in the cost-containment incentive group when they received the gift, that is, Order 2 in Part 1 and Order 1 in Part 2.

To evaluate the effect of the incentive δ to prescribe the generic drug, we compare *FFP* vs. *CCI* and *FFP+gift* vs. *CCI+gift*. The first comparison informs the incentive's impact without the gift interference, and the second considering also the effect of the gift. We do not find an effect on the prescription decision for the first comparison. However, for the second comparison, when the gift is present, the physicians prescribe more generic in the CCI group than in the FFP group (see Table 2.2).

The difference between *FFP* and *CCI*, without or with the gift, is statistically significant for pupil dilation (Mann-Whitney test p-value of 0.0284 and 0.0156, respectively). This result means that the pupillary diameter is always higher if the subjects

[17]In Colombia, there is a classification called "socioeconomic stratum", which is a household designation in six categories to implement crossed subsidies from rich to poor households in the bills utilities. We use this categorization to cluster the subjects into three categories: low, medium, and upper.

belong to the *CCI* group, regardless if they have the gift. The number of fixations is higher in the *CCI* group than in the *FFP* group. As shown in Table 2.2, the difference is statistically significant only for the decisions when the subjects have the gift.

Overall, we observed no differences in prescribing decisions and attention levels by patient except for some cases (see Table B.4, in the Appendix). For the 4th patient, we observe more generic than brand prescriptions in *CCI* instead of *FFP*, and the differences are significant with or without the gift (Mann-Whitney test p-value of 0.0778 and 0.0791, respectively). We also observe greater pupil diameter and higher fixations in *CCI+gift* than in *FFP+gift* for the 2nd patient (Mann-Whitney test p-value of 0.0417 and 0.0609, respectively). Finally, for the 3rd patient, the number of fixations is greater under *CCI+gift* compare to *FFP+gift* (Mann-Whitney test p-value of 0.0954). These cases may contain important characteristics driving such differences.

Table 2.2: Cost-containment incentive effect.

	Group				
	FFP	*CCI*	p-value	Full sample	N
Generic prescriptions (proportion)	0.7837	0.8198	0.5016	0.8018	222
	(0.413)	(0.386)		(0.399)	
Pupil diameter (mm)	3.556	3.752	0.0284	3.655	189
	(0.630)	(0.758)		(0.703)	
Number of fixations	84.250	99.930	0.1854	91.487	156
	(74.333)	(79.382)		(76.856)	
	FFP+gift	*CCI+gift*	p-value	Full sample	N
Generic prescriptions (proportion)	0.7657	0.8738	0.0365	0.8198	222
	(0.425)	(0.333)		(0.385)	
Pupil diameter (mm)	3.460	3.716	0.0156	3.590	189
	(0.691)	(0.750)		(0.731)	
Number of fixations	78.523	99.013	0.0269	99.472	156
	(71.137)	(74.253)		(76.593)	

The table shows the Mann-Whitney test to evaluate treatments effects. FFP stands for the fixed fee per patient, and CCI is the cost-containment incentive.

We explore the effect of the gift τ comparing *FFP* vs. *FFP+gift* and *CCI* vs. *CCI+gift*. We do not observe a statistical difference in the proportion of generic prescriptions for the treatment (CCI) or the control (FFP) groups (see Table 2.3). According to Table 2.3, there is no gift's effect on pupil diameter and the number of

visual fixations within the FFP group or the CCI group. We also explore how the order in which physicians received the gift affects the prescriptions and the attention measures. We find that order does not affect the prescriptions, but the pupil's diameter and the number of fixations are lower for subjects who received the gift first than those who received it later in the FFS group. This result could suggest that, contrary to our hypothesis 5, early gift exposure is related to lower attention levels (see Table 2.3).

Table 2.3: Gift's effect by treatment group and order-block.

	Group			Order-block				
	FFP	*FFP+gift*	p-value	Order 1	Order2	p-value	Full sample	N
Generic prescriptions	0.7837	0.7657	0.7485	0.7807	0.7685	0.8284	0.7747	222
(proportion)	(0.413)	(0.425)		(0.415)	(0.423)		(0.418)	
Pupil diameter (mm)	3.556	3.460	0.5212	3.612	3.382	0.0057	3.508	186
	(0.630)	(0.691)		(0.633)	(0.676)		(0.661)	
Number of fixations	84.250	78.523	0.5712	93.455	67.461	0.0174	81.386	168
	(74.333)	(71.137)		(82.411)	(56.674)		(72.591)	
	CCI	*CCI+gift*	p-value	Order 1	Order2	p-value	Full sample	N
Generic prescriptions	0.8198	0.8738	0.2646	0.8421	0.8518	0.8406	0.8468	222
(proportion)	(0.386)	(0.333)		(0.366)	(0.356)		(0.360)	
Pupil diameter (mm)	3.752	3.716	0.6253	3.796	3.673	0.7259	3.734	192
	(0.758)	(0.750)		(0.672)	(0.823)		(0.752)	
Number of fixations	99.930	99.013	0.7904	106.803	93.269	0.9393	99.472	144
	(79.382)	(74.253)		(87.796)	(65.596)		(76.593)	

The table presents the results of the Mann-Whitney test to evaluate the gift's effect. FFP stands for the fixed fee per patient, and CCI is the cost-containment incentive. Order-block refers to the order in which the subjects receive the gift; that is Order 1 and 2 as in Figure 2.1.

We study the above suggestive results through regression analysis in the next section.

2.4.2 Regression analysis

In our main regression analysis we estimate linear regressions for our outcomes of interest according to the following equation:

$$Y_{ij} = \beta_0 + \beta_1 CCI_i + \beta_2 gift_j + \beta_3 part + \beta_4 (CCI_i \text{ x } gift_j) + \beta_5 (part \text{ x } CCI_i) + \beta_6 (part \text{ x } gift_j) + \beta_7 (part \text{ x } CCI_i \text{ x } gift_j) + \gamma' Z_i + \mu_i + \varepsilon_{ij}$$

where Y_{ij} is the prescription decision made or the attention level exhibited by the subject i for each patient j. Our independent variables of interest are CCI and $gift$. CCI takes the value of 1 if the subject i belongs to the CCI group and zero if the subject was in the FFP group. The variable $gift$ captures if the subject received the gift while treating the patient j. That is, it takes the value of 1 when the subjects receive the gift, 0 otherwise. We also have the variable *part*, a dummy that takes the value of 1 for the first part of the experiment and 0 for the second part. Note that during the first part, the physicians see the patients 1st, 2nd, and 3rd (see Figure 2.1).

We include the interaction between CCI and $gift$ to capture the effect of receiving both the cost-containment incentive and the gift simultaneously. The interactions *part* x CCI and *part* x $gift$ show the impact of receiving the containment incentive and the gift in the first part of the experiment, respectively. The triple interaction *part* x CCI x $gift$ presents the effect of receiving both payments at the same time for the first part. Last, Z_i corresponds to the vector of characteristics that vary between subjects but are invariant over the patients and ε_{ij} is the standard error term.

We present the regression analysis for prescription decisions and attention levels. The decisions are dummy variables equal to 1 if the subject i prescribes generic to patient j, and zero if the physician chose the brand drug. The attention levels are the average diameter of the subject i's pupil while she was facing the patient j's information and the number of fixations of the subject i when she saw the patient j. We control for individual-level characteristics, such as age, female, socioeconomic level, marital status, educational level of the mother, year, score,[18] university, the control task accounting for subject's type,[19] and JPI risk-scale.[20]

Prescription decision

Table 2.4 shows the main results from the regression analysis for prescription decisions. The first column includes the independent variables of interest, that is, *treat*, $gift$,

[18]Colombian grading system in which the minimum score is 0, and the maximum is 5.

[19]For detailed results in the control tasks, see section B.3 in the Appendix.

[20]Particularly, we use the JPI risk-taking scale instead of the risk-aversion results since we can not categorize 9.5% of the participants in the risk-aversion task due to multiple switching. Then, it represents a considerable loss of sample.

and *part*, the second column the interactions between such variables, and the last two columns include controls. We do not observe statistical significance for the gift or the treatment variables and its interactions. We find the generic prescriptions increase in the first part of the experiment compared to the second part. The characteristics of the patients in the first part of the experiment could explain this result. Furthermore, the subjects can be more relaxed during the second part of the experiment, and they can stop feeling observed in that part. However, we performed the same regression analysis considering only the first part, and we found similar results concerning the treatment effects. In addition, as expected, we find when the subjects are of the generic type instead of the brand type, they chose the generic drug more frequently. We also include a probit regression analysis as a robustness check (see Table B.5, in the Appendix). In general, the results are similar to the ones presented in the OLS analysis.

Table 2.4: Treatment effects for prescription decisions.

	Generic precriptions			
	(1)	(2)	(3)	(4)
Treatment (CCI=1)	0.072	0.074	0.053	0.056
	(0.047)	(0.086)	(0.075)	(0.072)
Gift	0.020	-0.003	0.044	0.036
	(0.025)	(0.092)	(0.086)	(0.087)
1^{st} part	0.082***	0.120	0.167**	0.159**
	(0.025)	(0.077)	(0.070)	(0.072)
Treatment x gift		0.049	0.073	0.056
		(0.121)	(0.106)	(0.107)
Treatment x 1^{st} part		-0.074	-0.050	-0.067
		(0.105)	(0.092)	(0.096)
Gift x 1^{st} part		-0.024	-0.118	-0.102
		(0.150)	(0.138)	(0.142)
Treatment x gift x 1^{st} part		0.044	-0.005	0.030
		(0.188)	(0.159)	(0.162)
Type (generic=1)			0.209***	0.187***
			(0.053)	(0.046)
JPI risk-taking (from 0 to 1)			-0.166	-0.222
			(0.175)	(0.170)
Constant	0.724***	0.722***	1.536***	1.863**
	(0.042)	(0.066)	(0.552)	(0.759)
Controls	No	No	Yes	Yes*
Observations	444	444	444	444
Subjects	74	74	74	74

OLS regressions for prescription decision (=1 if it is generic and 0 if it is the brand drug). CCI: if the subject receives the cost-containment incentive, 0 if she gets a fixed fee per patient. $Gift = 1$ if the participant obtains the gift for that decision, 0 if not. 1^{st} part=1 for the first part of the experiment, and 0 for the second part. Controls: age, female, socioeconomic strata, marital status, educational level of the mother, year, score, subject's type (1 if the subject is of the "generic" type and 0 if she is of the "brand" type), and the Jackson Personality Inventory (JPI) risk-taking scale, and university dummies*. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

From Column (4) in Table 2.4, we calculate the coefficients of every subgroup of Figure 2.1. In Table 2.5, we present the p-values corresponding to the Wald test that contrasts if the coefficient associated with every sub-sample is statistically different from zero. Since we reject the hypothesis that the coefficients are equal to zero, we perform additional tests to check the treatment and gift's effects.

Table 2.5: Testing coefficients from OLS regressions for prescriptions decisions.

	Part 1		**Part 2**	
	Gift	p-value	Gift	p-value
FFP	No	0.0126	Yes	0.0188
	Yes	0.0123	No	0.0164
	Gift	p-value	Gift	p-value
CCI	No	0.0144	Yes	0.0135
	Yes	0.0114	No	0.0166

p-values correspond to the Wald test contrasting $H_0 = 0$ vs. $H_a \neq 0$ for coefficients associated to each subgroup in Figure 2.1. FFP stands for the fixed fee per patient, and CCI is the cost-containment incentive.

We do not observe differences between subjects in CCI and FFP with or without the gift in any part of the experiment (see A. in Table 2.6). Comparing the coefficients from all sub-samples in FFP vs. CCI, we observe a similar result of no effect (Wald test p-value of 0.1732). However, we observe significant differences when comparing the coefficients attached to subgroups receiving the CCI and the gift simultaneously with the others subgroups (Wald test p-value of 0.0165). This last result is in line with what we had obtained in the non-parametric analysis section. We find the subjects who face the cost-containment incentive and the gift simultaneously prescribe the generic drug more frequently.

Table 2.6: CCI and gift's effects on prescriptions from OLS coefficients (p-values).

A. Treatment effect				**B. Gift effect**			
	FFP vs. CCI		*Order*		*Part 1 vs. Part 2*		Early
Gift	Part 1	Part 2	*effect*		No early gift	Yes early gift	exposure
No	0.8482	0.4455	0.0138	*FFP*	0.0089	0.0125	0.4718
Yes	0.1952	0.1697	0.4714	*CCI*	1	0.0426	0.4465

p-values correspond to the Wald test of equality of coefficients. For example, p-value= 0.8482 comes from compare if the coefficient for the subgroup FFP without a gift in Part 1 is equal to the one for CCI without a gift in Part 1. FFP stands for the fixed fee per patient, and CCI is the cost-containment incentive. *Order effect* compares Order 1 vs. Order 2 with or without gift.

Result 1: Although we find no effect of the cost-containment incentive on the prescription decisions, we have evidence showing that generic prescriptions are greater by receiving the containment incentive and the gift simultaneously.

Contrarily to the results of the non-parametric analysis, we observe within-subject differences for participants receiving the gift in the FFP treatment regardless of the part in which they receive it (see B. in Table 2.6). We do not find evidence supporting that early exposure to the gift affects prescriptions decisions, either within treatment (see Table 2.6) or in general (Wald test p-value of 0.3293).

Result 2: The presence of the gift negatively affects generic prescriptions, regardless of the timing of the exposure to the gift.

Attention levels

Table 2.7 presents the results for OLS regressions for both attention measures: the pupil diameter and the number of visual fixations, using standard errors clustered at the individual level. In the table, columns (1) and (5) include the independent variables of interest, while columns (2) and (6) introduce interactions. Finally, in columns (3), (4), (7), and (8), we include controls. We control for age, female, year, score, university dummies, subject's type, and the JPI risk-taking scale. We find that the attention levels are greater in the first part of the experiment compared to the second part. This finding suggests the subjects expended more attention to the clinical tasks when they chose the generic drug more frequently. Indeed, the correlation between generic prescriptions and pupil diameter is positive in the first part of the experiment (Persons' correlation of 0.0511), and it is negative during the second part (Persons' correlation of -0.0070). Since the regression analysis for attention levels consider fewer observations than the one for prescription decision, as a robustness check, we include a regression for generic prescriptions considering the same observations used for pupil diameter (see Table B.6, in the Appendix).

Result 3: Subjects expend more attention during the part of the experiment in which they also prescribe more generic drugs.

Table 2.7: Treatment effects for attention levels.

	Pupil diameter				Visual fixations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (CCI=1)	0.226	0.219	0.228	0.247	18.085	24.231	19.439	16.259
	(0.166)	(0.270)	(0.285)	(0.272)	(19.335)	(22.288)	(21.618)	(21.192)
Gift	-0.062*	0.138	0.221	0.287	-3.506	20.851	30.726	26.125
	(0.034)	(0.235)	(0.252)	(0.234)	(3.109)	(22.307)	(22.801)	(23.001)
1^{st} part	0.079**	0.263	0.346	0.412*	8.109**	34.162	44.037*	39.436
	(0.034)	(0.208)	(0.234)	(0.221)	(3.109)	(25.165)	(25.233)	(25.505)
Treatment x gift		-0.051	-0.024	-0.160		-8.879	-16.838	-8.777
		(0.365)	(0.375)	(0.361)		(36.553)	(38.479)	(39.898)
Treatment x 1^{st} part		-0.019	0.008	-0.128		-12.887	-20.846	-12.785
		(0.332)	(0.351)	(0.338)		(41.028)	(43.034)	(44.506)
Gift x 1^{st} part		-0.460	-0.626	-0.757*		-51.988	-71.738	-62.536
		(0.420)	(0.457)	(0.429)		(48.393)	(48.899)	(49.502)
Treatment x gift x 1^{st} part		0.213	0.160	0.432		24.920	40.839	24.716
		(0.662)	(0.696)	(0.673)		(77.685)	(81.978)	(85.183)
Type (generic=1)			-0.064	-0.106			16.438	20.359
			(0.174)	(0.203)			(29.692)	(32.144)
JPI risk-taking (from 0 to 1)			-0.189	-0.171			6.857	11.536
			(0.616)	(0.630)			(61.783)	(62.874)
Constant	3.500***	3.412***	8.325***	6.040***	79.086***	65.949***	-55.002	88.279
	(0.112)	(0.166)	(2.051)	(2.190)	(12.292)	(14.035)	(180.719)	(190.461)
Controls	No	No	Yes	Yes*	No	No	Yes	Yes*
Observations	378	378	378	378	312	312	312	312
Subjects	63	63	63	63	52	52	52	52

OLS regressions for the average of the pupil diameter and the number of visual fixations. CCI: if the subject receives the cost-containment incentive, 0 if she gets a fixed fee per patient. $Gift$ takes the value of 1 if the participant obtains the gift for that decision, 0 if not. 1^{st} part=1 for the first part of the experiment, and 0 for the second part. Controls: age, female, year, score, subject's type (1 if the subject is of the "generic" type and 0 if she is of the "brand" type), and the Jackson Personality Inventory (JPI) risk-taking scale, and university dummies*. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Coefficients associated with every subgroup of Figure 2.1 are also statistically different from zero for pupil diameter (see Table 2.8).

Table 2.8: Testing coefficients from OLS regressions for pupil diameter.

	Part 1		**Part 2**	
	Gift	p-value	Gift	p-value
FFP	No	0.0053	Yes	0.0062
	Yes	0.0086	No	0.0076
	Gift	p-value	Gift	p-value
CCI	No	0.0061	Yes	0.0075
	Yes	0.0067	No	0.0078

p-values correspond to the Wald test contrasting $H_0 = 0$ vs. $H_a \neq 0$ for coefficients associated to each subgroup in Figure 2.1. FFP stands for the fixed fee per patient, and CCI is the cost-containment incentive.

Regarding the treatment effect, we observe for the pupillary diameter the same pattern of results that we obtained for the prescription decisions in subsection 2.4.2. That is, we have no differences between CCI and FFP with or without the gift in any part of the experiment (see A. in Table 2.9), and no differences in general (Wald test p-value of 0.2202). However, we have differences between sub-samples receiving the gift and the cost-containment incentive at the same time concerning all sub-samples (Wald test p-value of 0.0067). This last finding is consistent with the result of greater attention levels for *FFP+gift* compared to *CCI+gift* in the non-parametric analysis in section 2.4.1.

Result 4: Although we find no effect of the cost-containment incentive on the attention levels, we find that the pupil diameter is greater when subjects simultaneously receive the containment incentive and the gift.

Table 2.9: CCI and gift's effects on pupil diameter from OLS coefficients (p-values).

A. Treatment effect				**B. Gift effect**			
	FFP vs. CCI		*Order*		*Part 1 vs. Part 2*		Early
Gift	Part 1	Part 2	*effect*		No early gift	Yes early gift	exposure
No	0.5769	0.3673	0.0363	*FFP*	0.0701	0.3730	0.0827
Yes	0.1114	0.7246	0.2418	*CCI*	0.0081	0.2579	0.5142

p-values correspond to the Wald test of equality of coefficients. For example, p-value= 0.5769 comes to compare if the coefficient for the subgroup FFP without a gift in Part 1 is equal to the one for CCI without a gift in Part 1. FFP stands for the fixed fee per patient, and CCI is the cost-containment incentive. *Order effect* compares Order 1 vs. Order 2 with or without gift.

We observe within-subject differences for participants receiving the gift in both FFP and CCI treatments when exposed to the gift in the second part of the experiment (see B. in Table 2.9). In these cases, the pupil diameter reduces when the subjects face the gift compared to when they did not face it. These results also differ from the non-parametric analysis, in which we observe no difference in the attention levels. Finally, we have weak evidence that early exposure affects the attention levels measured as pupil diameter (Wald test p-value of 0.0953). In particular, early exposure affects subjects in the FFP treatment to a greater extent (see Table 2.9).

Result 5: The presence of the gift negatively affects attention levels. The timing of the exposure to the gift also affects the pupil diameter measures. In particular, early exposure to the gift reduces visual attention levels.

2.5 Conclusions

This paper investigates the effect of two different incentives on prescription decisions and physician's attention levels. We conducted an experiment where medical students faced six hypothetical patients organized in two blocks of three patients. The subjects prescribed one of two versions of the same molecule for each patient while using an eye-tracker device to measure pupil diameter and visual fixations. We evaluate the effect of a containment incentive to prescribe the generic drug in the presence of a transfer to promote the brand drug prescription. A critical difference between the containment

incentive and the transfer is that while the former requires the subjects to choose the generic, the second acts as a gift.

We find that there is no effect of the cost-containment incentive on the prescription or the attention levels. Still, we find more generic prescriptions and greater levels of attention measured as pupil diameter when the subjects receive the containment incentive and the gift simultaneously. Cognitive dissonance may lead subjects to pay more attention, and then they are aware of higher earnings if they prescribe more generic. Contrary to our hypothesis of similar prescriptions and attention levels in the presence of a gift compared to its absence, we find that the gift affects both generic prescriptions and attention levels. The early exposure to the gift affects the pupil diameter of the subjects but not the number of generic prescriptions.

