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Abstract

Physicians are no strangers to situations where they have to decide with resource restrictions and uncertainty on the relative needs of future beneficiaries of the scarce resources. We propose a lab experiment to understand if such an environment affects physicians' 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 what is best for the patient.

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JEL Classification: C91, D81, D91, I19.

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 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

[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).

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.

The rest of the paper is organized as follows. In Section 2, we describe the experimental design and procedures. Then, in Section 3 we move to detail our hypotheses. In Section 4, we present the results. In Section 5, we conclude.

2 Experimental design and procedures

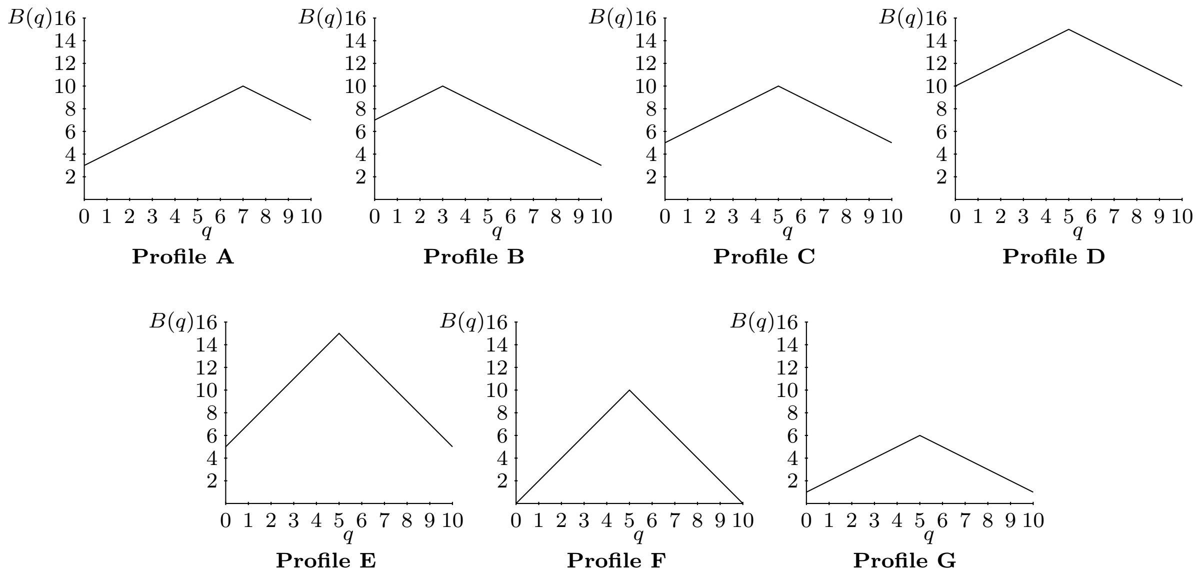
2.1 Experimental design

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 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

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

(see Figure 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).

Figure 1: Profiles of patient health benefits (EMUs)



Notes: 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 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 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

Notes: 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 A.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 selfish physicians from those with an equal split rule.[6] Second, we want to make the constraint

[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 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 A.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.

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 2). In BC, subjects have complete information to allocate ten service units to the three patients of each group (see Figure A.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 A.4 and A.5, in the Appendix). As in Part 1, we discount the units allocated to the total budget after each decision. In the BC and BC+U treatments, this limits the number of units they can distribute to future patients.

[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 A.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.

Table 2: Treatments.

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

Notes: 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.

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

[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.

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 A.1 and A.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 A.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 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

[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%).

[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 A.6 and A.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).

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 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 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 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.

4 Results

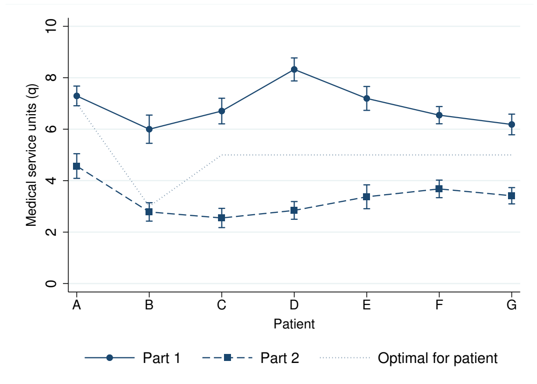
This section explores the decisions of 154 subjects in both parts of the experiment and by treatment.[15] We first answer if budget constraints and uncertainty affect the allocation decisions of physicians. Then we move to explore the mechanisms.