Surprisingly, we find that the part of the experiment is relevant to explain our results. Subjects expend more attention during the first part of the experiment, and also, in this part, they prescribe more generic drugs. The fact that subjects no longer feel observed in the second part or even the level of fatigue at the end of the activity could drive these unexpected results. We perform additional analysis as robustness checks, and we find that our main findings concerning the effects of the containment incentive and the gift remain.

Further research will examine the data available for attention levels to answer other questions related to the choice process employed by the subjects during decision-making. In particular, we can consider the pupil fixations in its time dimension and study how much of the variability on the pupil diameter depends on certain variables such as the treatment or the gift. Also, we can investigate how subjects incorporate cost-effectiveness criteria to choose one type of drug.

Chapter 3

Physician's Allocation Preferences under Scarcity and Uncertainty

3.1 Introduction

The COVID-19 contingency has forced doctors worldwide to prioritize the intensive care units, indirectly choosing who lives or who dies. More recently, governments have had a requirement to define a schedule to administer an insufficient number of vaccines. This situation has unveiled a decision problem that was already present in other medical settings, such as the battlefield and rural doctors, general practitioners who act as gatekeepers of the health system, and emergency room physicians who have infrastructure limitations. In such a setting, the physician must decide on the sequential allocation of the limited resources in a context in which, when facing a patient, she is unaware of the needs of potential future beneficiaries of the same resource pool. We propose a lab experiment to understand if resource constraints and uncertainty (on potential beneficiaries' relative needs) affect resource allocation in a medical context. If so, how these conditions interact with physicians' types and patients' characteristics, and if they induce redistributing effects that determine which beneficiaries achieve higher levels of well-being.

We focus on a medical setting for several reasons. First, in this case, the scarcity principle is apparent for the decision-maker. Here, each medical service allocated to a patient necessarily makes it unavailable to other patients who may, or may not, have a greater need for it (Orentlicher, 1996). Additionally, physicians typically

have patient-regarding preferences (Arrow, 1963; Hennig-Schmidt and Wiesen, 2014), so that this context is helpful for understanding allocation decisions. Finally, this setting allows us to incorporate in the design potential heterogeneous beneficiaries concerning their initial health status, their capacity to benefit from additional medical services, their relative needs, and their maximum health benefit in a clear way for the experimental subjects. Still, these decision-making problems are not alien to other contexts. For example, altruistic or inequality-averse resource managers in a company, the public sector, or a university also have to sequentially decide how to distribute the department's budget during a given period.

Experimental health economics studying allocation decisions is extensive. From the seminal paper of Hennig-Schmidt et al. (2011), a series of works have emerged to answer the empirical question of how payment schemes affect physician's provision behavior (Brosig-Koch et al., 2013, 2016, 2017, 2019; Keser et al., 2014, 2020). In these studies, students in the lab face alternative incentives for medical service assignments in a context where there is no constraint.[1] Resource constraints also appear concurrently as a critical feature in the allocation decisions research. One branch of such literature examines the distribution principles that may drive these decisions when resources are limited (Ahlert et al., 2012; Ahlert and Funke, 2012; Ahlert et al., 2013; Ahlert and Schwettmann, 2017). These works share a similar setup that they implement with students (medical or others), using a medically or neutrally framed experiment. Other studies analyze the performance of different payment schemes under resource restrictions (Di Guida et al., 2019; Oxholm et al., 2019, 2021).

Harnessing the versatility of the experimental setup from Hennig-Schmidt et al. (2011) and Brock et al. (2016), some recent papers include uncertainty on the patient's health benefit (Martinsson and Persson, 2019; Hafner et al., 2017) or budget restrictions on the number of medical units to allocate to patients with known characteristics (Brendel et al., 2021). We contribute to this literature of resource restrictions and allocations decisions in two ways. First, we introduce uncertainty in the subject pool's characteristics in an environment with scarcity. We acknowledge uncertainty only in its risk dimension since physcians are unaware of the relative needs of future beneficiaries of the scarce resources. We argue that physicians accurately estimate the probability

[1]Other studies with payment schemes in a setting without constraint but using a different experimental design are Green (2014), Bejarano et al. (2017), and Lagarde and Blaauw (2017).

distribution of the patients' health status since they are aware of the epidemiological prevalence and incidence of diseases. Thus, we are not interested in ambiguity. Second, different from Brendel et al. (2021), we assume that physicians have incentives to assign medical services to patients.

In our experimental design, all participants decide as physicians on the number of medical service units to allocate to seven different patient profiles. For each profile, it is possible to identify the efficiency of the allocations since the optimal provision is known. We randomly assign university students connected virtually to the sessions to three alternative treatments. In the Budget Constraint (BC) treatment, subjects face a restriction on the total number of medical service units they can allocate to a group of three patients. In the Uncertainty (U) treatment, we include uncertainty on the profile of the last patient of the group. In the Budget Constraint and Uncertainty (BC+U) treatment, subjects simultaneously face uncertainty and resource restrictions. Subjects participate in a control treatment without constraints or uncertainty before the treatment round. The randomization takes place at the session level. Our setup follows the basic features of Hennig-Schmidt et al. (2011) and incorporates elements from Brosig-Koch et al. (2016) and Martinsson and Persson (2019).

To answer if resource constraints and uncertainty affect physicians' behavior, our outcome variables are the allocation decisions, the percent deviation from the patient's optimal level, and the effect on patient's health benefits. Then, we study how constraints and uncertainty change the within-group prioritization of patients. We understand this prioritization as a redistribution of resources and evaluate how patients' characteristics and physicians' types interact with our treatments to answer which patients achieve better outcomes from this redistribution process.

We find that when there are no resource constraints or uncertainty, the incentives to treat translate into over-provision of resources to all patient profiles. On the contrary, when subjects face budget constraints (with or without uncertainty), there is under-provision. Interestingly, in absolute terms, the under-provision is smaller than the over-provision, which means that patients are more distant from their optimal allocation when they are over-provided. We also find that a combination of budget constraint and uncertainty increases patient's benefits between parts compared to when physicians are under uncertainty alone. In addition, these conditions induce within-

group redistribution that benefits patients with better initial health conditions, greater capacity to benefit from additional medical services, lower optimal needs, and those whose potential maximum benefit is the smallest among all.

Finally, in the presence of constraints with or without uncertainty, only selfish physicians, as categorized using the prioritization criteria, change their behavior, turning into higher benefits for patients. This finding is of particular interest because it justifies budget constraints when there are incentives to over-treat in an uncertain environment. As a result, using constraints as an expense-containment strategy, when physicians are unaware of future patients' relative needs, generally improves patient outcomes, compared to when there are no restrictions.

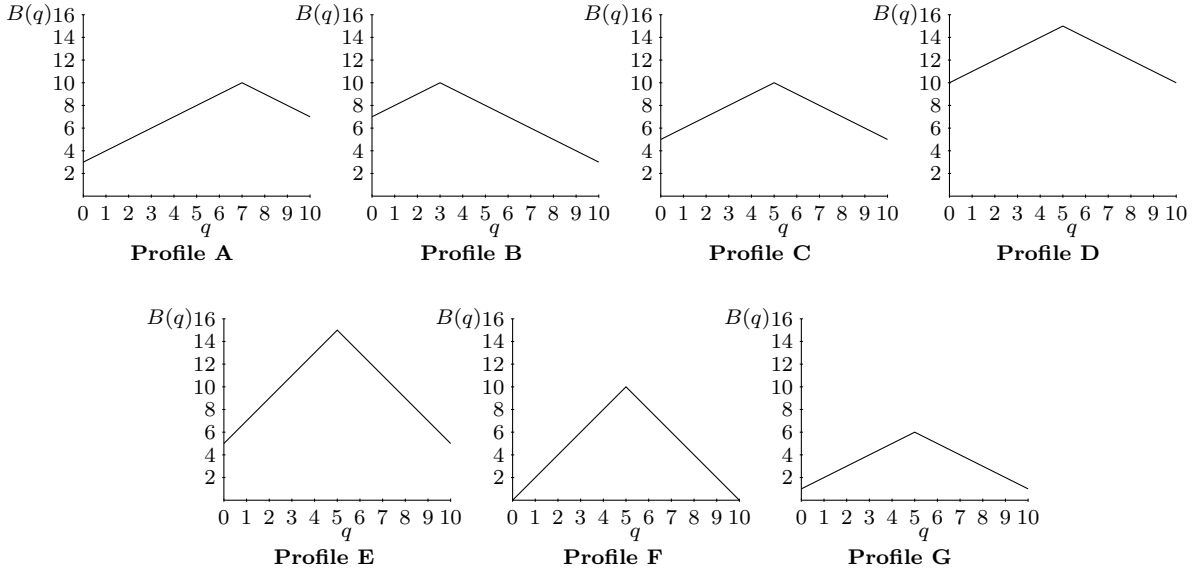
3.2 Experimental design and procedures

3.2.1 Experimental design

Participants decide as physicians on the number of medical service units $q \in [0, 10]$ to provide to seven patient profiles (A to F). The number of service units defines each patient's profile health benefits $B(q)$ (see Figure 3.1). If, for example, a patient with profile A receives five units of medical services from a physician, she will procure a health benefit of 8 Experimental Currency Units -EMUs-.[2] We use the terms patient and profile interchangeably from here onward. The seven profiles differ in four dimensions (see Figure 3.1): the optimal amount of medical services $\hat{q}$ in the x-axis (either 3, 5, or 7), that maximizes $B(q)$ in the y-axis (either 6, 10, or 15), the capacity to benefit from each additional unit of service (marginal benefit of either 1 or 2), and patient's initial health status in the absence of medical care (either 0, 1, 3, 5, 7, or 10). Note that the benefit function is symmetric around the optimum (Ellis and McGuire, 1986). Since the optimal amount of provision is known, it is a reference point to define under-provision and over-provision of the services (efficiency of the allocation decisions).

[2]EMUs are converted into COP at a rate of 1:0.8.

Figure 3.1: Profiles of patient health benefits (EMUs)



These figures depict patients' health benefits in EMUs (on the y-axis) over the number of medical service units (on the x-axis). Profiles A, B, and C come from Brosig-Koch et al. (2016), and E from Martinsson and Persson (2019). We introduce three additional patient profiles: D, F, and G.

The physician faces a trade-off when she decides on the units to allocate to the patient between her profit $\Pi(q)$ and the patient's health benefit.[3] The physician's profit depends positively on her revenue ($R(q)$) and negatively on the cost ($c(q)$) (see Table 3.1). We argue that physicians have conflicting incentives as they aspire to signal ability to patients, families, and others by allocating resources (positive revenue) while also facing pressures to ration these resources from employers, colleagues, government, or insurers (cost) (Dusheiko et al., 2006; Brock et al., 2016; Godager et al., 2016). Both the payment and the cost increase on the number of medical services assigned.

[3]This idea was first introduced by Ellis and McGuire (1986), where they define a cost-sharing model in which physicians decide on the level of services and consider both the patient's benefit and the hospital profits. Choné and Ma (2011) propose an adaptation of the model in which the physician optimizes a utility function that depends on both her profit and the patient's health benefit. We follow the latter approach.

Table 3.1: The physician's profits, revenues and costs by number of medical services allocated (EMUs).

	Number of medical services (q)										
	0	1	2	3	4	5	6	7	8	9	10
$R(q)$	0	2	4	6	8	10	12	14	16	18	20
$c(q)$	0	0,1	0,4	0,9	1,6	2,5	3,6	4,9	6,4	8,1	10
$\Pi(q)$	0	1.9	3.6	5.1	6.4	7.5	8.4	9.1	9.6	9.9	10

The physician's profit is $\Pi(q) = R(q) - c(q)$. $R(q) = pq$ is the payment, where p is a fee per service (assumed as 2 following Brosig-Koch et al. (2016)). The cost $c(q) = \beta q^2$, with $\beta = 0.1$ following Hennig-Schmidt et al. (2011).

Our experiment has two parts. In Part 1, we arrange the seven profiles into three groups of three patients.[4] Here, subjects have 30 units of medical services available to allocate to the three patients of each group (control condition). At the top of the screen, participants can observe the 30 units they have available for allocating to the group's three patients (see Figure C.1, in the Appendix). This means that a physician can potentially obtain her maximum profit level for every patient, and that the optimal number of medical services is always achievable. The information on group composition and order of the patients is complete, and decisions are sequential. It is important to note that once they make an allocation decision, the previously allocated services get discounted from the medical services' total budget.

In Part 2, we include two possible conditions: budget constraint and uncertainty. Budget constraint in our setting means that the physician has only ten (and not 30) medical service units to distribute to each group of three patients.[5] We decided on the ten-unit benchmark for two main reasons. First, we need a constraint that separates

[4]We have two alternative configurations: ABD, DGC, FEG, or ABC, DGF, FED. Note that the profiles do not repeat within a group but can appear in more than one group. This means that a physician who faces the first configuration initially sees profiles A, B, and D. Alternatively, a physician who faces the second configuration meets a third group consisting of patients F, E, and D. We randomly assign the configurations at the individual level and change profiles' labels to avoid subjects' recollection of the group configurations: participants observe labels F instead of A and vice versa and C instead of E and vice versa.

[5]As before, subjects observe one of the two alternative configurations. This means that subjects

selfish physicians from those with an equal split rule.[6] Second, we want to make the constraint salient so that the physician cannot allocate all three patients with their optimal, and, as a result, it requires her to make distributional decisions. Uncertainty means that each physician will encounter three groups with four (instead of three) patients each. A physician under uncertainty has complete certainty over the first two patients and is aware of the order in which they will arrive. However, the third and last patient is of one of two profiles with a 50% probability.[7] We include uncertainty on the third patient, instead of the pool of patients, as we are interested in the medical decision to the current patient, with known characteristics, when the prospective patients' features are unknown. Furthermore, we focus on the risk dimension of uncertainty as we argue that physicians have a prior on the epidemiological distribution of the patients they will face, limiting ambiguity.[8]

In this part, we randomly assign participants to one of three treatments that use one or two of the described conditions: Budget Constraint -BC-, Uncertainty -U-,[9] and Budget Constraint and Uncertainty -BC+U- (see Table 3.2). In BC, subjects have complete information to allocate ten service units to the three patients of each group (see Figure C.3, in the Appendix). In U and BC+U, subjects must decide allocations to patients in an uncertain environment. The critical difference between U and BC+U is the number of medical service units available for allocation. Subjects in treatment U have 30 medical service units to allocate to the three patients of each group. Subjects in the BC+U treatment have ten medical service units to distribute within each group (see Figures C.4 and C.5, in the Appendix). As in Part 1, we discount the units allocated from the total budget after each decision. In the BC and BC+U treatments,

who faced ABD, DGC, FEG, in Part 1, can either face ABD, DGC, FEG, or ABC, DGF, FED in Part 2, resulting in 4 types of subjects (depending on the combination of both configurations in both parts of the experiment) (see Table C.1, in the Appendix).

[6]This principle rules out all multiples of three as a selfish physician would maximize her profit when she equally splits treatment units.

[7]All physicians have information that the first group of patients will be AB C/D. This means that patient A will arrive first, and B will arrive second; however, the third and last patient can be C or D with a 50% probability. The same follows for groups 2 (DG C/F) and 3 (FE G/D) (see Table C.1, in the Appendix).

[8]In this context, two patients are enough for studying the allocation decisions under risk. However, as we are also interested in the distributional principles that arise in the presence of a restriction, we require to have at least three patients.

[9]We include this treatment to ensure completeness in our design and to be able to separate the effects of resource restriction and uncertainty in situations such as those that motivate us.

this limits the number of units they can distribute to future patients.

Table 3.2: Treatments.

	Constraint	
	Not binding	Binding
No uncertainty	Control	BC
Uncertainty	U	BC+U

All subjects play Part 1. In Part 2 they are randomly allocated (at the session level) to one of three treatments: Budget Constraint -BC-, Uncertainty -U-, and Budget Constraint and Uncertainty -BC+U-.

The computer randomly selects one group from Part 1 and one group from Part 2 to determine participants' earnings. Although all subjects decide as physicians, we randomly match participants with three other subjects connected to the same session for payment purposes (payment-group). The composition of the payment-group is entirely anonymous for everyone. We randomly assign group members to a role: Physician, Patient 1, Patient 2, or Patient 3. The decisions of participants in the role of physician will determine the payments for all group members.[10] Subjects in a physician's role obtain the monetary equivalent of the sum of the profits corresponding to her allocation to the three patients of her group. Subjects in each patient's role receive the monetary equivalent of the health benefit that matches her group's physician decision.

[10]With this design feature, we depart from what is standard in the literature that uses similar designs. Typically, subjects in the physician's role decide how much to allocate to potential patients, and these allocation decisions become transfers to medical-related institutions or charities. Since we are interested in understanding distributional decisions, having a single final beneficiary does not make sense in our context. An alternative can be to select several potential recipients. However, in this case, subjects' preferences for a particular recipient can distort her distributional decisions.

3.2.2 Experimental procedures

We carried out nine sessions of the online experiments (3 per treatment) with students from Universidad del Rosario between June 26 and July 14 of 2020, during a mandatory lockdown from the national government. We invited participants to an activity that could last for 2 hours, including an identity check-up, and asked them to be available 5 minutes before the beginning of the session. The experiments were programmed in z-Tree (Fischbacher, 2007) and conducted using z-Tree unleashed (Duch et al., 2020). We used the Online Recruitment System for Economic Experiments (ORSEE) (Greiner et al., 2004) from Rosario Experimental and Behavioral Economics Lab (REBEL) to recruit the subjects and the Zoom platform for the experimental sessions. We admitted participants to the session from a waiting room one by one. Once in the session, we changed their screen name for an id they used for all the following experimental procedures. We randomly selected four subjects from each session for identity verification; for this, we used Zoom's private rooms. Only in one case, we could not verify the subject's identity; we excluded this participant from the experiment before the beginning of the session and replaced her with another subject.

At the beginning of each session, we read aloud both the general and Part 1's instructions to all the participants via Zoom. The remaining instructions were available on the experimental screens. The chat was open for questions throughout the session.[11] Before the decision round, we presented participants with the group of patients they were to face (Group Screen). We detailed the health benefit for each patient in the group and at every medical service level (see Figures C.1 and C.3, in the Appendix). Participants decided at their own pace when to begin with the decision rounds. Once they moved from the Group Screen, they faced each patient's screen. A Patient Screen included information on physician's profits and on that particular patient's benefits at every medical service level (see Figure C.2, in the Appendix). At this point, subjects had to decide on the number of medical services to allocate to the current patient. Once they chose, they could continue selecting the allocation for the group's second

[11] We included pop-up windows to verify that the participants were paying attention; the attention checker emerged after five minutes of inactivity in two randomly allocated screens. Once this pop-up window came up, the subject had to confirm she was still connected. If she did not validate her active status, her session concluded. We detailed this procedure in the general instructions and lost two participants for this reason (less than 2%).

patient and then for the group's third patient.[12] This procedure is the same in both parts and for all treatments.

Once subjects finished the decision rounds in a physician's role, which produced our variables of interest, we collected additional information on preferences for risk, prudence,[13] and altruism.[14] The activities for collecting this information also represented monetary payoffs for our subjects. Last, participants answered an unincentivized socioeconomic questionnaire.

The participants spent an average of 105 minutes in the activity and received an average payment of COP 37.000 (about $10). They received feedback on roles assigned and earnings at the end of the experiment. The feedback screen only appeared once all subjects in a session concluded their participation. We included a final survey in Google forms where participants provided the bank account for receiving their earnings from the activity. We followed the experimental procedures in Zhao et al. (2020).

3.3 Hypotheses

Next, we consider the hypotheses that we test in our results. We focus on whether budget constraints and uncertainty affect the allocation decisions of physicians and on how these decisions are made. An essential design feature is that the incentive structure favors over-provision when resources are abundant (see Table 3.1). Furthermore, we expect under-provision as a consequence of the constraint. Hence, we are particularly interested in evaluating the magnitudes of the misallocation of resources with and without constraint. It can be expected that when resources are scarce, participants will devote more attention to how these resources are distributed, which will reflect in more efficient allocations.

Hypothesis 1. The misallocation of resources decreases when subjects are constrained

[12] We included the possibility for subjects to revise the group screen before deciding each allocation.

[13] For this we use two certainty equivalence lotteries, one for risk preferences and one for prudence (Tarazona-Gomez, 2004) (see Figures C.6 and C.7, in the Appendix). In this case, we had a maximum of 5 ECUs for the risk task and of 4.75 ECUs for the prudence task.

[14] We elicit altruism through the Dictator Game. In our version of the game participants decide how much money from an endowment of 5 ECUs to allocate to an anonymous and randomly matched participant. Payments depend on the match and the randomly assigned role (dictator or receiver).

with or without uncertainty.

The higher efficiency in the allocations under scarcity, will also allow patients to be closer to their maximum achievable benefit, such that,

Hypothesis 2. Patients' health benefit is greater when physicians face a budget constraint than when they do not face resources restrictions.

On the other hand, we argue that uncertainty does not affect the incentive structure for physicians to provide medical services. As such, we should not observe changes in the benefits of patients nor on the efficiency of allocations whenever subjects have incomplete information on the composition of a group.

Hypothesis 3. Uncertainty does not affect allocation decisions compared to a setting with complete information.

Since our design also includes heterogeneous patients in several dimensions, we expect physicians to consider these characteristics for their allocation and distributional decisions. In particular, when resources are scarce, physicians, on average, should be likely to prioritize patients with a higher health improvement potential (think of COVID-19). However, it is not uncommon that physicians tend to patients in the worse initial status first, as with clinical triage, where time, facilities, and personnel are scarce. Last, patients with the lowest service needs are easy to prioritize even when resources are limited.

Hypothesis 4. Patients with a greater capacity to benefit from medical service units allocated, those with below-median initial health status, and with below-median optimal medical services needed see an improvement in their prioritization.

3.4 Results

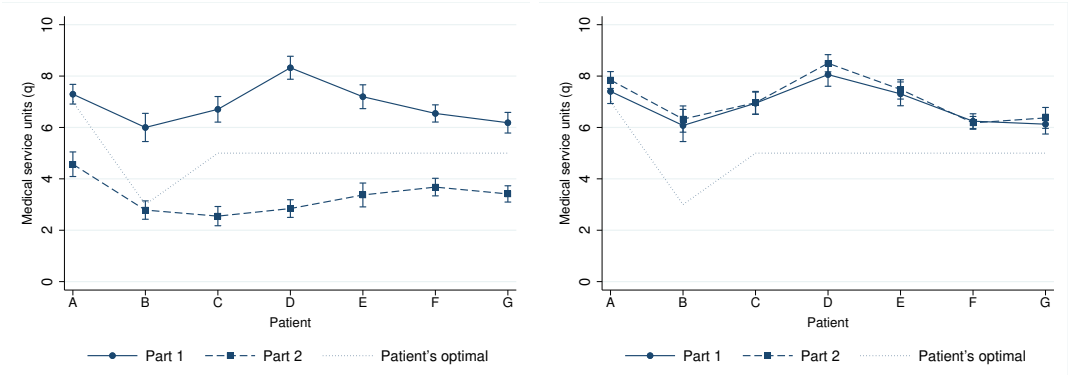
This section explores the decisions of 154 subjects in both parts of the experiment and by treatment.[15] We first answer if budget constraints and uncertainty affect the allocation decisions of physicians. Then we move to explore the mechanisms.

3.4.1 Do budget constraints and uncertainty affect the allocation decisions of physicians?

We begin the analysis by plotting the average allocation to each profile by part (Figure 3.2). The solid lines represent the allocations in Part 1, while the dashed line shows Part 2. The dotted line outlines the optimal level for each patient. From the figure, we can assess that, in the absence of constraints and uncertainty in Part 1, subjects allocate more medical service units to patients than what is optimal (over-provision). This result is consistent for all profiles ($p < 0.01$ using t-tests) and compatible with the experiment's incentive structure. In Table 3.3 we present further information to support this evidence. This result is line with other results in the literature (see Hennig-Schmidt et al. (2011), Brosig-Koch et al. (2016), and Brosig-Koch et al. (2017)).

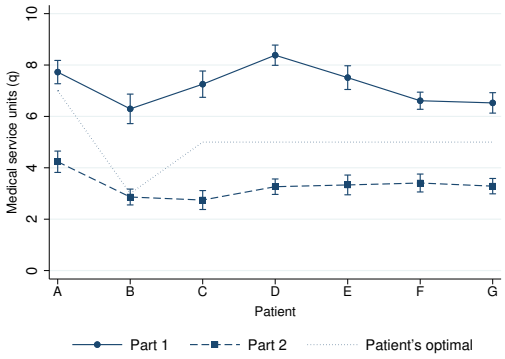
[15] Our groups are balanced in the socioeconomic characteristics within treatment (see C.2, in the Appendix). Moreover, we find no statistically significant differences at the 5% level in the distribution of the allocation decisions in our three treatments in Part 1 of the experiment ($p = 0.035$), using the Kruskal-Wallis test of equality of populations. Also, BC $\cup$ U is statistically different from BC+U ($p < 0.01$).

Figure 3.2: Medical services allocated by profile.



(a) BC

(b) U



(c) BC+U

These figures present the average quantity allocated to each patient profile by part of the experiment (y-axis). Panel (a) includes information for subjects in the Budget Constraint treatment; Panel (b) does the same for the Uncertainty treatment; and Panel (c) for Budget Constraint and Uncertainty. Solid lines relate to Part 1. Dashed lines correspond to Part 2. Dotted lines represent the $\hat{q}$ for each patient profile. Confidence intervals at the 95% using t-tests (x-axis).

Table 3.3: Medical services allocated, percentage deviation from patient's optimal level, and patient health benefits.

	BC			**U**			**BC+U**		
	Part 1	Part 2	$Part1 = Part2$	Part 1	Part 2	$Part1 = Part2$	Part 1	Part 2	$Part1 = Part2$
	(mean)		p-value	(mean)		p-value	(mean)		p-value
q	6.99	3.29	< 0.01	6.93	7.16	0.011	7.25	3.31	< 0.01
$\frac{q-\hat{q}}{\hat{q}}\%$	44.13	-32.98	< 0.01	42.98	47.60	0.018	49.43	-32.35	< 0.01
$B(q)$	8.26	8.58	0.236	8.41	8.34	0.412	8.07	8.64	0.013

Mean of units allocated, percentage deviation from units allocated to patients' optimal level, and patient's benefit by treatment and Part. BC stands for Budget Constraint, U for Uncertainty, and BC+U to Budget Constraint and Uncertainty treatments. P-values calculated from Wilcoxon matched-pairs signed-rank test.

Result 1: When information is complete and resources are abundant, there is over-provision to all patients' profiles.

The over-provision from Part 1 shifts to under-provision in Part 2 for subjects who face a budget constraint, but not to those facing only uncertainty (see Figure 3.1 and row 2 of Table 3.3). We perform a within-subjects analysis using a Wilcoxon matched-pairs sign-rank test. For BC and BC+U, we find that the number of units allocated to patients differs in both parts and is higher for Part 1 than for Part 2. This result is not surprising as the constraint forces downward subject decisions on how much they can allocate to patients.[16] Interestingly, in BC and BC+U, the average over- provision exhibited in part 1 is larger than the under-provision observed in part 2 ($p < 0.01$). For U, unlike expected, we find that the average medical service units assigned to patients is higher in Part 2 (at the 5% significance level). The same is true when we test the allocation from the patient's optimal level (see Table 3.3).

Table 3.4 presents additional evidence for these results. Here, we include OLS estimations for a within-subject analysis (difference in our outcome variables between parts). Columns (1), (3), and (5) include all patients for which a physician makes an allocation decision. Columns (2), (4), and (6) exclude the third patients of each group. This exclusion guarantees that we only consider patients common to all physicians and treatments.[17] Controls include the patient's profile, subjects' age, gender, econ or finance major, socioeconomic strata, if parents are medical professionals, and if they

[16] 94.4% of medical decisions in BC and BC+U exactly exhaust the entire budget.

[17] We also tried specifications only excluding decisions to third patients in U and BC+U, and patients in BC when physicians had configurations 3 and 4 (see Table C.1, in the Appendix). We do not report these specifications as results are similar to those in columns (1), (3), and (5).

made mistakes in control questions. Our excluded category is U. We observe that considering each physician as her control, she allocates around 4 fewer units when she faces budget constraints, with or without uncertainty than those facing uncertainty alone. This result is almost mechanical. However, the relative allocation to the patient's optimum reduces whenever physicians face a constraint, while for those in U, it increases. Introducing constraints is generally managing to reduce the inefficiency of allocations. We find comparable results when we estimate the Average Treatment Effects (results upon request).

Table 3.4: Within-subjects analysis.

	$q_2 - q_1$		$\frac{q_2-\hat{q}}{\hat{q}}$ % - $\frac{q_1-\hat{q}}{\hat{q}}$ %		$B(q_2) - B(q_1)$	
	All	First two	All	First two	All	First two
	(1)	(2)	(3)	(4)	(5)	(6)
BC	-3.873***	-3.392***	-80.06***	-71.73***	0.332	0.395*
	(0.198)	(0.200)	(4.185)	(4.344)	(0.210)	(0.212)
BC+U	-4.226***	-3.931***	-87.64***	-83.29***	0.597**	0.769***
	(0.213)	(0.220)	(4.633)	(4.930)	(0.243)	(0.261)
Prudence	-0.159	-0.295	-1.866	-3.925	0.402**	0.155
	(0.185)	(0.190)	(3.997)	(4.236)	(0.199)	(0.210)
Altruism	0.290**	0.279**	7.214***	7.694***	-0.380***	-0.403***
	(0.112)	(0.107)	(2.378)	(2.350)	(0.119)	(0.117)
Risk aversion	-0.286	-0.185	-6.069	-4.217	0.769***	0.751***
	(0.238)	(0.255)	(5.028)	(5.559)	(0.281)	(0.286)
Constant	1.158	1.413	37.89*	44.65**	-2.059*	-1.820
	(0.984)	(1.022)	(20.77)	(22.17)	(1.065)	(1.150)
Observations	1,215	810	1,215	810	1,215	810
Clusters	135	135	135	135	135	135
BC=BC+U (p-value)	0.142	<0.05	0.139	<0.05	0.291	0.168

OLS regressions. Dependent variables: within number of units allocated, percentage deviation from patient's optimal level, and patient's benefit. BC: Budget Constraint; BC+U: Budget Constraint and Uncertainty; U: Uncertainty (reference category). Columns (1), (3), and (5) presents regressions for all patients and (2), (4), and (6) for the first two patients of each patient's group. The variable Altruism corresponds to the amount sent to the other player in a Dictator Game. Controls (all regressions): age, female, econ or finance students, strata, if parents are medical professionals, mistakes in control questions, and dummies for each patient profile. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Result 2: Budget restrictions, with or without uncertainty, reduce allocation to all patient profiles and cause under-provision. Notably, this under-provision is smaller

(in absolute terms) than the over-provision in the control condition and than under uncertainty.

Regarding the patient's health benefit (row 3 of Table 3.3), we observe that, on average, patients in BC+U receive allocations that lead to higher benefits in Part 2 than in Part 1 even when they receive fewer medical service units. Furthermore, in Table 3.4 we see that the first two patients in a group marginally receive higher benefits in Part 2 when treated by constrained physicians, instead of physicians in U. Interestingly, all patients receive higher benefits if physicians decide under uncertainty on top of constraints. The benefits are even higher when we only consider the first two patients in a group. A remarkable finding is that patient's benefits are higher for risk averse physicians in U. These results indicate that constraints generally lead to better conditions to patients when there are incentives to over-provide medical services.

Result 3: The benefits of patients increase between parts whenever physicians face constraints, with or without uncertainty, compared to those facing uncertainty only. On top of constraints, uncertainty favors all patients in the group in terms of relatively increasing their benefits.

3.4.2 How does this happen?

To study how uncertainty and constraints affect behavior, we perform a within-subject analysis that accounts for patient's characteristics and physician's prioritization criteria. We calculate a variable that ranks the position of each patient within a group according to the number of medical service units assigned, the percentage-wise absolute deviation from the optimal level,[18] and the patient's benefit.[19] The between-parts difference of these ranking variables reflect the redistributive effects of treatments in our outcomes variables, as they allow us to account for how the physician prioritizes among patients in a group. Then, our dependent variables are a discrete result of subtracting the rank

[18]We use the absolute deviation and not the percentage deviation we have been using up to this point. This is because we are interested in highlighting improvements in the distance to the patient's optimum, regardless of whether they are under or over-provided. For example, suppose that in the same group, profile A is under-provided by 3 units (-3), B is under-provided by 6 units (-6), and C is over-provided by 5 units (+5). Here, an ascendant ranking will assign a higher position to C than to B and to A than to B. However, A is closer to her optimum than both B and C. Using the absolute value, patient A achieves a better position than B and C in the ranking.

[19]Ties share the same position in the ranking.

in Part 1 from the rank in Part 2, leading to five ordinal categories. The lower category represents the case in which the patient at the top of the ranking in Part 1 drops to the bottom in Part 2. The higher category represents the opposite case.

Table 3.5 presents the results for the OLS regressions of the variables we described above for two different samples: decisions to all patients and decisions to the first two patients.[20] All regressions have our usual controls. The excluded category for the treatment variable is U. We include the four dimensions describing the health benefit functions of the seven patient profiles: initial health status (dummy of 1 when patients initial health benefit is above 5 UMEs, instead of less than 3), capacity to benefit from an additional medical service unit (dummy of 1 when the marginal benefit of an additional unit is 2 instead of 1), the number of medical services needed in the optimum (dummy of 1 when patients need 3 units of medical services for achieving their optimum, rather than 5 or 7), and the maximum benefit achievable (dummy of 1 when a patient's potential benefit at the optimum is above 10 UMEs, instead of 6). As can be seen, once we include patient's characteristics, those treated by physicians under constraint with or without uncertainty, improve their position in the ranking of allocations, but deteriorate in the deviation from the optimum compared to physicians in U. In the appendix, we present three separate analyses of patients' characteristics by treatment group (see Table C.3). The results are in line with our analysis of the ranking variables.

[20]The results are equivalent when we treat these variables as categories. Estimations using ordered logit are available upon request.

Table 3.5: How? Patient's characteristics (within-subjects analysis)

	Rank q_2 - Rank q_1		Rank $\left\lvert\frac{q_2-\hat{q}}{\hat{q}}\right\rvert$ % - Rank $\left\lvert\frac{q_1-\hat{q}}{\hat{q}}\right\rvert$ %		Rank $B(q_2)$-Rank $B(q_1)$	
	All patients	First two patients	All patients	First two patients	All patients	First two patients
	(1)	(2)	(3)	(4)	(5)	(6)
BC	0.273*	0.815***	-0.371***	-0.388***	0.000779	-0.00515
	(0.157)	(0.162)	(0.135)	(0.127)	(0.119)	(0.0577)
BC+U	0.171	0.380**	-0.350**	-0.341**	0.0481	0.0930
	(0.176)	(0.168)	(0.166)	(0.154)	(0.115)	(0.0644)
Initial Health ≥ 5	0.0377	0.0444	0.00794	0	-0.187**	-0.0889
	(0.122)	(0.139)	(0.103)	(0.130)	(0.0805)	(0.0756)
Initial Health $\geq 5 \times$ BC	-0.668***	-0.840***	0.798***	1.010***	0.502***	0.466***
	(0.205)	(0.222)	(0.174)	(0.200)	(0.124)	(0.125)
Initial Health $\geq 5 \times$ BC+U	-0.719***	-0.788***	1.214***	1.439***	0.739***	0.711***
	(0.212)	(0.228)	(0.147)	(0.185)	(0.127)	(0.128)
Capacity to benefit of 2	0.0512	0.0444	-0.0968	-0.0889	-0.0128	-0.111
	(0.125)	(0.138)	(0.105)	(0.110)	(0.124)	(0.150)
Capacity to benefit of $2 \times$ BC	0.355**	0.527**	0.331**	0.120	0.413**	0.448**
	(0.161)	(0.206)	(0.163)	(0.171)	(0.171)	(0.199)
Capacity to benefit of $2 \times$ BC+U	0.0695	0.138	0.704***	0.479***	0.510***	0.538***
	(0.170)	(0.207)	(0.148)	(0.158)	(0.169)	(0.195)
$\hat{q} = 3$	0.0295	0.0444	-0.0687	-0.0778	0.0690	-0.0778
	(0.134)	(0.169)	(0.103)	(0.144)	(0.0681)	(0.0771)
$\hat{q} = 3 \times$ BC	0.735***	0.792***	1.035***	0.726***	1.281***	1.389***
	(0.205)	(0.267)	(0.200)	(0.243)	(0.146)	(0.154)
$\hat{q} = 3 \times$ BC+U	0.708***	0.754**	1.324***	1.017***	1.305***	1.389***
	(0.246)	(0.327)	(0.198)	(0.256)	(0.135)	(0.131)
$B(\hat{q}) \geq 10$	-0.228*	-0.111	0.312***	0.189*	-0.168	0.122
	(0.134)	(0.164)	(0.102)	(0.114)	(0.112)	(0.0925)
$B(\hat{q}) \geq 10 \times$ BC	-0.132	-0.542*	-0.397**	-0.276	-0.636***	-0.709***
	(0.228)	(0.276)	(0.160)	(0.173)	(0.165)	(0.142)
$B(\hat{q}) \geq 10 \times$ BC+U	0.102	-0.0413	-0.799***	-0.689***	-0.873***	-0.958***
	(0.250)	(0.279)	(0.197)	(0.200)	(0.158)	(0.138)
Constant	0.120	0.251	-0.312	-0.199	0.350**	0.205
	(0.257)	(0.328)	(0.213)	(0.271)	(0.138)	(0.146)
Observations	1,215	810	1,215	810	1,215	810
Clusters	135	135	135	135	135	135
BC=BC+U (p-value)	0.580	0.0267	0.899	0.779	0.674	0.215

OLS regressions. Dependent variables: within group ranking of units allocated, percentage deviation from patient's optimal level, and patient's benefit. In columns tagged "First two patients" we excluded the third patient from each group for the regressions. U: Uncertainty; BC+U: Budget Constraint and Uncertainty; BC: Budget Constraint. Reference categories: U, initial health status below 3, capacity to benefit of 1, maximum achievable benefit of 6, and $\hat{q} > 3$. Controls (all regressions): age, female, econ or finance students, strata, if parents are medical professionals, mistakes in control questions, risk-aversion, prudence, altruism, and dummies for each patient profile. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Overall, physicians under uncertainty alone do not appear to be treating patients differently according to their characteristics, except for some minor exceptions.

Result 4: Physicians do not respond to patients' characteristics when facing uncertainty alone.

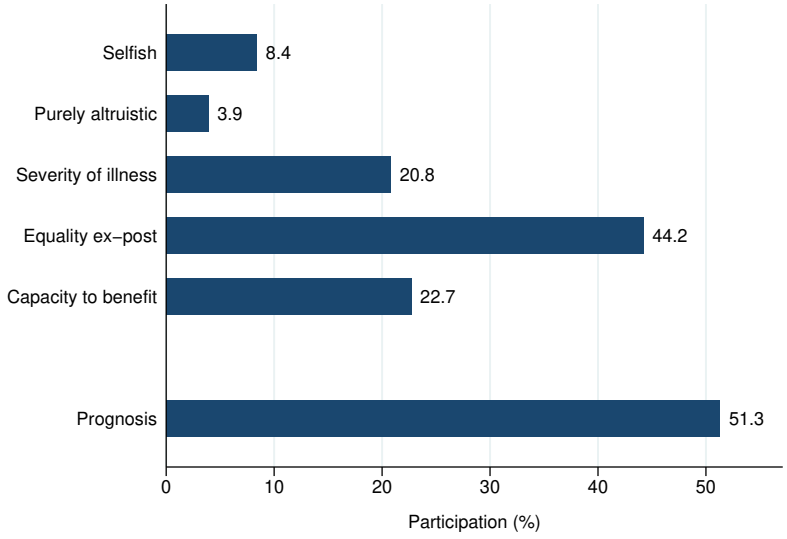
However, constrained physicians, with or without uncertainty, do redistribute resources. Physicians reallocate resources towards patients with a relatively better initial health status, a higher capacity to benefit, and the lowest needs when moving from the control treatment to a situation with budget constraints, with or without uncertainty. In all cases, uncertainty, on top of constraints, represents more significant gains for these patients. These effects are not in place for physicians that move from the control to an uncertainty-only situation. The allocation ranking only worsens for those with an initial health benefit above 5 UMEs. Last, constrained physicians who face patients whose maximum achievable benefit is $B(\hat{q}) \leq 6$ (lowest possible among all profiles) prioritize them in terms of benefit and deviation to the optimum.

Result 5: Constrained physicians improve the prioritization of patients in relatively better conditions in terms of initial health status, capacity to benefit, and optimal needs, and those whose maximum benefit is the relatively lowest. If physicians also face uncertainty, on top of constraints, these patients are even better.

Next, we present the results of estimates where we include a classification of the physicians according to which patient they prioritize. This classification follows Martinsson and Persson (2019). We compare the allocation decisions to patients C and E in Part 1 and determine that physicians are selfish when they allocate $q = 10$ to both and purely altruistic if $q = 5$ for both C and E. Next, we classify subjects as prioritizing under equality ex-post when they allocate service units closer to the optimum to patient C compared to patient E. In contrast, subjects that favor the capacity to benefit allocate service units closer to the maximum benefit of E instead of C. Last, physicians whose prioritization criterion is the patient's severity of illness allocate the same number of units to both patients, but at a different level from selfish or purely altruistic physicians. In Figure 3.3, we present the frequency of these prioritization principles in our sample. Different to Martinsson and Persson (2019),[21] most of our subjects (44% of the sample) follow an equality ex-post criterion when allocating with complete information and no constraints.

[21] Their sample is primarily classified as prioritizing under severity of illness and under capacity to benefit.

Figure 3.3: Distribution of physician types.