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

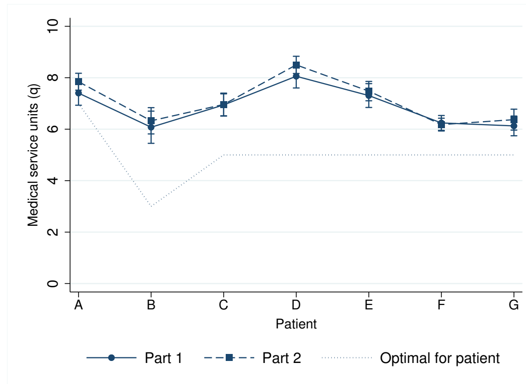
We begin the analysis by plotting the average allocation to each profile by part (Figure 2). The solid lines represent the allocations in Part 1, while the dashed line shows Part 2. The dotted line outlines the optimal level for each patient. From the figure, we can assess that, in the absence of constraints 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 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 A.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 ($p < 0.01$).

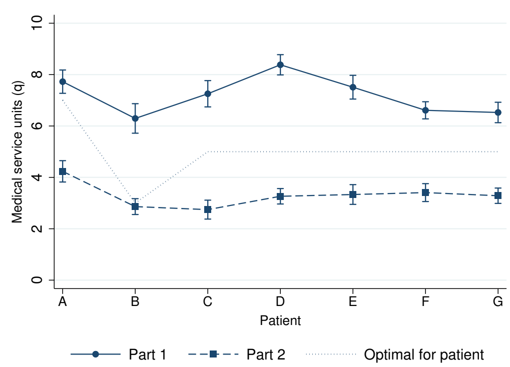
Figure 2: Medical services allocated by profile.



(a) BC



(b) U



(c) BC+U

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

	BC			**U**			**BC+U**		
	Part 1 (mean)	Part 2 (mean)	$Part1 = Part2$ p-value	Part 1 (mean)	Part 2 (mean)	$Part1 = Part2$ p-value	Part 1 (mean)	Part 2 (mean)	$Part1 = Part2$ 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

Notes: 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 1 and row 2 of Table 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).

Table 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 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).

[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 A.1, in the Appendix). We do not report these specifications as results are similar to those in columns (1), (3), and (5).

Table 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

Notes: 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), 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 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.

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 in Part 1 to 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 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.

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

[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.

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

Table 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 ≥ 5 × 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 ≥ 5 × 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 × 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 × 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)
$\hat{q} = 3$ × 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)
$\hat{q} = 3$ × 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)
$B(\hat{q}) \geq 10$ × 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)
$B(\hat{q}) \geq 10$ × 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

Notes: 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.

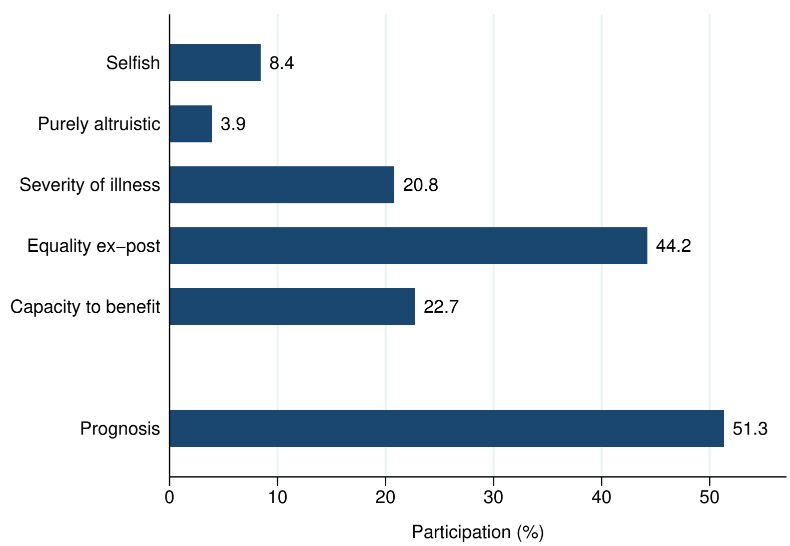
Result 4: Physicians do not respond to patients' characteristics when facing uncertainty alone.