The figure presents the proportion of subjects (x-axis) classified in each principle of priority from Martinsson and Persson (2019) and prognosis (y-axis).

We formulate an additional principle referred to as prognosis (initial health status and maximum benefit achievable). When the allocation to profile D (E) is greater than the allocation to patient G (F), we categorize subjects as prioritizing according to the prognosis of patients. We classify physicians using this principle only for subjects whose behavior is consistent in D vs. G (capacity to benefit of 1) and E vs. F (capacity to benefit of 2). More than half of our subjects use the prognosis criterion, which means they over-provide more to patients with better prognoses.[22]

In Table 3.6 we present the OLS estimations for our variables of interest in Part 2 vs. Part 1: allocation, deviation from the optimum, and patient's health benefits. Once more, we include the two patient samples we are considering (all patients and the first two patients in each group). All columns have the usual controls, and the excluded

[22]This criterion implies that physicians with incentives to treat are over-providing more to patients whose benefit will not suffer as much from that over-provision. When resources are ample, that means that prognosis will lead to a more conscious choice of how much to over-provide to patients whose prognosis is relatively worse.

categories are U for the treatments and selfish for the priority setting principles.

From the results, it is clear that selfish physicians allocate fewer units between parts under constraint, with or without uncertainty than under uncertainty alone. Besides this seemingly mechanical result, the distance to the optimum also reduces in Part 2 concerning Part 1, and the patient's benefits increase. It is worth noting that changes in the between-parts allocations for all other physician types are not statistically different from those of selfish physicians in U. The same is true for the relative distance to the optimum and patient's benefits. These results mean that uncertainty alone does not appear to be affecting physician behavior, except for those classified as selfish. In addition, when we move to analyze the interactions between physician types and BC and BC+U, we confirm that patients tended by selfish constrained physicians see a reduction in the relative distance to the optimum and an increase in benefits, compared to all other types. These differences can be seen more clearly in Figure C.8 in the appendix. This is a direct result of these patients being forced to make broader adjustments in their decisions regarding the control condition from Part 1.

Result 6: Selfish physicians behave closer to the patients' interests whenever they are resource-constrained, compared to when they are under uncertainty alone. If physicians are not selfish, treatments do not affect their behavior significantly.

Table 3.6: How? Physician's type (within-subjects analysis)

	$q_2 - q_1$		$\frac{q_2-\hat{q}}{\hat{q}}$ % - $\frac{q_1-\hat{q}}{\hat{q}}$ %		$B(q_2) - B(q_1)$	
	All	First two	All	First two	All	First two
	(1)	(2)	(3)	(4)	(5)	(6)
BC	-6.338***	-6.056***	-133.8***	-131.7***	3.286***	3.775***
	(0.392)	(0.363)	(8.160)	(7.724)	(0.593)	(0.465)
BC+U	-6.044***	-5.945***	-129.3***	-131.5***	2.869***	3.064***
	(0.451)	(0.464)	(9.589)	(9.620)	(0.595)	(0.509)
Priority concern:						
Purely altruistic	-0.188	-0.0831	-7.606	-7.419	-0.563	-1.106
	(0.536)	(0.599)	(11.44)	(13.22)	(0.699)	(0.721)
Purely altruistic × BC	4.491***	3.960***	96.21***	88.78***	-4.560***	-4.719***
	(0.553)	(0.685)	(11.87)	(14.99)	(0.784)	(0.791)
Purely altruistic × BC+U	4.096***	3.603***	93.64***	89.65***	-3.792***	-3.538***
	(0.649)	(0.763)	(13.79)	(16.20)	(0.829)	(0.852)
Severity of illness	0.231	0.139	2.839	0.113	-0.231	-0.389
	(0.438)	(0.391)	(9.146)	(8.286)	(0.516)	(0.453)
Severity of illness × BC	2.511***	2.576***	54.40***	57.78***	-2.837***	-3.260***
	(0.563)	(0.516)	(11.75)	(10.88)	(0.738)	(0.630)
Severity of illness × BC+U	1.358**	1.396**	30.99***	33.68***	-2.150***	-2.129***
	(0.547)	(0.562)	(11.53)	(11.48)	(0.724)	(0.694)
Equality ex-post	0.449	0.253	8.502	4.334	-0.209	-0.135
	(0.474)	(0.439)	(10.10)	(9.873)	(0.538)	(0.483)
Equality ex-post × BC	2.746***	2.875***	59.25***	64.00***	-3.315***	-3.911***
	(0.615)	(0.607)	(12.89)	(13.21)	(0.745)	(0.631)
Equality ex-post × BC+U	1.478**	1.532**	33.26**	36.18***	-1.878**	-1.832**
	(0.618)	(0.654)	(13.10)	(13.80)	(0.750)	(0.724)
Capacity to benefit	0.117	-0.0321	1.630	-1.716	-0.419	-0.609
	(0.452)	(0.414)	(9.660)	(9.137)	(0.540)	(0.507)
Capacity to benefit × BC	1.589**	2.266***	31.84**	45.43***	-1.964**	-2.567***
	(0.620)	(0.533)	(12.85)	(12.18)	(0.792)	(0.674)
Capacity to benefit × BC+U	1.274**	1.811***	27.85**	39.80***	-1.818***	-1.617***
	(0.554)	(0.609)	(11.70)	(12.51)	(0.653)	(0.604)
Overall prognosis	-0.368	-0.301	-8.273	-7.385	0.133	-0.00326
	(0.299)	(0.329)	(6.731)	(7.734)	(0.307)	(0.280)
Overall prognosis × BC	0.00876	0.0405	1.995	3.543	-0.110	0.0599
	(0.460)	(0.489)	(9.964)	(11.05)	(0.460)	(0.424)
Overall prognosis × BC+U	0.908**	0.968*	21.89**	24.95**	-0.853	-0.980*
	(0.443)	(0.489)	(9.442)	(10.59)	(0.524)	(0.513)
Constant	1.650*	1.969**	51.32***	61.15***	-2.591**	-2.227**
	(0.917)	(0.965)	(19.10)	(20.49)	(1.033)	(1.016)
Observations	1,215	810	1,215	810	1,215	810
Clusters	135	135	135	135	135	135
BC=BC+U (p-value)	0.345	0.784	0.478	0.975	0.446	0.0756

OLS regressions. Dependent variables: within number of units allocated, percentage deviation from patient's optimal level, and patient's benefit. In columns tagged "All" we include all patients; in columns tagged "First two" we excluded the third patient from each group for the regressions. U: Uncertainty; BC+U: Budget Constraint and Uncertainty; BC: Budget Constraint. Reference categories: U and selfish, for physicians type. Controls: age, female, econ or finance students, strata, if parents are medical professionals, mistakes in control questions, risk-aversion, prudence, altruism, and dummies for each patient profile. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

3.5 Discussion and conclusions

We propose a decision-making experiment in which subjects decide as physicians on the sequential allocation of resources. We evaluate if and how constraints and uncertainty on the relative need of patients affect behavior. We find that when physicians do not face any constraint or uncertainty, they allocate around 7.06 medical services to patients. Hennig-Schmidt et al. (2011), Brosig-Koch et al. (2016), and Brosig-Koch et al. (2017) found an overprovision equal to 6.6, 6.91, and 7.11 respectively, when they have similar incentives to ours. It appears that the design features we introduce, namely grouping patients by three and making salient the resources available for allocating to each group, do not affect average behavior in the lab. Once we include resource restrictions, we find that, with or without uncertainty, the over-provision previously observed becomes an under-provision for most patient profiles. In contrast, when physicians have incomplete information on the characteristics of the patients from the group but are not constrained, over-provision increases on average. Although some of these results can be considered somewhat mechanical, we find that the efficiency loss for the under-provision is smaller than for the over-provision and that patients can achieve relatively higher health benefits. Hence, we argue that when physicians have incentives to treat and are in the very probable scenario of not having complete information on the characteristics of the patients, there are gains in efficiency and health from the resource restrictions. We add to the existing literature, which centers on studying how financial incentives can help with a more efficient service provision (Hennig-Schmidt et al. (2011); Brosig-Koch et al. (2016, 2017), and others).

Furthermore, patients' characteristics interact with constraints and uncertainty, influencing physicians' behavior and forcing a within-group redistribution. In these situations, physicians reallocate in terms of efficiency and benefits towards patients in a relatively better situation. Patients whose benefit in the absence of medical services is relatively higher, those with twice the marginal benefit from an additional unit and who need the least number of services to be at their optimum, receive more efficient allocations and have higher benefits. The distributional decisions of physicians indicate that under these circumstances, resources and care are destined towards those who can achieve more with less and have the highest improving potential. Although constraints originate these results, the inclusion of uncertainty magnifies them.

A final result comes from the physician's type. After determining physicians' priority setting principles under resource abundance and complete information, we observe that selfish physicians come closer to the patient's optimum and favor higher health benefits only when introducing constraints.

Overall, budget constraints in a medical decision-making setting improve patients' outcomes whenever physicians have incentives to over-treat. In addition, physicians respond to patient's characteristics and reallocate towards patients that can achieve better outcomes with scarce resources. Interestingly, in the more realistic case of uncertainty, in addition to constraints, the better outcomes intensify. Last, the restrictions will only affect the decisions of selfish physicians. As a result, introducing restrictions on the number of services available when there are incentives to over-provide, and when this over-provision is harmful to patients, will generally improve patients' conditions and only affect physicians with no patient-regarding preferences.

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Appendices

Appendix A

Chapter 1

Proof of Lemma 1

If the physician prescribes d_t, the expected utility is $\mathbb{EU}(e, d_t)$ in equation (1.3) and if the physician prescribes d_0, the expected utility is $\mathbb{EU}(b, e, d_0)$ in equation (1.4). By comparing equations (1.3) and (1.4), the physician prescribes d_0 if $\mathbb{EU}(b, e, d_0) \geq \mathbb{EU}(e, d_t)$. Hence, $t \leq \frac{b(1+\alpha+\beta e)}{2}$. Let $\tilde{t} = \frac{b(1+\alpha+\beta e)}{2}$ for any $e \in [0, 1]$. If we use a tie-breaking rule $t = \tilde{t}$, then we have that the physician prescribes the generic drug if $t \leq \tilde{t} = \frac{b(1+\alpha+\beta e)}{2}$. □

Proof of Lemma 2

To obtain the optimal effort level when the physician prescribes d_t, we maximize the expected utility in equation (1.3) with respect to e:

$$\max_e \mathbb{EU}(e, d_t) = m + t - \frac{ke^2}{2}$$
$$\text{such that } e \in [0, 1].$$

Then, $\frac{\partial \mathbb{EU}(e,d_t)}{\partial e} = 0$ implies $e^* = 0$.
To obtain the optimal effort level when the physician prescribes d_0, we maximize the expected utility in equation (1.4) with respect to e:

$$\max_e \mathbb{EU}(b, e, d_0) = \frac{1}{2}\left[(1 + \alpha + \beta e)(m + b) + (1 - \alpha - \beta e)m\right] - \frac{ke^2}{2}$$
$$\text{such that } e \in [0, 1].$$

Then, $\frac{\partial \mathbb{EU}(b,e,d_0|h)}{\partial e} = 0$ implies $e^* = \frac{\beta b}{2k}$. As $\beta \in (0,1)$, $b \geq 0$, and $k > 0$, then $e^* = \frac{\beta b}{2k} > 0$.
Since $e \in [0,1]$, the optimal effort level when the physician prescribes d_0, has to be the minimum between $\frac{\beta b}{2k}$ and 1. Hence, $e^* = min\left\{\frac{\beta b}{2k}, 1\right\}$. □

Proof of Proposition 1

If PS's contract induces the strategy Aed_0, then the problem is:

$$\min_{b,e,d} \mathbb{EC}(b,e,d_0) = \frac{1}{2}\left[(1+\alpha+\beta e)(m+b) + (1-\alpha-\beta e)(m+\rho)\right]$$

such that

$$\mathbb{EU}(b,e,d_0) = \frac{1}{2}\left[(1+\alpha+\beta e)(m+b) + (1-\alpha-\beta e)m\right] - \frac{ke^2}{2} \geq m, \quad (PC)$$
$$b \geq 0, \quad (LC)$$
$$e \in [0,1].$$

After we use the Karush-Kuhn-Tucker Theorem (KKT) to solve the problem,[1] we find that PC should be binding at the optimum to ensure the physician accepts the contract. Hence, it has to be fulfilled that $\frac{b}{2}(1+\alpha+\beta e) - \frac{ke^2}{2} = 0$. By Lemma 1.2, we know the effort is a relevant variable when PS desires the physician to prescribe d_0. Since PS has to offer $b > 0$ to ensure $e > 0$, then LC is not binding at the optimum.

Restrictions related to e could not be binding at the optimum at the same time since it would induce a contradiction where $e = 0$ and $e = 1$. Note that there are two possible cases.

First, when one of the restrictions is binding at the optimum, but the other does not, we have $e = 1$. By Lemma 1.2, we know $e = min\left\{\frac{\beta b}{2k}, 1\right\}$, then condition $\frac{\beta b}{2k} > 1$ implies that $\beta\rho > 2k$. Hence, from $\frac{b}{2}(1+\alpha+\beta e) - \frac{ke^2}{2} = 0$, we have $b = \frac{k}{1+\alpha+\beta}$.

Second, when both restrictions are not binding at the optimum at the same time, we have that $e \geq 0$ and $e \leq 1$. Then, to find the optimal level of e that ensures PC and LC are fulfilled, we optimize the $\mathbb{EC}(b,e,d_0)$ with respect to e. From $\frac{\partial \mathbb{EC}(b,e,d_0)}{\partial e} = 0$ and by Lemma 1.2, we have $e = \frac{\beta\rho}{2k}$. As it should be satisfied that $e \leq 1$, then $\beta\rho \leq 2k$.

[1] Detailed proofs are available upon request.

Hence, from $\frac{b}{2}(1+\alpha+\beta e)-\frac{ke^2}{2}=0$, we have $b=\frac{\beta^2\rho^2}{4k(1+\alpha)+2\beta^2\rho}$.

Then, the optimal contracts are $C_1^S=\left(\frac{k}{1+\alpha+\beta},1,d_0\right)$ if $\beta\rho>2k$, and $C_2^S=\left(\frac{\beta^2\rho^2}{4k(1+\alpha)+2\beta^2\rho},\frac{\beta\rho}{2k},d_0\right)$ if $\beta\rho\leq 2k$. Under both contracts $\mathbb{EU}(b,e,d_0)=0$. Under C_1^S, $\mathbb{EC}(b,e,d_0)=m+\frac{k+\rho(1-\alpha-\beta)}{2}$ if $\beta\rho>2k$. Under C_2^S, $\mathbb{EC}(b,e,d_0)=m+\frac{4k\rho(1-\alpha)-\beta^2\rho^2}{8k}$ if $\beta\rho\leq 2k$.

If PS's contract induces the strategy Aed_t, then the problem is:

$$\min_{b,e,d}\mathbb{EC}(d_t)=m+c$$

such that

$$\mathbb{EU}(e,d_t)=m+t-\frac{ke^2}{2}\geq m,\quad (PC)$$
$$b\geq 0,\quad (LC)$$
$$e\in[0,1].$$

Again, using KKT, we have that the restrictions related to e could not be binding at the optimum at the same time since it would induce a contradiction where $e=0$ and $e=1$. The unique feasible case is when $e=0$, which implies one of the restrictions is binding at the optimum, and the other is never binding at the optimum. As a consequence, PC is not binding at the optimum and the physician obtain some rents since $t>0$. Note, that PS's objective function does not depend on b. Then, $b=0$, since PS never pays b in this case. The optimal contract is $C_3^S=(0,0,d_t)$, and the expected payments are $\mathbb{EU}(e,d_t)=m+t$ and $\mathbb{EC}(d_t)=m+c$.

Finally, we have the contracts C_1^S and C_2^S for the strategy Aed_0 and the contract C_3^S for the strategy Aed_t. $\mathbb{EC}(b,e,d_0)\leq\mathbb{EC}(d_t)$ if $c\geq\frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$ and $c\geq\frac{2(\sqrt{k^2\alpha^2+2k^2\alpha+k^2+2k\gamma\beta^2}-k(1+\alpha))}{\beta^2}-\gamma$. Then, PS prefers C_1^S instead of C_3^S if $c\geq\frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$ and $\beta\rho>2k$. PS prefers C_2^S instead of C_3^S if $c\geq\frac{2(\sqrt{k^2\alpha^2+2k^2\alpha+k^2+2k\gamma\beta^2}-k(1+\alpha))}{\beta^2}-\gamma$ and $\beta\rho\leq 2k$. □

Proof of Proposition 2

If PS prefers the physician to follow the strategy Aed_0, and considering that the optimal effort level the physician chooses is $e = min\left\{\frac{\beta b}{2k}, 1\right\}$ from Lemma 1.2, the problem is:

$$\min_{b,d} \mathbb{EC}(b, e, d_0) = \frac{1}{2}\left[(1 + \alpha + \beta e)(m + b) + (1 - \alpha - \beta e)(m + \rho)\right]$$

such that

$$\mathbb{EU}(b, e, d_0) = \frac{1}{2}\left[(1 + \alpha + \beta e)(m + b) + (1 - \alpha - \beta e)m\right] - \frac{ke^2}{2} \geq m, \quad (PC)$$
$$b \geq 0, \quad (LC),$$
$$e \leq \frac{\beta b}{2k}, \text{ and}$$
$$e \leq 1.$$

As in the previous proof, using the KKT Theorem to solve the problem, we find that PC should be binding at the optimum to ensure the physician accepts the contract. Hence, it has to be fulfilled that $\frac{b}{2}(1 + \alpha + \beta e) - \frac{ke^2}{2} = 0$. Since PS has to offer $b > 0$ to ensure $e > 0$, then LC is not binding at the optimum. The feasible case is when $e = 1$ and $e \leq \frac{\beta b}{2k}$. Hence, we have $b = \frac{k}{1+\alpha+\beta}$. As it should be satisfied that $e \leq \frac{\beta b}{2k}$, then $b \geq \frac{2k}{\beta}$. Note that $b = \frac{k}{1+\alpha+\beta} \geq \frac{2k}{\beta}$ since $\frac{(1+\alpha+\beta)}{\beta} \geq \frac{1}{2}$.

Then, the optimal contract is $C_4^S = \left(\frac{k}{1+\alpha+\beta}, d_0\right)$. The expected utility of the physician under C_4^S is $\mathbb{EU}(b, e, d_0) = 0$, and the expected cost for PS is $\mathbb{EC}(b, e, d_0) = m + \frac{k}{2} + \frac{\rho}{2}(1 - \alpha - \beta)$

If PS prefers the physician to follow the strategy Aed_t and considering that $e = 0$ from Lemma 1.2, the problem is:

$$\min_{b,d} \mathbb{EC}(d_t) = m + c$$

such that

$$\mathbb{EU}(e, d_t) = m + t - \frac{ke^2}{2} \geq m, \quad (PC)$$
$$b \geq 0, \quad (LC), \text{ and}$$
$$e = 0.$$

PC is satisfied if $t \geq 0$. As b is not part of the PS's objective function, the optimal level of the bonus is $b = 0$ and LC is satisfied. Then, the optimal contract is $C_5^S = (0, d_t)$. Under the contract, $\mathbb{EU}(e, d_t) = m + t$ and $\mathbb{EC}(d_t) = m + c$.

Finally, we have the contract C_4^S for the strategy Aed_0 and the contract C_5^S for the strategy Aed_t. $\mathbb{EC}(b, e, d_0) \leq \mathbb{EC}(d_t)$ if $c \geq \frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$. □

Proof of Proposition 3

We present the incentive compatibility constraints that PS faces according to physician's strategies. When PS prefers the physician to follow the strategy Aed_0 instead of Aed_t, the incentive compatibility constraint (IC_1) is:

$$\mathbb{EU}(b, e, d_0) \geq \mathbb{EU}(d_t) \Rightarrow b(1 + \alpha + \beta e) \geq 2t \quad (IC_1).$$

and when PS prefers the physician to follow the strategy Aed_t instead of Aed_0, the incentive compatibility constraint (IC_2) is:

$$\mathbb{EU}(b, e, d_0) < \mathbb{EU}(d_t) \Rightarrow b(1 + \alpha + \beta e) < 2t \quad (IC_2),$$

By Lemma 1.2, the optimal effort level the physician chooses is $e = min\left\{\frac{\beta b}{2k}, 1\right\}$. Then, if PS prefers the physician to follow the strategy Aed_0, then the problem is:

$$\min_b \mathbb{EC}(b, e, d_0) = \frac{1}{2}\left[(1 + \alpha + \beta e)(m + b) + (1 - \alpha - \beta e)(m + \rho)\right]$$

such that

$$\mathbb{EU}(b, e, d_0) = \frac{1}{2}\left[(1 + \alpha + \beta e)(m + b) + (1 - \alpha - \beta e)m\right] - \frac{ke^2}{2} \geq m, \quad (PC)$$

$$b \geq 0, \quad (LC)$$

$$b \geq \frac{2t}{(1 + \alpha + \beta e)} \quad (IC_1),$$

$$e \leq \frac{\beta b}{2k}, \text{ and}$$

$$e \leq 1.$$

From KKT we know that feasible solutions implies the IC is binding at the optimum.

As a consequence, $b = \frac{2t}{1+\alpha+\beta e}$. Since $t > 0$, then $b > 0$, and restrictions PC and LC are always fulfilled. Note both PC and LC are not binding at the optimum. Regarding the restrictions for e, we have two possibilities.

First, when both restrictions are binding at the optimum, we have $e = \frac{\beta b}{2k} = 1$. Then, b could be equal to $b = \frac{2k}{\beta}$ or to $\frac{2t}{1+\alpha+\beta}$. As $b = \min\left\{\frac{2k}{\beta}, \frac{2t}{1+\alpha+\beta}\right\}$, the contract is $C = \frac{2t}{1+\alpha+\beta}$ if $t \leq \frac{k}{\beta}(1+\alpha+\beta)$ and $C = \frac{2k}{\beta}$ if $t > \frac{k}{\beta}(1+\alpha+\beta)$. To satisfy PC the condition is $t \geq \frac{k}{2}$ when the contract is $C = \frac{2t}{1+\alpha+\beta}$ and $\frac{(1+\alpha+\beta)}{\beta} \geq \frac{1}{2}$ when the contract is $C = \frac{2k}{\beta}$. Note that as $\beta \in [0,1]$, the condition $\frac{(1+\alpha+\beta)}{\beta} \geq \frac{1}{2}$ is always fulfilled. As $\frac{k}{2} < \frac{k}{\beta}(1+\alpha+\beta)$ for any k, the condition for $C = \frac{2t}{1+\alpha+\beta}$ is $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)\right]$.

Second, when one of the restrictions is binding at the optimum, but the other does not, we have $e = \frac{\beta b}{2k}$. Then, from $b = \frac{2t}{1+\alpha+\beta e}$, we have that $b = \frac{\sqrt{16\beta^2 kt + (2k(1+\alpha))^2} - 2k(1+\alpha)}{2\beta^2}$. PC is always satisfied. Since it should be fulfilled that $e \leq 1$, we have the condition: $t \leq \frac{k}{\beta}(1+\alpha+\beta)$. Then, the contract is $C = \frac{\sqrt{16\beta^2 kt + (2k(1+\alpha))^2} - 2k(1+\alpha)}{2\beta^2}$ if $t \leq \frac{k}{\beta}(1+\alpha+\beta)$. The contract induces to $e = \frac{\sqrt{16\beta^2 kt + (2k(1+\alpha))^2}}{4\beta k} - \frac{(1+\alpha)}{2\beta}$. Note that since $t > 0$, then $e > 0$.

The optimal contracts are: $C_6^A = \frac{2k}{\beta}$ if $t > \frac{k}{\beta}(1+\alpha+\beta)$, $C_7^A = \frac{2t}{1+\alpha+\beta}$ if $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)\right]$, and $C_8^A = \frac{\sqrt{16\beta^2 kt + (2k(1+\alpha))^2} - 2k(1+\alpha)}{2\beta^2}$ if $t \leq \frac{k}{\beta}(1+\alpha+\beta)$.

Under the contracts C_6^A, C_7^A, and C_8^A we have:

$$\mathbb{EC}(b, e, d_0) = m + \tfrac{k}{\beta}(1+\alpha+\beta) + \tfrac{\rho}{2}(1-\alpha-\beta).$$

$$\mathbb{EC}(b, e, d_0) = m + t + \tfrac{\rho}{2}(1-\alpha-\beta).$$

$$\mathbb{EC}(b, e, d_0) = m + \frac{\sqrt{16kt\beta^2 + (2k\alpha+2k)^2} - 2k(1+\alpha)}{16k\beta^2}$$
$$\left[\frac{8k(1+\alpha)+4\beta^2\rho}{2} + \sqrt{16kt\beta^2 + (2k\alpha+2k)^2} - 2k(1+\alpha)\right] + \tfrac{\rho}{2}(1-\alpha).$$

Note C_7^A and C_8^A could be implemented if $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)\right]$ and $t \leq \frac{k}{\beta}(1+\alpha+\beta)$, respectively. Then, we can compare these two contracts. Since $e = 1$ in C_7^A, $e \leq 1$ in C_8^A, and b is greater in C_8^A than C_7^A, we know that $\mathbb{EC}(b, e, d_0)$ under C_7^A is lesser than $\mathbb{EC}(b, e, d_0)$ under C_8^A. Then, if $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)\right]$ PS always prefers C_7^A to C_8^A. Thus, the condition for C_8^A is if $t \leq \frac{k}{2}$.

The expected utility of the physician under the contracts C_6^A, C_7^A, and C_8^A is:
$\mathbb{EU}(b,e,d_0) = m + \frac{k}{\beta}(1+\alpha+\beta) - \frac{k}{2}$.
$\mathbb{EU}(b,e,d_0) = m + t - \frac{k}{2}$.
$\mathbb{EU}(b,e,d_0) = m + \frac{\sqrt{16\beta^2kt+(2k(1+\alpha))^2}-2k(1+\alpha)}{4\beta^2}\left(1+\alpha+\frac{\beta\sqrt{16\beta^2kt+(2k(1+\alpha))^2}}{4k} - \frac{\beta(1+\alpha)}{2}\right) - \frac{k}{2}\left(\frac{\sqrt{16\beta^2kt+(2k(1+\alpha))^2}}{4\beta k} - \frac{(1+\alpha)}{2\beta}\right)^2$.

If PS prefers the physician to follow the strategy Aed_t, then the problem is:

$$\min_b \mathbb{EC}(b,e,d_t) = m + c$$

such that

$$\mathbb{EU}(b,e,d_t) = m + t - \frac{ke^2}{2} \geq m, \quad (PC)$$
$$b \geq 0, \quad (LC)$$
$$b(1+\alpha+\beta e) < 2t \quad (IC_2), \text{ and}$$
$$e = 0.$$

By Lemma 1.2, $e = 0$. Then, PC and IC_2 are satisfied if $t \geq 0$ and $b < \frac{2t}{1+\alpha}$, respectively. As b is not part of the PS's objective function, the optimal level of the bonus is $b = 0$. Then, the optimal contract is $C_9^A = 0$. Under the contract, $\mathbb{EU}(b,e,d_t) = m + t$ and $\mathbb{EC}(b,e,d_t) = m + c$.

Finally, we have the contracts C_6^A, C_7^A, and C_8^A for the strategy Aed_0 and the contract C_9^A for the strategy Aed_t. $\mathbb{EC}(b,e,d_0) \leq \mathbb{EC}(b,e,d_t)$ if $c \geq \frac{2k}{\beta} + \frac{\gamma(1-\alpha-\beta)}{(1+\alpha+\beta)}$, $c \geq \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, and $c \geq \frac{\sqrt{16kt\beta^2+(2k\alpha+2k)^2}-2k(1+\alpha)}{2\beta^2} - \frac{\gamma\sqrt{k\left(k(\alpha+1)^2+4\beta^2t\right)}-\gamma k(\alpha+1)}{k(1+\alpha)+\sqrt{k}\sqrt{4\beta^2t+k(\alpha+1)^2}} + \frac{\gamma(1-\alpha)2\sqrt{k}}{\sqrt{k}(1+\alpha)+\sqrt{4\beta^2t+k(\alpha+1)^2}}$.
For simplicity, let $\diamondsuit = \frac{\sqrt{16kt\beta^2+(2k\alpha+2k)^2}-2k(1+\alpha)}{2\beta^2} - \frac{\gamma\sqrt{k\left(k(\alpha+1)^2+4\beta^2t\right)}-\gamma k(\alpha+1)}{k(1+\alpha)+\sqrt{k}\sqrt{4\beta^2t+k(\alpha+1)^2}}$. Then:
$c \geq \diamondsuit + \frac{\gamma(1-\alpha)2\sqrt{k}}{\sqrt{k}(1+\alpha)+\sqrt{4\beta^2t+k(\alpha+1)^2}}$.
Again, condition $c \geq \frac{\gamma(1-\alpha)2\sqrt{k}}{\sqrt{k}(1+\alpha)+\sqrt{4\beta^2t+k(\alpha+1)^2}}$ implies $c \geq \diamondsuit + \frac{\gamma(1-\alpha)2\sqrt{k}}{\sqrt{k}(1+\alpha)+\sqrt{4\beta^2t+k(\alpha+1)^2}}$.
Then PS prefers C_6^A instead of C_9^A if $c \geq \frac{2k}{\beta} + \frac{\gamma(1-\alpha-\beta)}{(1+\alpha+\beta)}$, PS prefers C_7^A instead of C_9^A if $c \geq \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, and PS prefers C_8^A instead of C_9^A if $c \geq \frac{\gamma(1-\alpha)2\sqrt{k}}{\sqrt{k}(1+\alpha)+\sqrt{4\beta^2t+k(\alpha+1)^2}}$. $\square$

Proof of Proposition 4

If PS's contract induces the strategy Aed_0, then the problem is:

$$\min_{b,e,d} \mathbb{EC}(b,e,d_0) = \frac{1}{2}\left[(1+\alpha+\beta e)(m+b)+(1-\alpha-\beta e)(m+\rho)\right]$$

such that

$$\mathbb{EU}(b,e,d_0) = \frac{1}{2}\left[(1+\alpha+\beta e)(m+b)+(1-\alpha-\beta e)(m-\gamma)\right] - \frac{ke^2}{2} \geq m, \quad (PC)$$

$$b \geq 0, \quad (LC)$$

$$e \in [0,1].$$

Since PC should be binding at the optimum to ensure the physician accepts the contract, it has to be fulfilled that $b(1+\alpha+\beta e)-\gamma(1-\alpha-\beta e)-ke^2=0$. We know that PS has to offer $b>0$ to ensure $e>0$, then LC is not binding at the optimum. Additionally, restrictions related to e could not be binding at the optimum at the same time. Then, we have two possible contracts:

1 when one of the restrictions is binding at the optimum, but the other does not, we have $e=1$. Since the optimal effort for the physician is $e = min\left\{\frac{\beta(b+\gamma)}{2k}, 1\right\}$, it has to be fulfilled that $\frac{\beta(b+\gamma)}{2k} > 1$. Since the optimal effort for PS is $e = \frac{\beta(\rho+\gamma)}{2k}$, then condition $\frac{\beta(b+\gamma)}{2k} > 1$ implies that $\beta(\rho+\gamma) > 2k$. Hence, from $b(1+\alpha+\beta e)-\gamma(1-\alpha-\beta e)-ke^2=0$, we have $b = \frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$.

2 when both restrictions are not binding at the optimum at the same time, we have that $e \geq 0$ and $e \leq 1$. Since the optimal effort for PS is $e = \frac{\beta(\rho+\gamma)}{2k}$. As it should be satisfied that $e \leq 1$, then $\beta(\rho+\gamma) \leq 2k$. Hence, from $b(1+\alpha+\beta e)-\gamma(1-\alpha-\beta e)-ke^2=0$, we have $b = \frac{\beta^2(\rho^2-\gamma^2)+4k\gamma(1-\alpha)}{4k(1+\alpha)+2\beta^2(\rho+\gamma)}$.

Then, the optimal contracts are $C_{10}^S = \left(\frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}, 1, d_0\right)$ if $\beta(\rho+\gamma) > 2k$, and $C_{11}^S = \left(\frac{\beta^2(\rho^2-\gamma^2)+4k\gamma(1-\alpha)}{4k(1+\alpha)+2\beta^2(\rho+\gamma)}, \frac{\beta(\rho+\gamma)}{2k}, d_0\right)$ if $\beta(\rho+\gamma) \leq 2k$, Under both contracts $\mathbb{EU}(b,e,d_0) = 0$. Under C_{10}^S, $\mathbb{EC}(b,e,d_0) = m + \frac{k+(1-\alpha-\beta)(\gamma+\rho)}{2}$ if $\beta(\rho+\gamma) > 2k$. Under C_{11}^S, $\mathbb{EC}(b,e,d_0) = m + \frac{k\beta^2(\rho^2-\gamma^2)+4k^2\gamma(1-\alpha)+\rho\left(2k(1-\alpha)-\beta^2(\rho+\gamma)\right)}{4k}$ if $\beta(\rho+\gamma) \leq 2k$.

If PS's contract induces the strategy Aed_t, then the problem is the same that in Proposition 1.1. Since PS's objective function does not depend on b, then $b=0$.

The unique feasible contract in this case is when $e = 0$. As a consequence, PC is not binding at the optimum and the physician obtain some rents since $t > 0$. The optimal contract is $C_3^S = (0, 0, d_t)$ as in Proposition 1.1, and the expected payments are $\mathbb{EU}(e, d_t) = m + t$ and $\mathbb{EC}(d_t) = m + c$.

We have the contracts C_{10}^S and C_{11}^S for the strategy Aed_0 and the contract C_3^S for the strategy Aed_t. $\mathbb{EC}(b, e, d_0) \leq \mathbb{EC}(d_t)$ if $c \geq \frac{k+2\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$ and $c \geq \frac{\gamma(1-2k)}{2(k-1)} + \frac{k(1+\alpha)}{\beta^2(k-1)} + \frac{\sqrt{4k\beta^2\gamma[\beta^2\gamma(5k-1)+(3-4k\alpha-\alpha)+4k^2(\alpha-1)]+4k^2(\alpha+1)^2}}{2\beta^2(k-1)}$.
Again, for simplicity, let $\clubsuit = \frac{\sqrt{4k\beta^2\gamma[\beta^2\gamma(5k-1)+(3-4k\alpha-\alpha)+4k^2(\alpha-1)]+4k^2(\alpha+1)^2}}{2\beta^2(k-1)}$.
Then, PS prefers C_{10}^S instead of C_3^S if $c \geq \frac{k+2\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$. PS prefers C_{11}^S instead of C_3^S if $c \geq \frac{\gamma(1-2k)}{2(k-1)} + \frac{k(1+\alpha)}{\beta^2(k-1)} + \clubsuit$. □

Proposition 4 When the drug choice and the effort level are contractible:

- If PS wants the physician to prescribe the drug without DDS and to exert the maximum effort level, $c \geq \frac{k+2\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$ and $\beta(\rho+\gamma) > 2k$, the optimal contract is $C_{10}^S = \left(\frac{k+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}, 1, d_0\right)$.
- If PS wants the physician to prescribe the drug without DDS and to exert a positive effort level, $c \geq \frac{\gamma(1-2k)}{2(k-1)} + \frac{k(1+\alpha)}{\beta^2(k-1)} + \frac{\sqrt{4k\beta^2\gamma[\beta^2\gamma(5k-1)+(3-4k\alpha-\alpha)+4k^2(\alpha-1)]+4k^2(\alpha+1)^2}}{2\beta^2(k-1)}$ and $\beta(\rho+\gamma) \leq 2k$, the optimal contract is $C_{11}^S = \left(\frac{\beta^2(\rho^2-\gamma^2)+4k\gamma(1-\alpha)}{4k(1+\alpha)+2\beta^2(\rho+\gamma)}, \frac{\beta(\rho+\gamma)}{2k}, d_0\right)$.
- Otherwise, if PS wants the physician to prescribe the drug with DDS, it will not offer any bonus since the physician does not have any incentive to exert effort. The optimal contract is $C_3^S = (0, 0, d_t)$.

Proof of Proposition 5

Now, the incentive compatibility constraints (IC) that PS faces are:

$$\mathbb{EU}(b, e, d_0) \geq \mathbb{EU}(d_t) \Rightarrow b(1+\alpha+\beta e) - \gamma(1-\alpha-\beta e) \geq 2t \quad (IC_1).$$
$$\mathbb{EU}(b, e, d_0) < \mathbb{EU}(d_t) \Rightarrow b(1+\alpha+\beta e) - \gamma(1-\alpha-\beta e) < 2t \quad (IC_2),$$

The optimal effort level the physician chooses is $e = min\left\{\frac{\beta(b+\gamma)}{2k}, 1\right\}$. Then, if PS prefers the physician to follow the strategy Aed_0, then the problem is:

$$\min_b \mathbb{EC}(b, e, d_0) = \frac{1}{2}\left[(1+\alpha+\beta e)(m+b) + (1-\alpha-\beta e)(m+\rho)\right]$$

such that

$$\mathbb{EU}(b, e, d_0) = \frac{1}{2}\left[(1+\alpha+\beta e)(m+b) + (1-\alpha-\beta e)(m-\gamma)\right] - \frac{ke^2}{2} \geq m, \quad (PC)$$

$$b \geq 0, \quad (LC)$$

$$b \geq \frac{2t+\gamma(1-\alpha-\beta e)}{(1+\alpha+\beta e)} \quad (IC_1),$$

$$e \leq \frac{\beta(b+\gamma)}{2k}, \text{ and}$$

$$e \leq 1.$$

The feasible solutions implies the IC is binding at the optimum, then $b = \frac{2t+\gamma(1-\alpha-\beta e)}{1+\alpha+\beta e}$. Since $t > 0$, then $b > 0$, and restrictions PC and LC are always fulfilled. Again, from restrictions for e, we have the following contracts:

1. when both restrictions are binding at the optimum, we have $e = \frac{\beta(b+\gamma)}{2k} = 1$. Then, b could be equal to $b = \frac{2k}{\beta} - \gamma$ or to $b = \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$. As $b = \min\left\{\frac{2k}{\beta} - \gamma, \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}\right\}$, the contract is $C = \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$ if $t \leq \frac{k}{\beta}(1+\alpha+\beta) - \gamma$ and $C = \frac{2k}{\beta} - \gamma$ if $t > \frac{k}{\beta}(1+\alpha+\beta) - \gamma$. To satisfy PC the condition is $t \geq \frac{k}{2}$ when the contract is $C = \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$ and $\frac{(1+\alpha+\beta)}{\beta} \geq \frac{1}{2} + \frac{\gamma}{k}$ when the contract is $C = \frac{2k}{\beta} - \gamma$. Note that as $\beta \in [0, 1]$, the condition $\frac{(1+\alpha+\beta)}{\beta} \geq \frac{1}{2} + \frac{\gamma}{k}$ is always fulfilled. When $\frac{k}{2} < \frac{k}{\beta}(1+\alpha+\beta) - \gamma$, the condition for $C = \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$ is $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta) - \gamma\right]$.

2. Second, when one of the restrictions is binding at the optimum, but the other does not, we have $e = \frac{\beta(b+\gamma)}{2k}$. Then, from $b = \frac{2t+\gamma(1-\alpha-\beta e)}{1+\alpha+\beta e}$, we have that $b = \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{(k+k\alpha)^2+4k\beta^2(t+\gamma)}}{\beta^2}$. PC is always satisfied. Since it should be fulfilled that $e \leq 1$, we have the condition: $t \leq \frac{k}{\beta}(1+\alpha+\beta) - \gamma$. Then, the contract is $C = \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{(k+k\alpha)^2+4k\beta^2(t+\gamma)}}{\beta^2}$ if $t \leq \frac{k}{\beta}(1+\alpha+\beta) - \gamma$. The contract induces to $e = \frac{(1+\alpha)}{2\beta} - \frac{\gamma\beta}{k} + \frac{\sqrt{k(k\alpha(\alpha+2)+k+4\beta^2(\gamma+t))}}{2k\beta}$. Note that since $t > 0$, then $e > 0$.

The optimal contracts are: $C_{12}^A = \frac{2k}{\beta} - \gamma$ if $t > \frac{k}{\beta}(1+\alpha+\beta) - \gamma$, $C_{13}^A = \frac{2t+\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$

if $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)-\gamma\right]$, and $C_{14}^A = \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{(k+k\alpha)^2+4k\beta^2(t+\gamma)}}{\beta^2}$ if $t \leq \frac{k}{\beta}(1+\alpha+\beta)-\gamma$.

Under the contracts C_{12}^A, C_{13}^A, and C_{14}^A we have:

$$\mathbb{EC}(b,e,d_0) = m + \tfrac{k}{\beta}(1+\alpha+\beta) - \tfrac{\gamma}{2}(1+\alpha+\beta) + \tfrac{\rho}{2}(1-\alpha-\beta).$$

$$\mathbb{EC}(b,e,d_0) = m + t + \left[\tfrac{\gamma}{2} + \tfrac{\rho}{2}\right](1-\alpha-\beta).$$

$$\mathbb{EC}(b,e,d_0) = m + \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{k(\alpha^2k+2k\alpha+k+4\beta^2(t+\gamma))}}{\beta^2}[1+\alpha] + \tfrac{\rho}{2}(1-\alpha) + \left[\frac{k(1+\alpha)-\gamma\beta^2+\sqrt{k(\alpha^2k+2k\alpha+k+4\beta^2(t+\gamma))}}{\beta^2} - \tfrac{\rho}{2}\right]\tfrac{(1+\alpha)}{2} - \tfrac{\gamma\beta^2}{k} + \frac{\sqrt{k(k\alpha(\alpha+2)+k+4\beta^2(\gamma+t))}}{2k}.$$

C_{13}^A and C_{14}^A could be implemented if $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)-\gamma\right]$ and $t \leq \frac{k}{\beta}(1+\alpha+\beta)-\gamma$, respectively. Since $e=1$ in C_{13}^A, $e \leq 1$ in C_{14}^A, and b is greater in C_{14}^A than C_{13}^A, when $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)-\gamma\right]$ PS always prefers C_{13}^A to C_{14}^A. Then, the condition for C_{14}^A is if $t \leq \frac{k}{2}$.