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, 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.

Figure 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).

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

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 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 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. 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.

[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.

Table 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

Notes: 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.

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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A Appendix

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

Group 1: patients with profiles F, B, and 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 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 A.1: Group Screen - Control

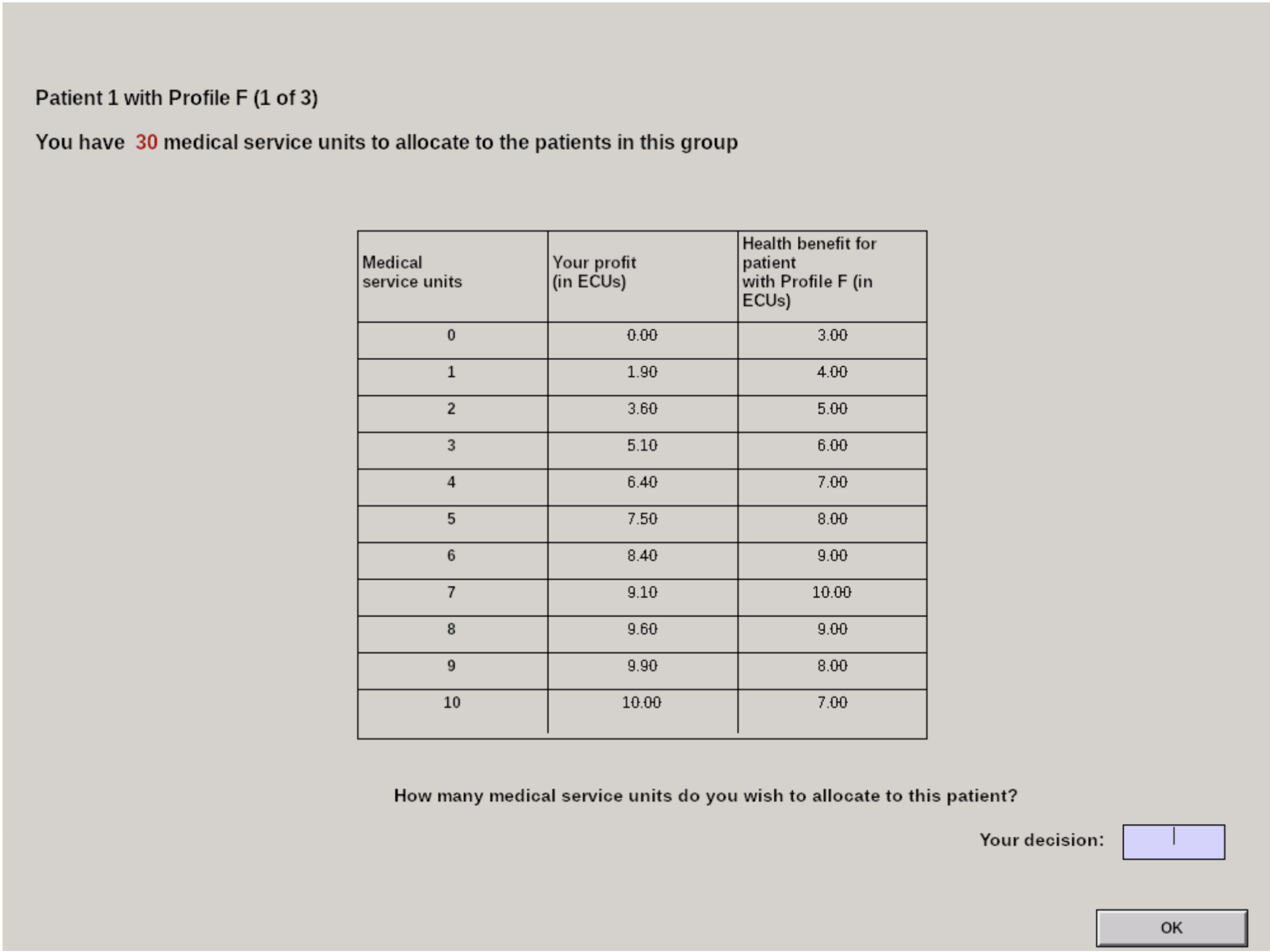


Figure A.2: Patient Screen - Control

Table A.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

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

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 A.3: Group Screen - BC Treatment