The expected utility of the physician under the contracts C_{12}^A, C_{13}^A, and C_{14}^A is:
$\mathbb{EU}(b,e,d_0) = m + \frac{2k-\gamma\beta}{2\beta}(1+\alpha+\beta) - \frac{\gamma}{2}(1-\alpha-\beta) - \frac{k}{2}$.
$\mathbb{EU}(b,e,d_0) = m + \frac{2t+\gamma(1-\alpha-\beta)}{2(1+\alpha+\beta)} - \frac{\gamma}{2}(1-\alpha-\beta) - \frac{k}{2}$.
$\mathbb{EU}(b,e,d_0) = m + \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{k(\alpha^2k+2k\alpha+k+4\beta^2(t+\gamma))}}{2\beta^2}[1+\alpha] - \frac{\gamma}{2}(1-\alpha-\beta) + \frac{(1+\alpha)}{2} - \frac{\gamma\beta^2}{k} + \frac{\sqrt{k(k\alpha(\alpha+2)+k+4\beta^2(\gamma+t))}}{2k}\left[\frac{k(1+\alpha)-\gamma\beta^2+\sqrt{k(\alpha^2k+2k\alpha+k+4\beta^2(t+\gamma))}}{4\beta^2} + \frac{\gamma}{2}\right] - \frac{k(1+\alpha)}{4\beta} + \frac{\sqrt{k(k\alpha(\alpha+2)+k+4\beta^2(\gamma+t))}}{4\beta}$.

If PS prefers the physician to follow the strategy Aed_t, then the problem is the same that in Proposition 1.3. Since $e=0$, PC and IC_2 are satisfied if $t \geq 0$ and $b < \frac{2t}{1+\alpha}$, respectively. The optimal level of the bonus is $b=0$. Then, the optimal contract is $C_9^A = 0$. Under the contract, $\mathbb{EU}(b,e,d_t) = m+t$ and $\mathbb{EC}(b,e,d_t) = m+c$.

Finally, we have the contracts C_{12}^A, C_{13}^A, and C_{14}^A for the strategy Aed_0 and the contract C_9^A for the strategy Aed_t. $\mathbb{EC}(b,e,d_0) \leq \mathbb{EC}(b,e,d_t)$ if $c \geq \frac{2k(1+\alpha+\beta)-2\beta\gamma(\beta+\alpha)}{\beta(1+\alpha+\beta)}$, $c \geq \frac{2t+2\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, and $c \geq \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{(k+\alpha k)^2+4k\beta^2(t+\gamma)}}{\beta^2} + \frac{\gamma\left(k+2\gamma\beta^2-3k\alpha-\sqrt{k}\sqrt{k+k\alpha(\alpha+2)+4\beta^2(\gamma+t)}\right)}{3k+3k\alpha-2\gamma\beta^2+\sqrt{k}\sqrt{k+k\alpha(\alpha+2)+4\beta^2(\gamma+t)}}$.
Again, for simplicity, let $\blacktriangle = \frac{\gamma\left(k+2\gamma\beta^2-3k\alpha-\sqrt{k}\sqrt{k+k\alpha(\alpha+2)+4\beta^2(\gamma+t)}\right)}{3k+3k\alpha-2\gamma\beta^2+\sqrt{k}\sqrt{k+k\alpha(\alpha+2)+4\beta^2(\gamma+t)}}$. Then PS prefers C_{12}^A

instead of C_9^A if $c \geq \frac{2k(1+\alpha+\beta)-2\beta\gamma(\beta+\alpha)}{\beta(1+\alpha+\beta)}$, PS prefers C_{13}^A instead of C_9^A if $c \geq \frac{2t+2\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, and PS prefers C_{14}^A instead of C_9^A if $c \geq \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{(k+\alpha k)^2+4k\beta^2(t+\gamma)}}{\beta^2}$. □

Proposition 5 When the drug choice and the effort level are not contractible:

- If PS induces the physician to prescribe the drug without DDS and to exert the maximum effort level,
  - $c \geq \frac{2k(1+\alpha+\beta)-2\beta\gamma(\beta+\alpha)}{\beta(1+\alpha+\beta)}$, and $t > \frac{k}{\beta}(1+\alpha+\beta)-\gamma$, the optimal contract is $C_{12}^A = \frac{2k}{\beta}-\gamma$, or
  - $c \geq \frac{2t+2\gamma(1-\alpha-\beta)}{1+\alpha+\beta}$, and $t \in \left[\frac{k}{2}, \frac{k}{\beta}(1+\alpha+\beta)-\gamma\right]$, the optimal contract is $C_{13}^A = \frac{2t+\gamma(1-\alpha-\beta)}{(1+\alpha+\beta)}$.
- If PS induces the physician to prescribe the drug without DDS and to exert a positive effort level, $c \geq \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{(k+\alpha k)^2+4k\beta^2(t+\gamma)}}{\beta^2}$, and $t \leq \frac{k}{2}$, the optimal contract is $C_{14}^A = \frac{k(1+\alpha)-\gamma\beta^2+\sqrt{(k+k\alpha)^2+4k\beta^2(t+\gamma)}}{\beta^2}$, with $e = \frac{(1+\alpha)}{2\beta}-\frac{\gamma\beta}{k}+\frac{\sqrt{k(k\alpha(\alpha+2)+k+4\beta^2(\gamma+t))}}{2k\beta} > 0$.
- Otherwise, if PS induces the physician to prescribe the drug with DDS and, as a consequence, to exert none effort, the optimal contract is $C_9^A = 0$.

Appendix B

Chapter 2

B.1 Clinical cases

We present the clinical cases corresponding to the six hypothetical patients the subjects face. Subjects could observe all the information on the same screen and had a buttom to chose one of the drugs. They could not move to the next screen if they did not choose one of the drugs. The drugs' position changed for each clinical case; if the generic showed up on the left in the first case, then in the second case, it showed up on the right. In this document, we present anonymized the drugs and the disease's names, following a recommendation of the Universidad del Rosario's Institutional Review Board, who approved our protocols to run the experiment. Clinical cases in English are available upon request.

Figure B.1: Clinical case 1.

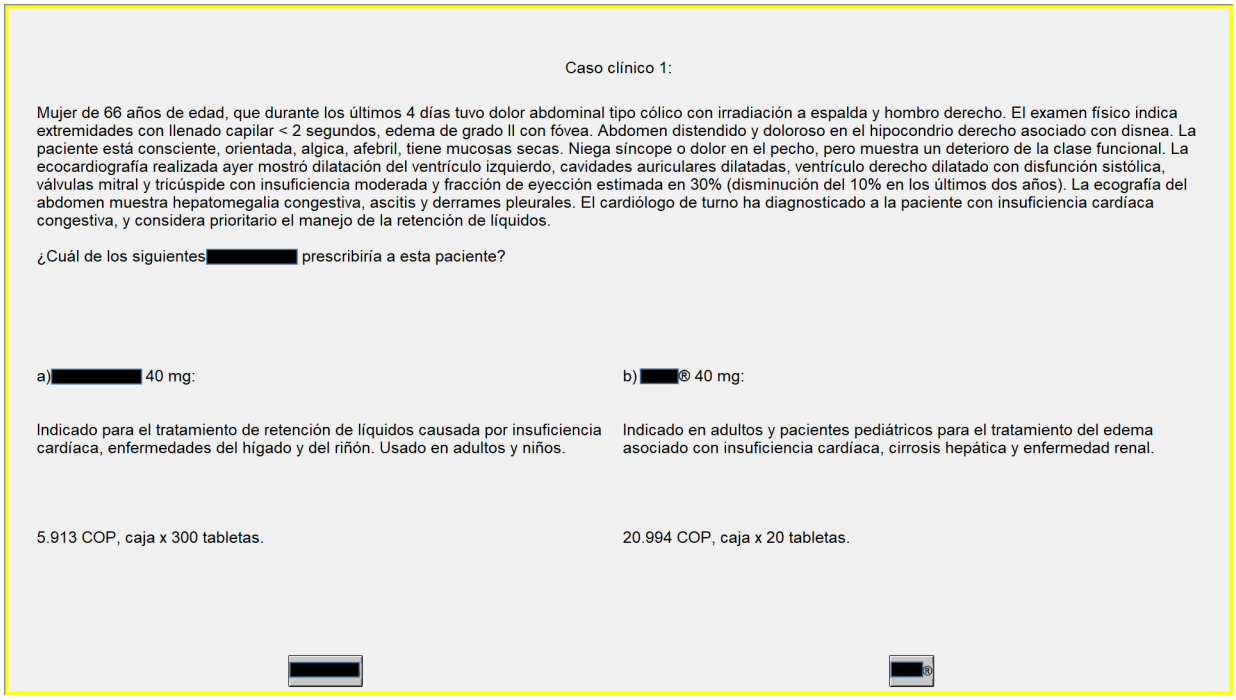


Figure B.2: Clinical case 2.

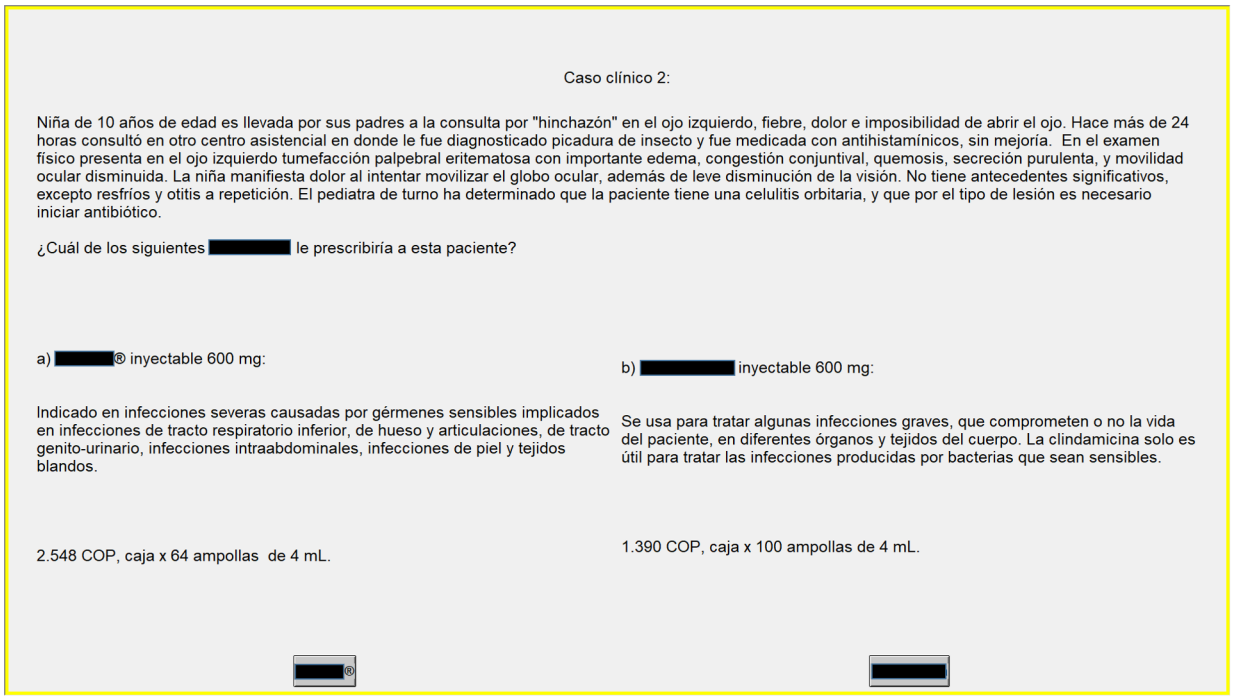


Figure B.3: Clinical case 3.

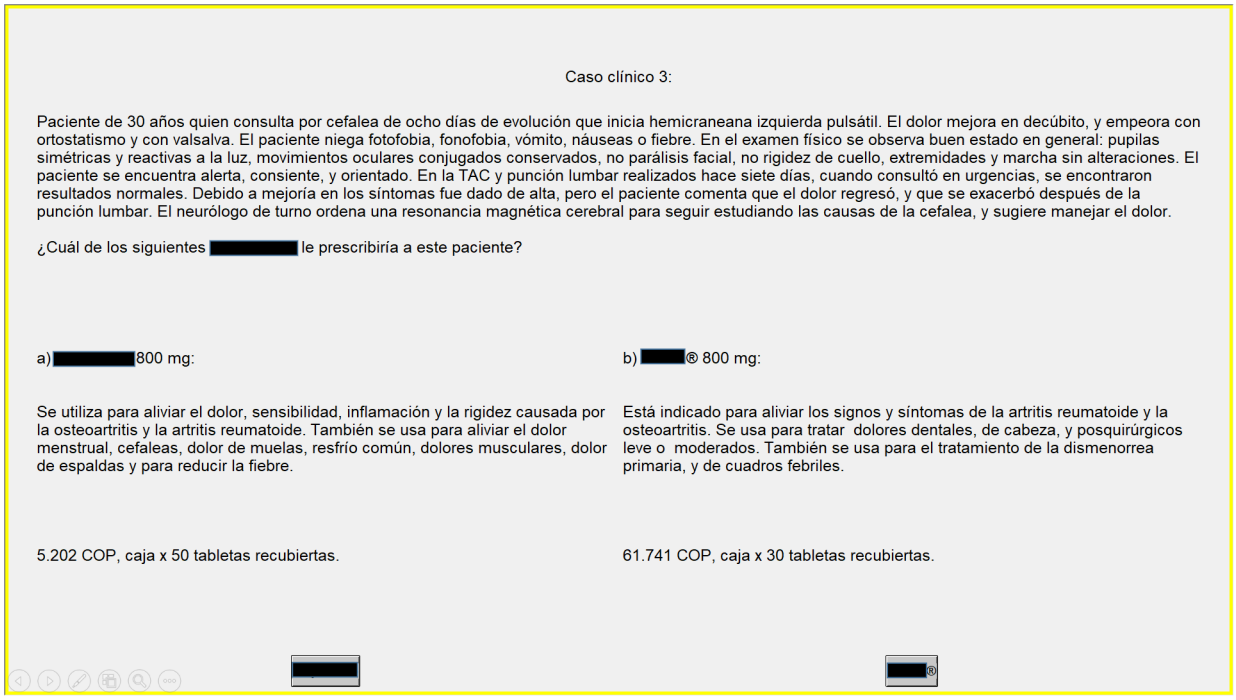


Figure B.4: Clinical case 4.

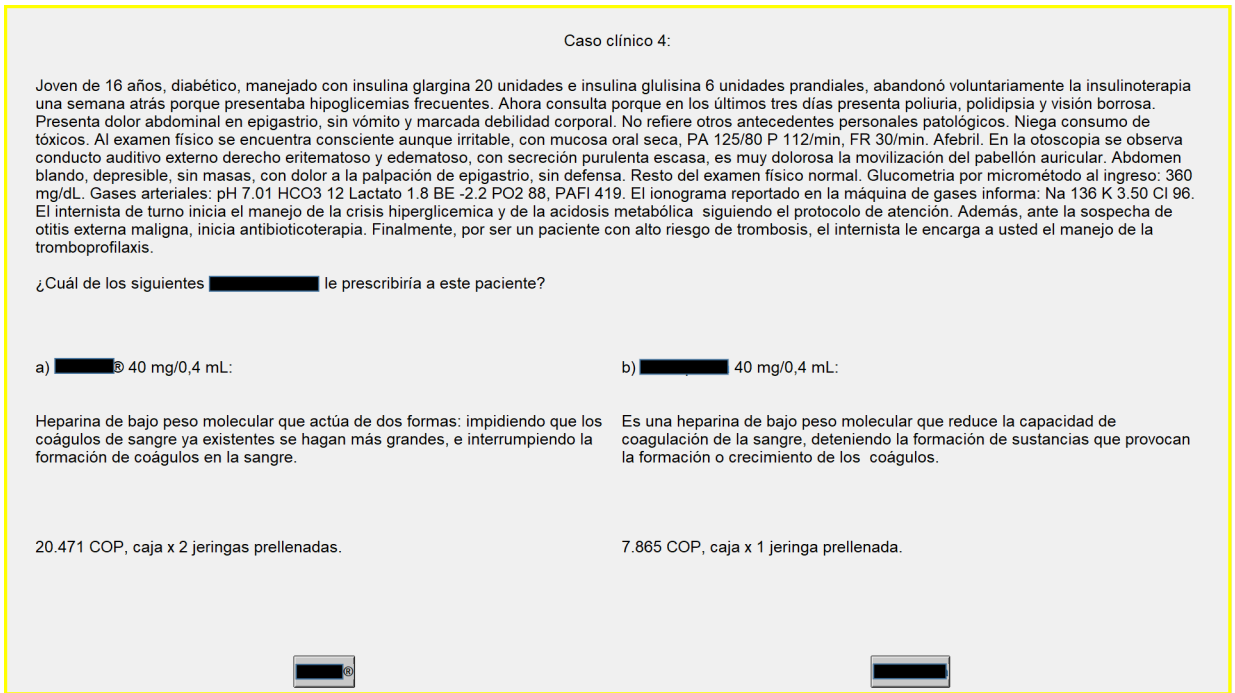


Figure B.5: Clinical case 5.

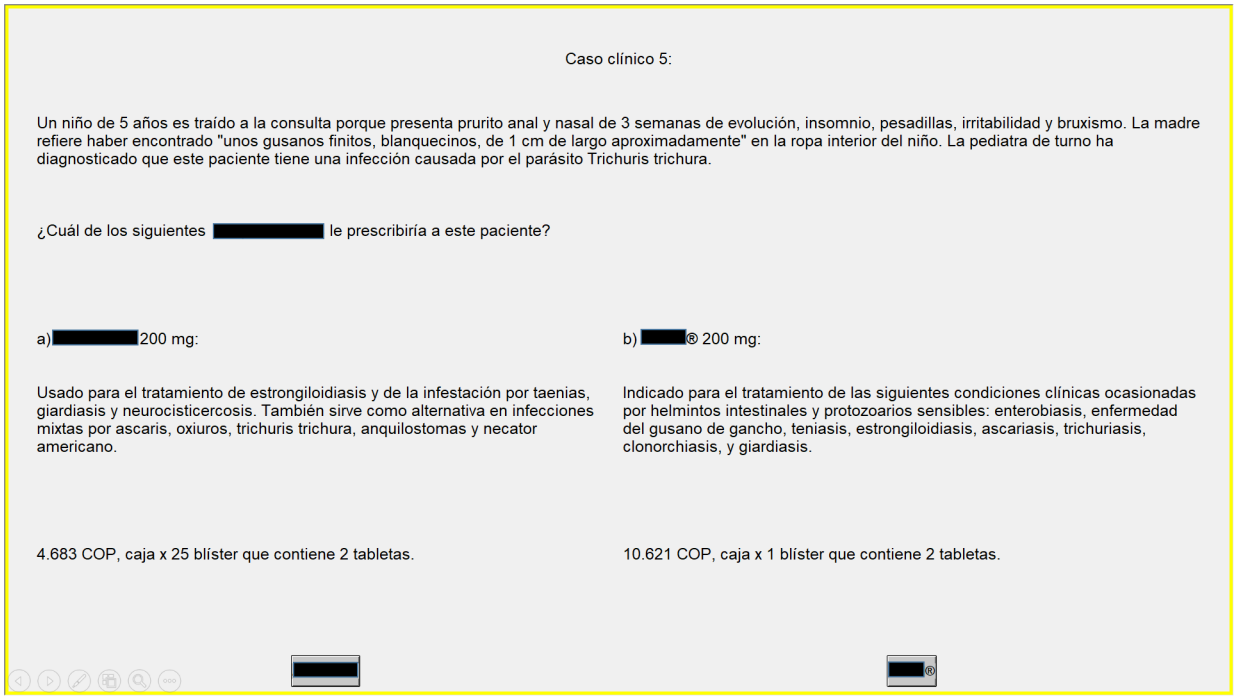
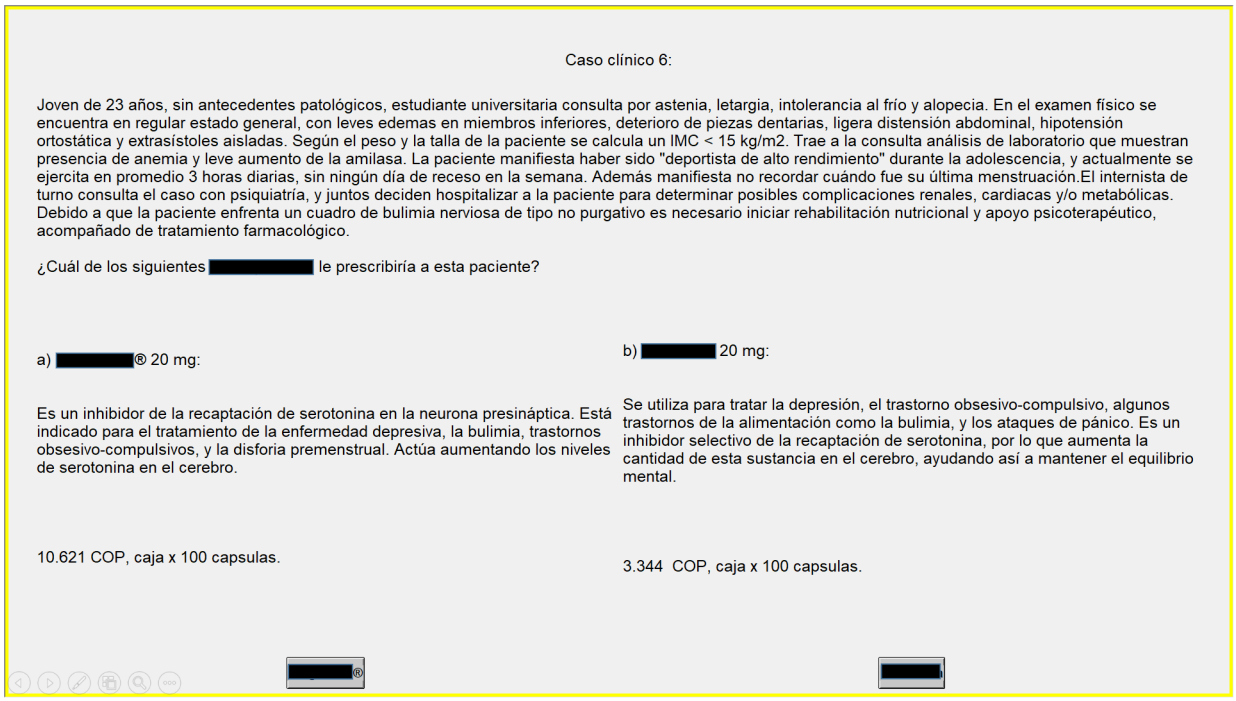


Figure B.6: Clinical case 6.