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

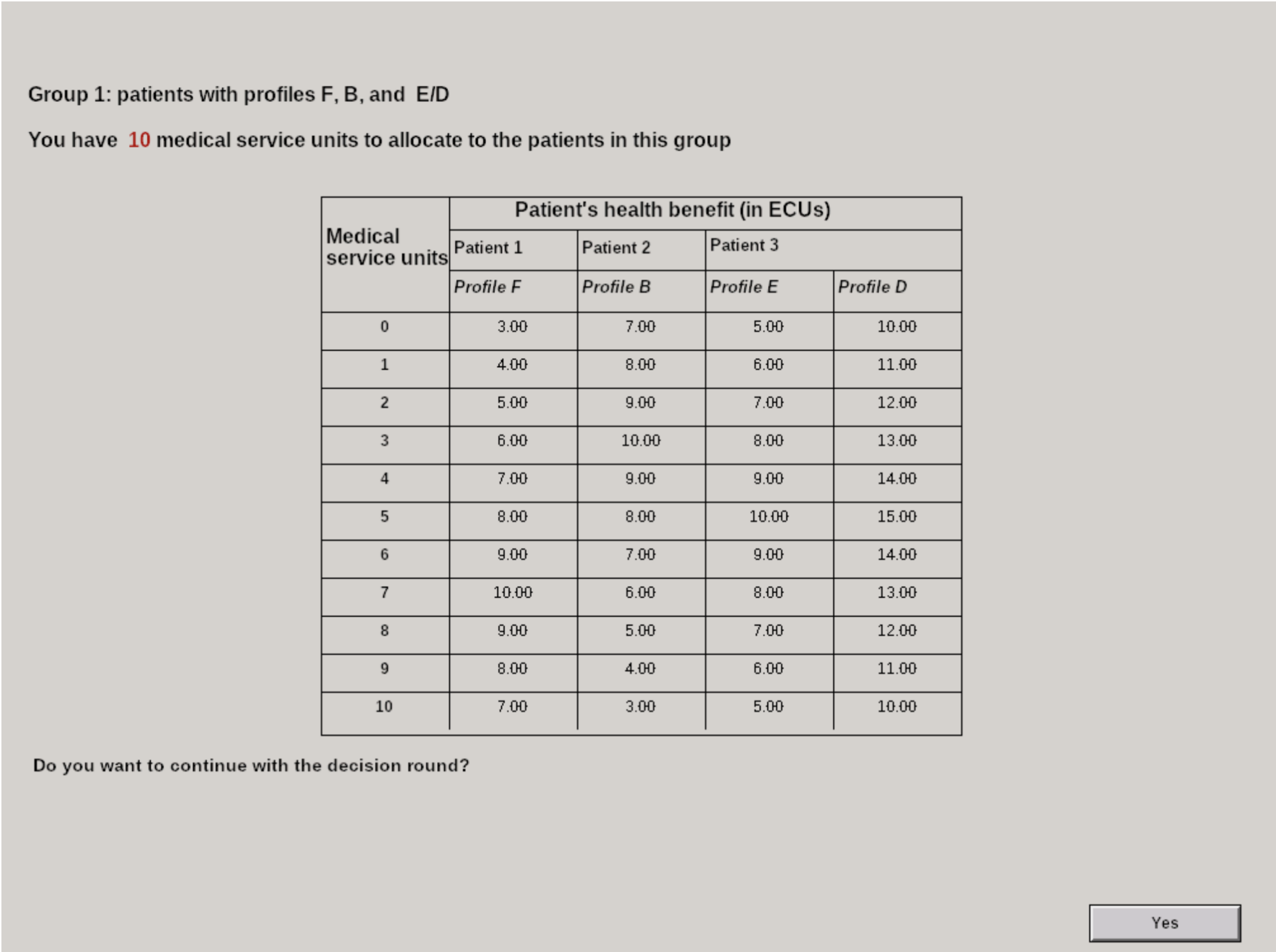
You have 30 medical service units to allocate to the patients in this group

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 A.4: Group Screen - U Treatment



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

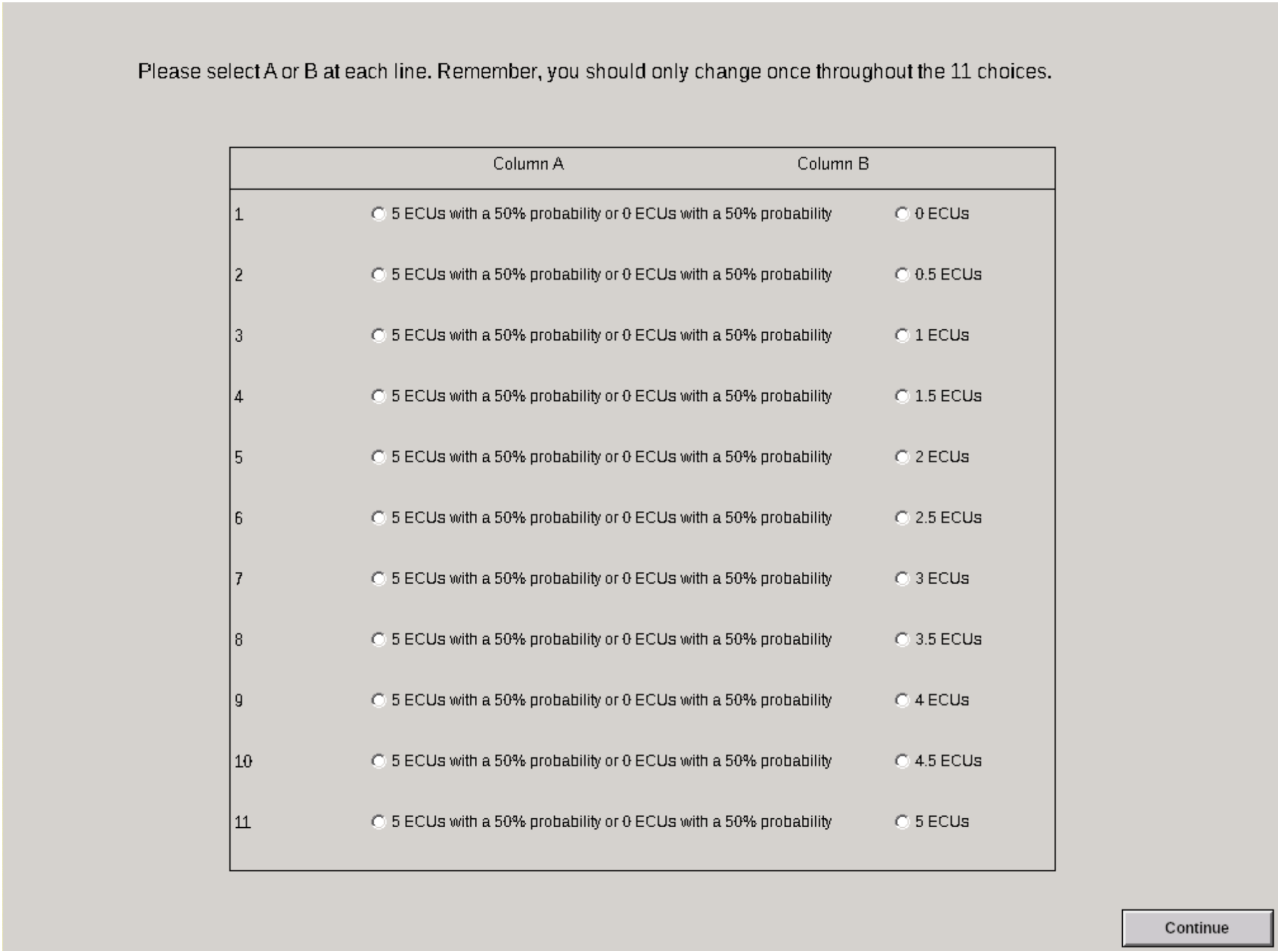
You have 10 medical service units to allocate to the patients in this group