B.2 Task of preferences on the type of drug.

"The false consensus effect" inspires the task (Ross et al., 1977). People overestimate how their preferences are normal and close to those of the general population, producing a kind of cognitive bias that tends to lead to the perception of a false consensus. Next, we present the two screens the subjects faced during this task. Versions in English are available upon request.

Figure B.7: First screen.

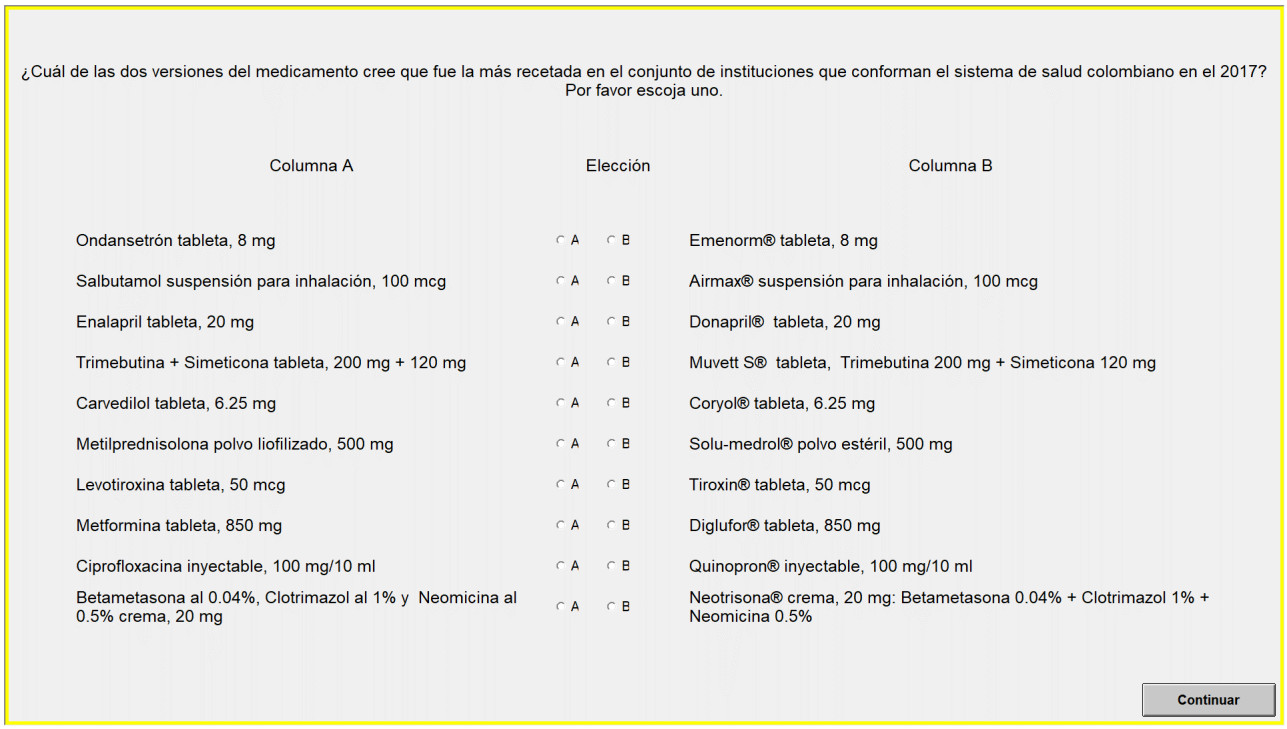


Figure B.8: Second screen.

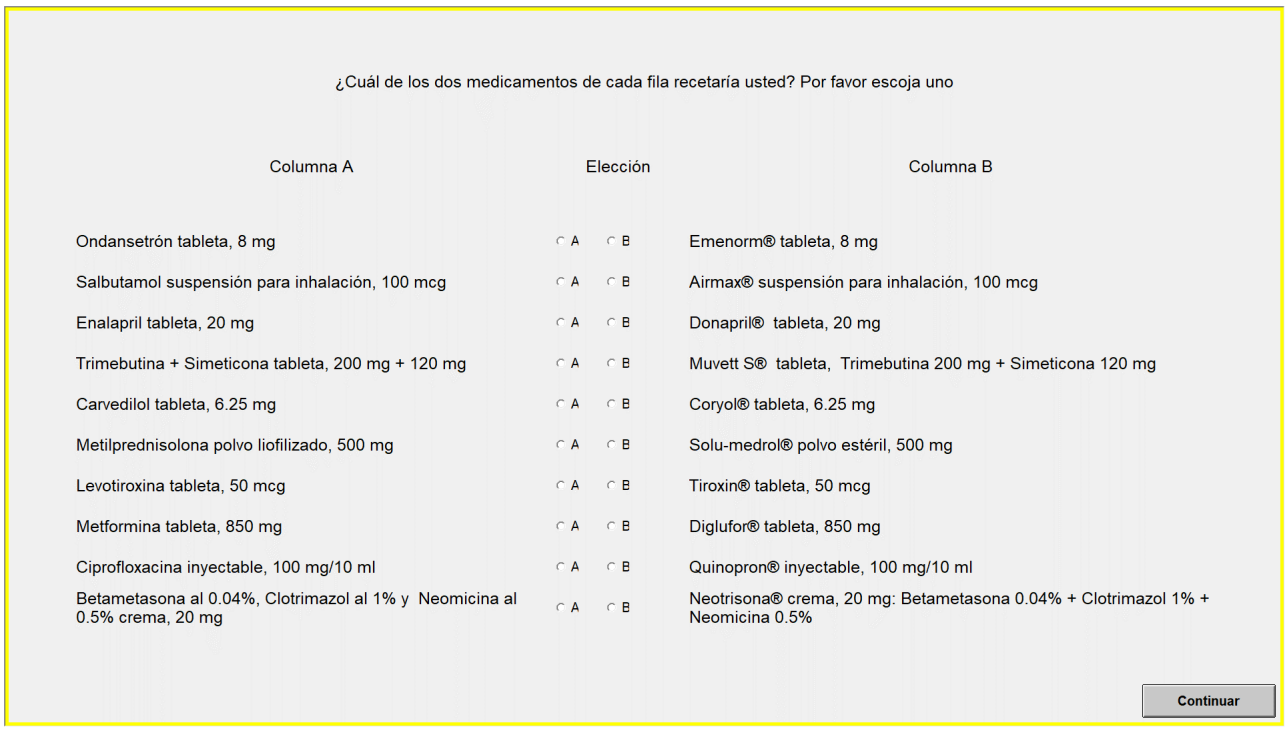


Table B.1: Risk aversion task.

Row number	**Column A**	**Column B**
1	5.000 COP with probability 50% or 0 COP with probability 50%	0 COP
2	5.000 COP with probability 50% or 0 COP with probability 50%	500 COP
3	5.000 COP with probability 50% or 0 COP with probability 50%	1000 COP
4	5.000 COP with probability 50% or 0 COP with probability 50%	1500 COP
5	5.000 COP with probability 50% or 0 COP with probability 50%	2000 COP
6	5.000 COP with probability 50% or 0 COP with probability 50%	2500 COP
7	5.000 COP with probability 50% or 0 COP with probability 50%	3000 COP
8	5.000 COP with probability 50% or 0 COP with probability 50%	3500 COP
9	5.000 COP with probability 50% or 0 COP with probability 50%	4000 COP
10	5.000 COP with probability 50% or 0 COP with probability 50%	4500 COP
11	5.000 COP with probability 50% or 0 COP with probability 50%	5000 COP

The subjects had to choose between column A and column B in each of eleven rows. Each lottery in column A has the same expected value. We asked the participants to change the column only once time during the eleven elections.

Figure B.9: Eye-tracking device.

We used a headset device with both a front and an eye camera that operates at 120 Hz, which means it measures the eye's position 120 times per second. Specifically, the device registers a measurement every 8.3 milliseconds, with an average error of 4.17 milliseconds.

Table B.2: Sample characteristics by treatment group and order-block

	FFP	CCI	mean diff.	Order 1	Order 2	mean diff.
Age	21.95	21.97	-0.027	22.26	21.64	0.624*
Demographics						
gender (female=1)	0.65	0.62	0.027	0.63	0.64	-0.007
marital status (married=1)	0.00	0.05	-0.054	0.03	0.03	0.001
Education						
year	4.89	4.95	-0.054	4.97	4.86	0.113
score (from 0 to 5)	4.11	4.14	0.027	4.15	4.09	0.053
university	4.16	4.05	0.108	4.05	4.17	-0.114
Socioeconomic						
socieconomic level	4.43	4.08	0.351*	4.32	4.19	0.121
educational level of the mother	5.30	4.73	0.568*	5.18	4.83	0.351
Observations	37	37		38	36	

The table shows the mean value for pre-treatment socioeconomic characteristics and the p-value for the mean differences test between the fixed fee per patient (FFP) and the cost-containment incentive group (CCI). We also test the mean differences between Order 1 and Order 2. * $p < 0.1$. p-values calculated from independent sample t-tests.

Table B.3: Kolmogorov-Smirnov test for equality of distribution functions.

	Treatment group.	Order-block.
Age	1.000	0.746
Education		
score (from 0 to 5)	0.888	0.989
Socioeconomic		
socieconomic level	0.715	0.999
educational level of the mother	0.522	0.913

FFP stands for the fixed fee per patient and CCI the cost-containment incentive. We cannot reject the null hypothesis that the distribution of age, score, socioeconomic level, and mother's education for FFP and CCI groups and Order 1 and Order 2 come from the same distribution (see p-values).

Table B.4: Cost-containment incentive effect by patient (p-values).

		Generic prescriptions (proportion)		Pupil diameter (mm)		Number of fixations	
		FFP vs. CCI	*FFP+gift vs. CCI+gift*	*FFP vs. CCI*	*FFP+gift vs. CCI+gift*	*FFP vs. CCI*	*FFP+gift vs. CCI+gift*
Patient	1st	0.1517	0.3173	0.3490	0.1345	0.9793	0.4265
	2nd	1	0.3047	0.2490	**0.0417**	0.6216	**0.0609**
	3rd	0.3800	0.3173	0.6396	0.1575	0.9793	**0.0954**
	4th	**0.0778**	**0.0791**	0.1345	0.4937	0.3427	0.8558
	5th	0.2845	1	0.4296	0.5644	0.2380	0.7554
	6th	0.2549	0.2587	0.1834	0.5890	0.3975	0.4209
Full sample		0.5016	**0.0365**	**0.0284**	**0.0156**	0.1854	**0.0269**

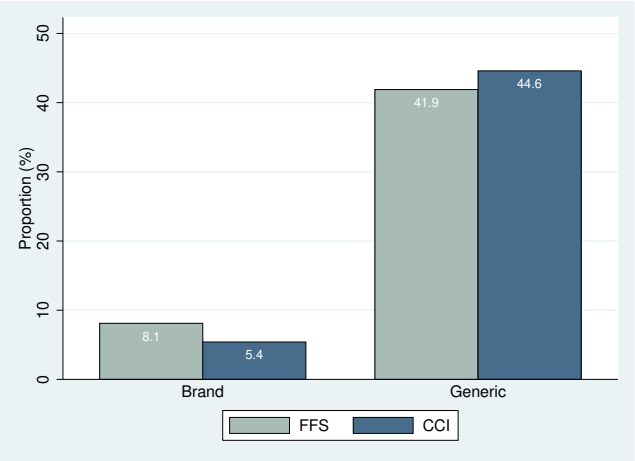
The table shows the Mann-Whitney test to evaluate treatments effects for all six patients. FFP stands for the fixed fee per patient and CCI the cost-containment incentive. p-values in bold are significant at least at 10%.

B.3 Control tasks

We have evidence of the consensus effect since the average correlation between the version the subjects thought was the most prescribed in the last year in Colombia and the type of drug they would prescribe was 0.73. On average, the subjects' choices coincide in 6.32 of 10 molecules (standard deviation of 2.43 and median of 6), and 85.4 % of the participants show consensus in six of the 10 active ingredients. In Figure B.10, we present the distribution of the subject's type by treatment group. As we mention in section 2.2, we classify the subjects as "generic type" when they report

prescribing at least 6 versions of the list of 10 molecules. The proportion of the generic type subjects is similar between treatment groups. However, the proportion of the FFP group's brand type participants is greater than in the CCI group. Last, we find evidence of the false consensus effect. The subjects who show consensus tend to believe more frequently something wrong (see Figure B.11).

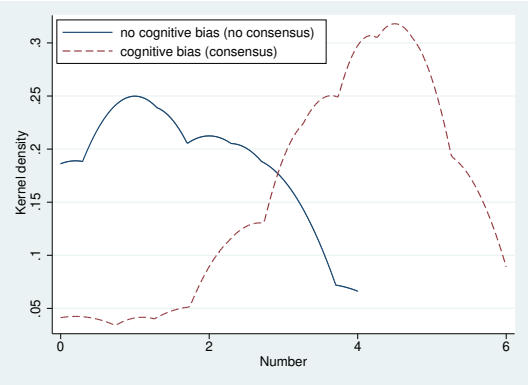
Figure B.10: Subject's type by treatment group.



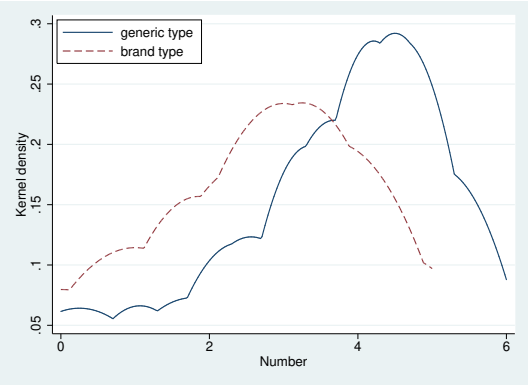
Subject's classification if they are of the generic or the brand type by treatment group. FFP: fixed fee per patient and CCI: cost-containment incentive.

Figure B.11: False consensus effect

(a) False beliefs by consensus



(b) False beliefs by subject's type



Panel (a) presents the subjects who show consensus (subjects who have a cognitive bias) and those who not. Participants with cognitive bias have false beliefs for more molecules than participants without the bias. From Panel (b), we can conclude that the generic type subjects tend to have more false beliefs than the bran type physicians.

Regarding the risk aversion task, 22.3% of the subjects are risk-averse, 23.8% are neutral, and 53.7% are risk lovers. We could not categorize 9.5% of the participants due to they have multiple switching points in the lotteries. Using the JPI risk-scale results, we have that 22.9% of the participants are risk-seeking, 56.7% are neutral, and 20.2% are risk-averse. The average correlation between the risk aversion task and the risk-taking scale was 0.18.

Table B.5: Treatment effects for prescription decisions (probit estimation).

	Generic precriptions			
	(1)	(2)	(3)	(4)
Treatment (CCI=1)	0.271	0.239	0.155	0.164
	(0.173)	(0.273)	(0.254)	(0.250)
Gift	0.081	-0.009	0.191	0.151
	(0.095)	(0.270)	(0.274)	(0.277)
1^{st} part	0.306***	0.414	0.663***	0.614**
	(0.092)	(0.253)	(0.251)	(0.257)
Treatment x gift		0.183	0.346	0.283
		(0.408)	(0.389)	(0.396)
Treatment x 1^{st} part		-0.239	-0.150	-0.206
		(0.369)	(0.355)	(0.373)
Gift x 1^{st} part		-0.099	-0.535	-0.429
		(0.498)	(0.497)	(0.507)
Treatment x gift x 1^{st} part		0.246	-0.004	0.143
		(0.694)	(0.639)	(0.649)
Type (generic=1)			0.712***	0.610***
			(0.176)	(0.170)
JPI risk-taking (from 0 to 1)			-0.711	-0.967
			(0.726)	(0.717)
Constant	0.571***	0.589***	4.628**	5.486*
	(0.135)	(0.197)	(2.238)	(3.024)
Controls	No	No	Yes	Yes*
Observations	444	444	444	444
Subjects	74	74	74	74

Probit regressions for prescription decision (=1 if it is generic and 0 if it is the brand drug). CCI: if the subject receives the cost-containment incentive, 0 if she gets a fixed fee per patient. $Gift = 1$ if the participant obtains the gift for that decision, 0 if not. 1^{st} part=1 for the first part of the experiment, and 0 for the second part. Controls: age, female, socioeconomic strata, marital status, educational level of the mother, year, score, subject's type (1 if the subject is of the "generic" type and 0 if she is of the "brand" type), and the Jackson Personality Inventory (JPI) risk-taking scale, and university dummies*. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.6: Treatment effects for prescription decisions.

	Generic precriptions			
	(1)	(2)	(3)	(4)
Treatment (CCI=1)	0.064	0.057	0.024	0.032
	(0.048)	(0.095)	(0.078)	(0.076)
Gift	0.041	0.050	0.077	0.075
	(0.026)	(0.093)	(0.084)	(0.086)
1^{st} part	0.092***	0.148*	0.175**	0.173**
	(0.026)	(0.086)	(0.074)	(0.078)
Treatment x gift		0.054	0.106	0.093
		(0.125)	(0.109)	(0.109)
Treatment x 1^{st} part		-0.044	0.008	-0.005
		(0.115)	(0.096)	(0.097)
Gift x 1^{st} part		-0.080	-0.133	-0.128
		(0.154)	(0.136)	(0.143)
Treatment x gift x 1^{st} part		0.017	-0.086	-0.062
		(0.195)	(0.161)	(0.163)
Type (generic=1)			0.212***	0.196***
			(0.050)	(0.044)
JPI risk-taking (from 0 to 1)			-0.204	-0.223
			(0.158)	(0.156)
Constant	0.729***	0.714***	1.585***	1.943**
	(0.044)	(0.076)	(0.553)	(0.734)
Controls	No	No	Yes	Yes*
Observations	378	378	378	378
Subjects	63	63	63	63

OLS regressions for prescription decision using observations available for pupil diameter (=1 if it is generic and 0 if it is the brand drug). CCI: if the subject receives the cost-containment incentive, 0 if she gets a fixed fee per patient. $Gift = 1$ if the participant obtains the gift for that decision, 0 if not. 1^{st} part=1 for the first part of the experiment, and 0 for the second part. Controls: age, female, socioeconomic strata, marital status, educational level of the mother, year, score, subject's type (1 if the subject is of the "generic" type and 0 if she is of the "brand" type), and the Jackson Personality Inventory (JPI) risk-taking scale, and university dummies*. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C

Chapter 3

Recall that participants observed labels F instead of A and vice versa and C instead of E and vice versa.

Figure C.1: Group Screen - Control

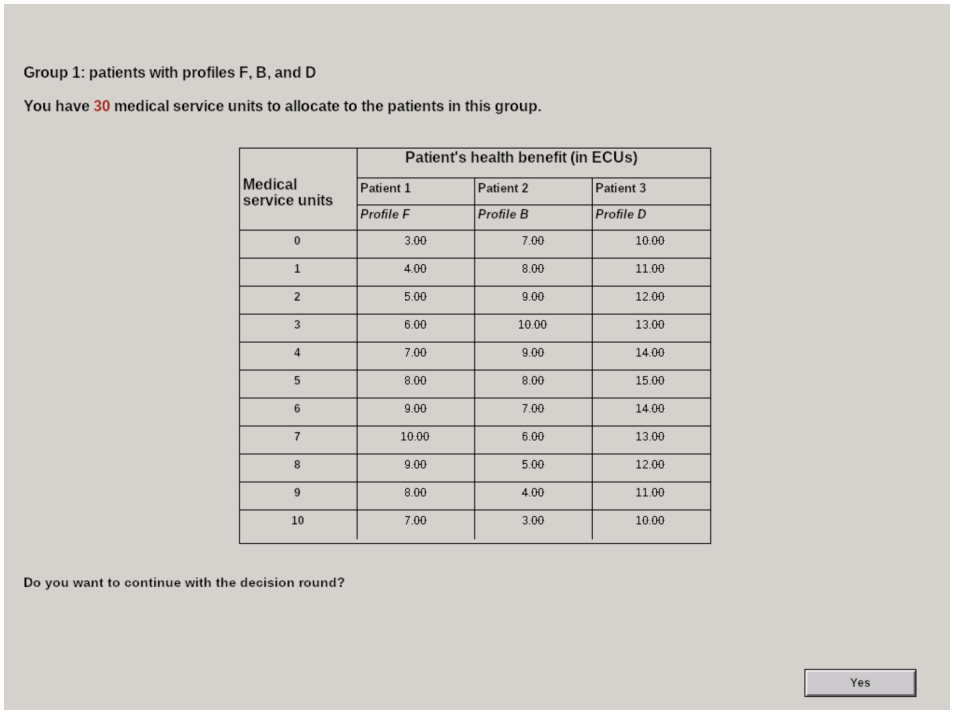


Figure C.2: Patient Screen - Control

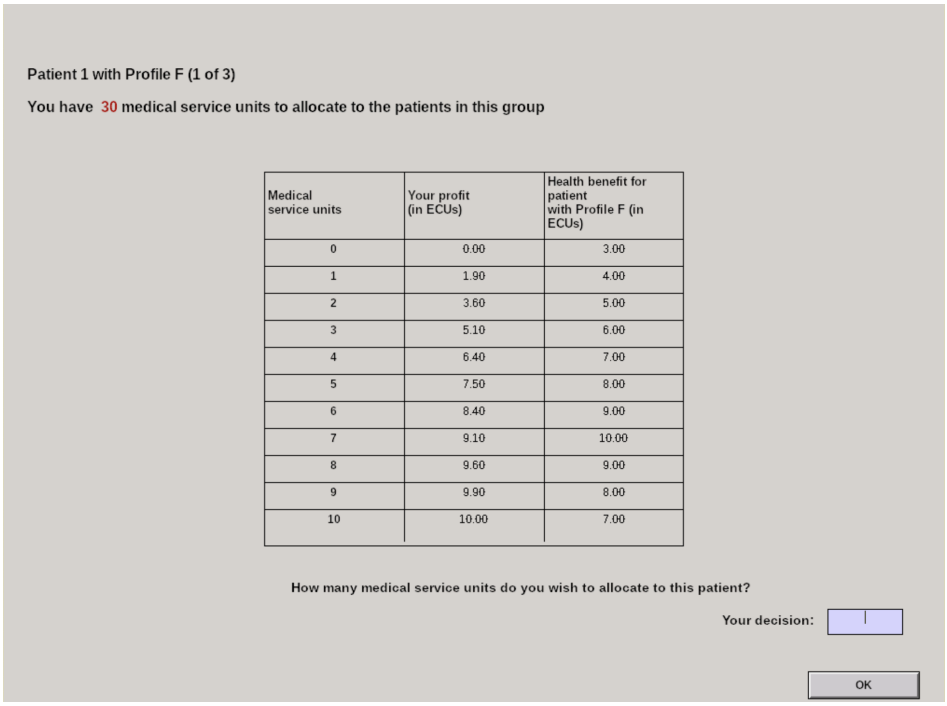
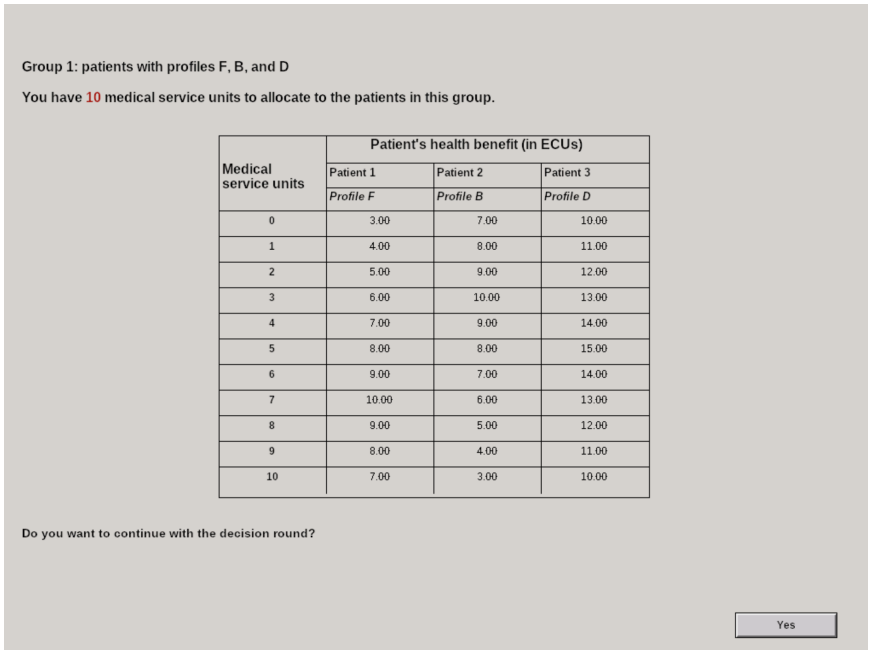


Table C.1: Physicians by configuration

BC								U and BC+U			
1		2		3		4		1 or 3		2 or 4	
Part 1	Part 2	Part 1	Part 2	Part 1	Part 2	Part 1	Part 2	Part 1	Part 2	Part 1	Part 2
ABD	ABD	ABC	ABC	ABD	ABC	ABC	ABD	ABD	AB D/C	ABC	AB D/C
DGC	DGC	DGF	DGF	DGC	DGF	DGF	DGC	DGC	DG C/F	DGF	DG C/F
FEG	FEG	FED	FED	FEG	FED	FED	FEG	FEG	FE G/D	FED	FE G/D

BC stands for Budget Constraint, U for Uncertainty and BC+U to Budget Constraint and Uncertainty treatments.

Figure C.3: Group Screen - BC Treatment



Group 1: patients with profiles F, B, and D

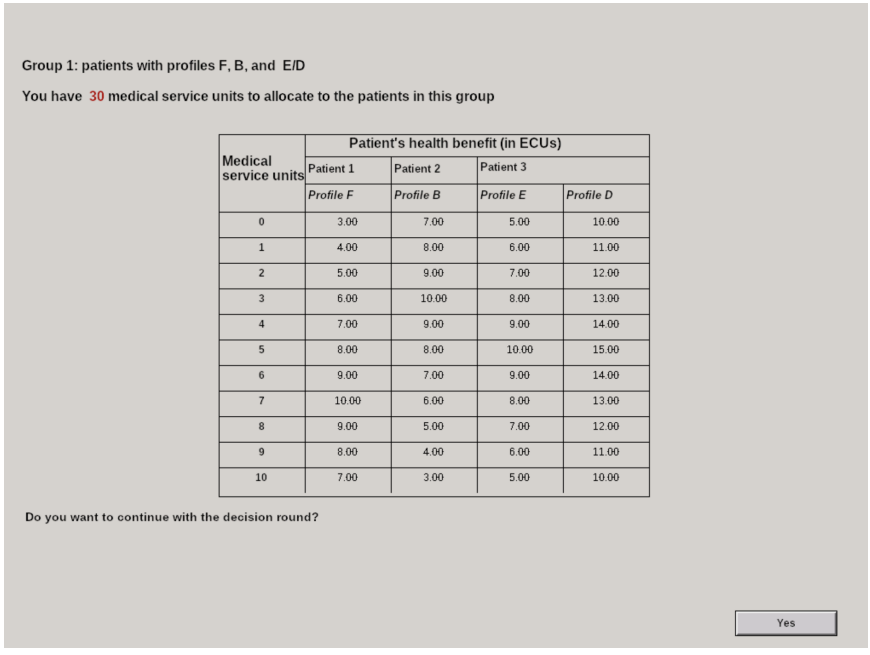
You have 10 medical service units to allocate to the patients in this group.

Medical service units	Patient's health benefit (in ECUs)		
	Patient 1	Patient 2	Patient 3
	Profile F	*Profile B*	*Profile D*
0	3.00	7.00	10.00
1	4.00	8.00	11.00
2	5.00	9.00	12.00
3	6.00	10.00	13.00
4	7.00	9.00	14.00
5	8.00	8.00	15.00
6	9.00	7.00	14.00
7	10.00	6.00	13.00
8	9.00	5.00	12.00
9	8.00	4.00	11.00
10	7.00	3.00	10.00

Do you want to continue with the decision round?

Yes

Figure C.4: Group Screen - U Treatment



Group 1: patients with profiles F, B, and E/D

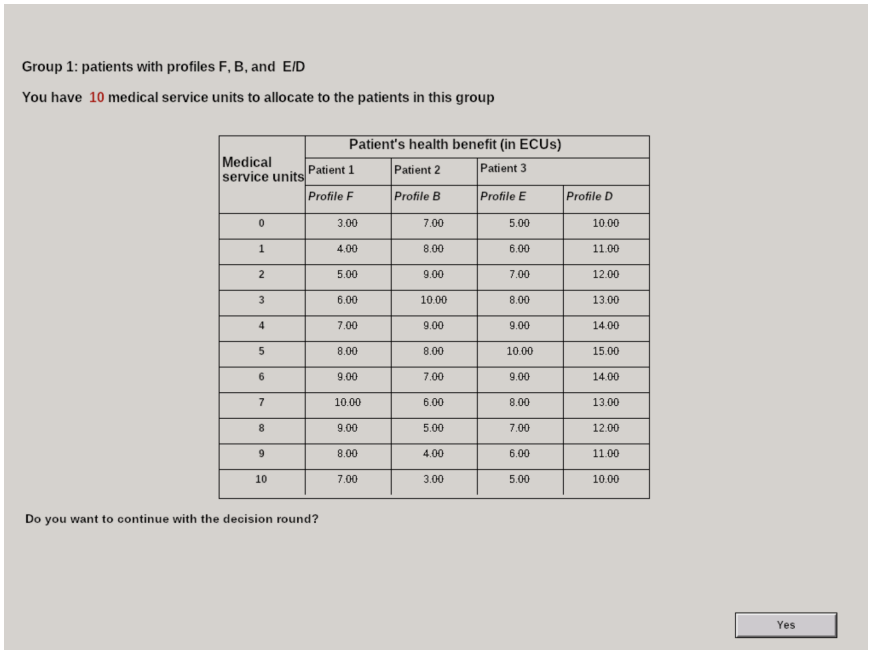
You have 30 medical service units to allocate to the patients in this group

Medical service units	Patient's health benefit (in ECUs)			
	Patient 1	Patient 2	Patient 3	
	Profile F	*Profile B*	*Profile E*	*Profile D*
0	3.00	7.00	5.00	10.00
1	4.00	8.00	6.00	11.00
2	5.00	9.00	7.00	12.00
3	6.00	10.00	8.00	13.00
4	7.00	9.00	9.00	14.00
5	8.00	8.00	10.00	15.00
6	9.00	7.00	9.00	14.00
7	10.00	6.00	8.00	13.00
8	9.00	5.00	7.00	12.00
9	8.00	4.00	6.00	11.00
10	7.00	3.00	5.00	10.00

Do you want to continue with the decision round?

Yes

Figure C.5: Patient Screen - BC+U Treatment



Group 1: patients with profiles F, B, and E/D

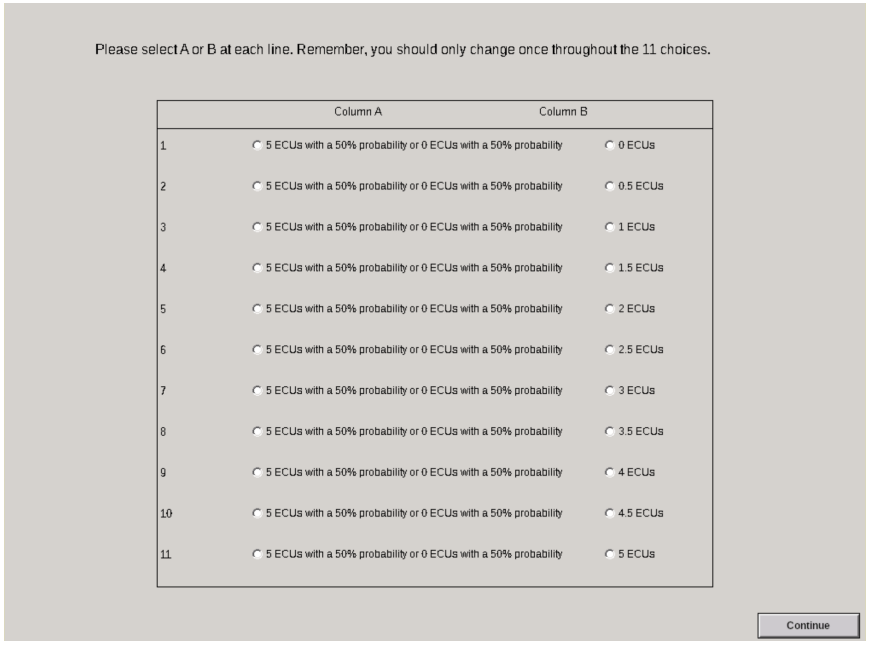
You have 10 medical service units to allocate to the patients in this group

Medical service units	Patient's health benefit (in ECUs)			
	Patient 1	Patient 2	Patient 3	
	Profile F	*Profile B*	*Profile E*	*Profile D*
0	3.00	7.00	5.00	10.00
1	4.00	8.00	6.00	11.00
2	5.00	9.00	7.00	12.00
3	6.00	10.00	8.00	13.00
4	7.00	9.00	9.00	14.00
5	8.00	8.00	10.00	15.00
6	9.00	7.00	9.00	14.00
7	10.00	6.00	8.00	13.00
8	9.00	5.00	7.00	12.00
9	8.00	4.00	6.00	11.00
10	7.00	3.00	5.00	10.00

Do you want to continue with the decision round?

Yes

Figure C.6: Lottery to measure risk aversion preference



Please select A or B at each line. Remember, you should only change once throughout the 11 choices.

	Column A	Column B
1	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	0 ECUs
2	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	0.5 ECUs
3	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	1 ECUs
4	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	1.5 ECUs
5	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	2 ECUs
6	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	2.5 ECUs
7	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	3 ECUs
8	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	3.5 ECUs
9	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	4 ECUs
10	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	4.5 ECUs
11	5 ECUs with a 50% probability or 0 ECUs with a 50% probability	5 ECUs

Continue

Figure C.7: Lotteries to measure prudence preference

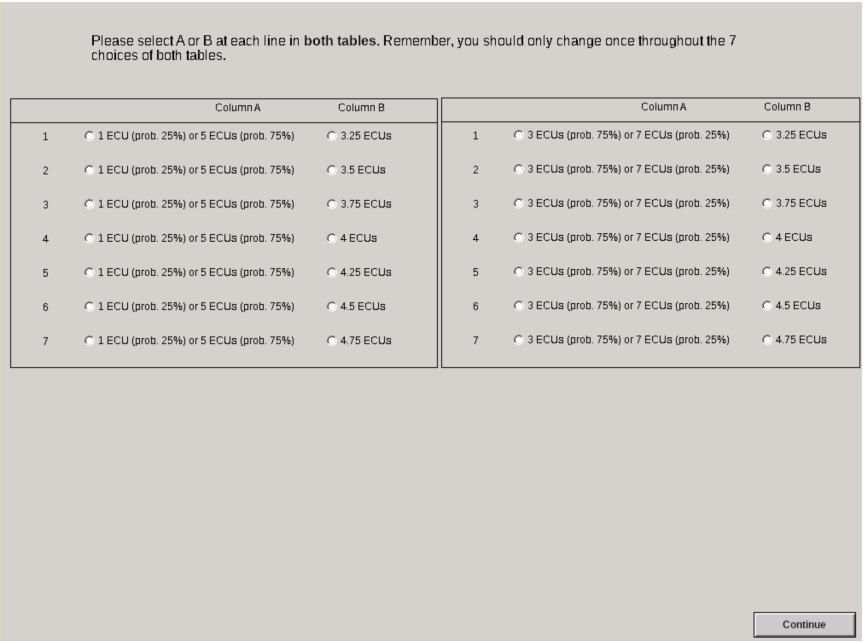


Table C.2: Summary statistics and mean comparison tests, by treatment

	Mean			p-value		
	BC	**U**	**BC+U**	**BC vs U**	**BC vs BC+U**	**U vs BC+U**
Age	21.10	21.88	21.43	0.103	0.488	0.321
Female	0.63	0.65	0.57	0.783	0.549	0.379
Siblings	1.59	2.02	1.31	0.068	0.203	0.002
Economics	0.12	0.12	0.12	0.972	1.000	0.972
Econ or Finance	0.29	0.23	0.27	0.470	0.828	0.613
Medicine	0.02	0.04	0.02	0.572	1.000	0.572
Med or Physiotherapy	0.20	0.25	0.22	0.515	0.809	0.684
Family Income at 18	3.41	3.37	3.18	0.793	0.185	0.256
Med Parents	0.14	0.10	0.16	0.521	0.782	0.359
Strata	3.63	3.65	3.14	0.912	0.028	0.030
Self-financed Expense	3.36	3.70	4.49	0.642	0.126	0.295

This table shows the mean by treatment for the main final survey variables and the p-value for the mean differences by treatment pair. BC: Budget Constraint; U: Uncertainty; BC+U: Budget Constraint and Uncertainty. We present results for age, gender, number of siblings, and if the participant is an Economics, Finance, Medicine or Physiotherapy major. We also add socioeconomic Strata (household classification specific to Colombia that correlates with income).

Table C.3: Patient's characteristics (within-subjects analysis) by treatment

	BC			U			BC+U		
	$q_2 - q_1$	$\frac{q_2-\hat{q}}{\hat{q}}$ % - $\frac{q_1-\hat{q}}{\hat{q}}$ %	$B(q_2) - B(q_1)$	$q_2 - q_1$	$\frac{q_2-\hat{q}}{\hat{q}}$ % - $\frac{q_1-\hat{q}}{\hat{q}}$ %	$B(q_2) - B(q_1)$	$q_2 - q_1$	$\frac{q_2-\hat{q}}{\hat{q}}$ % - $\frac{q_1-\hat{q}}{\hat{q}}$ %	$B(q_2) - B(q_1)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Health status ≥ 5	-1.680***	-42.06***	1.220***	-0.0787	-0.331	-0.860***	-1.269***	-37.36***	2.185***
	(0.286)	(5.262)	(0.311)	(0.188)	(3.272)	(0.278)	(0.293)	(5.177)	(0.354)
Capacity to benefit of 2	0.435*	1.772	1.393***	-0.0547	-0.0501	0.371	0.611***	2.590	1.595***
	(0.258)	(4.837)	(0.288)	(0.177)	(3.126)	(0.288)	(0.221)	(4.278)	(0.360)
$\hat{q} = 3$	1.588***	-12.69	2.277***	0.0697	4.321	0.693**	1.421***	-22.77**	2.277***
	(0.406)	(11.83)	(0.335)	(0.316)	(10.15)	(0.312)	(0.314)	(10.63)	(0.384)
$B(\hat{q}) \geq 10$	-0.107	7.869	-2.360***	-0.304	-7.517*	-0.947**	-0.251	9.253	-2.717***
	(0.356)	(6.767)	(0.428)	(0.233)	(4.157)	(0.407)	(0.386)	(7.284)	(0.471)
Constant	-2.852*	-58.68*	-0.0811	-0.618	-9.881	2.088	-0.519	-7.993	-1.820
	(1.453)	(29.22)	(1.416)	(1.199)	(26.01)	(1.343)	(2.120)	(46.94)	(2.408)
Observations	441	441	441	405	405	405	369	369	369

OLS regressions. Dependent variables: within number of units allocated, percentage deviation from patient's optimal level, and patient's benefit. Columns (1)-(3) presents regressions for BC: Budget Constraint; columns (4)-(6) for U: Uncertainty; and columns for (7)-(9) for BC+U: Budget Constraint and Uncertainty. Reference categories: initial health status below 3, capacity to benefit of 1, maximum achievable benefit of 6, and $\hat{q} > 3$. Controls (all regressions): age, female, econ or finance students, strata, if parents are medical professionals, mistakes in control questions, risk-aversion, prudence, altruism, and dummies for each patient profile. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Figure C.8: Physician's types by treatment