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 A.5: Patient Screen - BC+U Treatment



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 A.6: Lottery to measure risk aversion preference

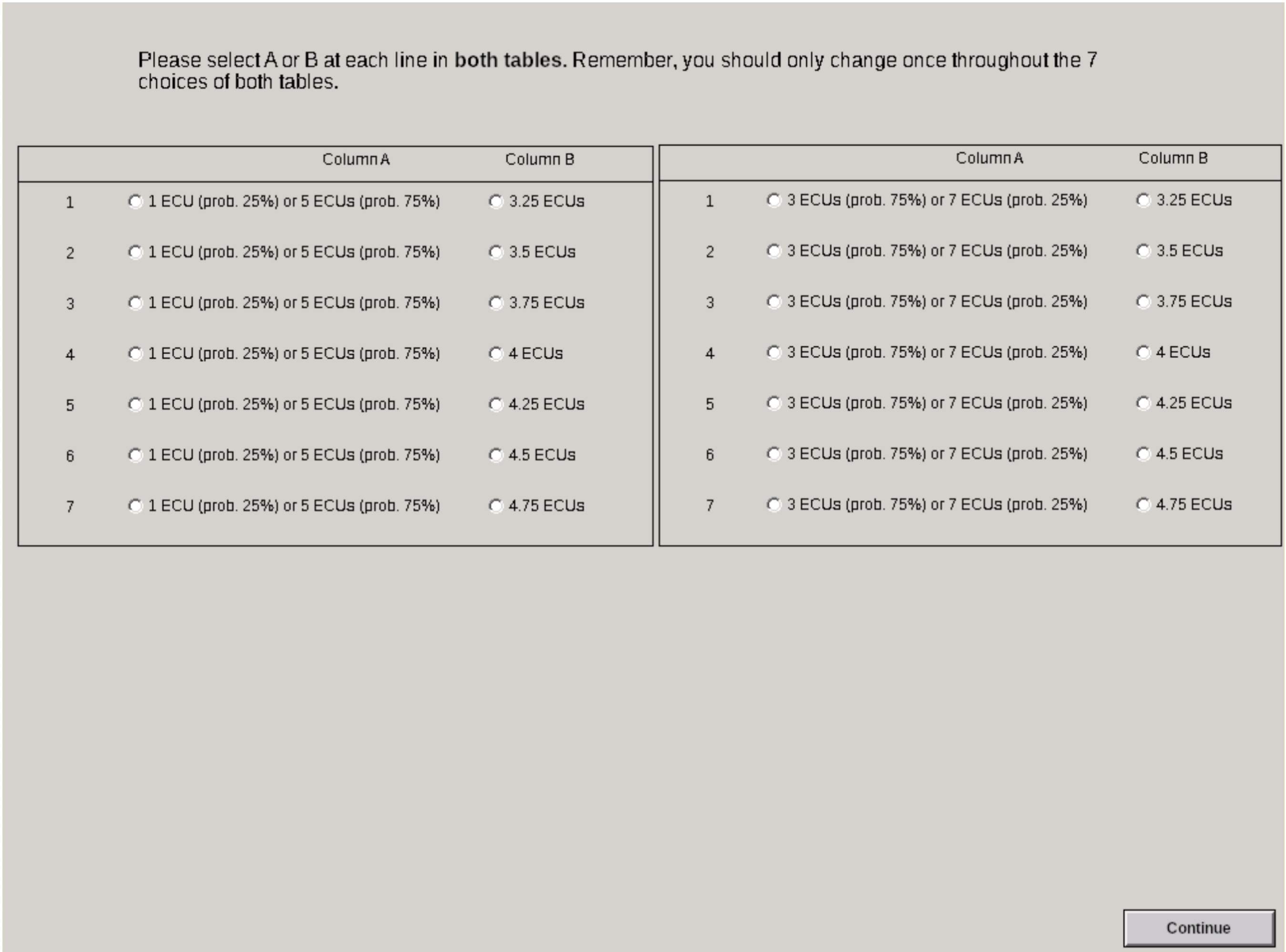


Figure A.7: Lotteries to measure prudence preference

Table A.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

Notes: 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).