Physicians' incentives to adopt personalized medicine: experimental evidence

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Abstract

We study physicians' incentives to use personalized medicine techniques, replicating the physician's trade-offs under the option of personalized medicine information. In a laboratory experiment, organized in two French Universities, where prospective physicians play a dual-agent real-effort game, we vary both the information structure (free access *versus* paid access to personalized medicine information) and the payment scheme (pay-for-performance (P4P), capitation (CAP) and fee-for-service (FFS)) by applying a within-subject design. Our results are threefold: i) Compared to FFS and CAP, the P4P scheme strongly and positively impacts the decision to adopt personalized medicine. ii) Although expected to dominate the other schemes, P4P is not always efficient in transforming free access to personalized medicine into higher quality patient care. iii) When it has to be paid for, personalized medicine is positively associated with quality, suggesting that subjects tend to make better use of information that comes at a cost. We conclude that this last result can be considered as a "commitment device" effect. However, quantification of our results suggests that its positive impact is not strong enough to justify generalizing the payment for personalized medicine access.

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1 Introduction

Personalized medicine (PM) involves profiling patients to determine decisions, treatments or medical interventions according to their predicted best response. While the idea dates back to Hippocrates, advances in genomics and epigenetics over the last two decades have helped promote this type of medicine. However, even when personalized medicine technology is available, physicians actually tend to under-use it, with the issue not appearing to be only one of cost. The literature has documented reasons for this under-use of personalized medicine techniques. A first argument is found in Antoñanzas *et al.* (2015) who report that there exists an uncertainty about personalized medicine test results. This uncertainty is likely to prevent physicians from relying on personalized medicine tests. A second argument is given by Howard *et al.* (2017) who argue that payment schemes might not provide enough incentives to adopt these new technologies. They find that physicians paid under a FFS plan tend to under-use PM technologies even when it is available for free. The inter-play between access to PM technologies (free *vs.* alternative modes) and physicians' payment systems will be the heart of our contribution. Health systems, and the populations covered, stand to benefit from the adoption of personalized medicine technologies, and better allocating treatments among patients is a promising way to reduce both health expenditure and adverse consequences of treatments (Nimmesgern *et al.* 2017). Here, to tackle the issue of effective adoption of personalized medicine, we examine how physicians' payment schemes affect their incentives to use personalized medicine techniques, and the extent to which their patients may benefit from such practice.

To study how physician payment schemes affect their decisions to use personalized medicine, we design an experiment to replicate the physician's trade-offs under the option of personalized medicine information. As implemented, subjects are placed in a real-effort task game, as per Green, (2014); Bejarano et *al.* (2017) and, less directly, Lagarde and Blaauw (2017). In our experiment, ninety-five prospective physicians perform a task simulating the option of access to information likely to help them to take better care of a patient. First, in order to imitate the relationship between the physician and the patient, our game is similar to that of Green (2014), consisting in proofreading short texts with potential positive benefits for a third party (the "patient") when the texts are corrected well. Second, we design the task to account for features of personalized medicine, viewed as a set of information that can guide physicians in

formulating medical decisions. While a physician without personalized medicine information needs to consider a wide set of symptoms when making a decision, personalized information allows the physician to focus on a limited subset of symptoms for quicker diagnosis and more effective treatment. To capture this feature, a subset of "priority sentences" is defined in the texts and only actions within this subset are considered to generate potential benefits for the third party. Thus, the proofreader's efficiency crucially depends on the informational input on priority sentences. Precise information on which sentences are "priority" is made available to the subjects, free of charge in some periods of the game but at a cost in others.

Depending on the payment scheme, the incentives to make corrections in priority sentences differ, as do motivations for buying personalized medicine. The prospective physicians are subjected to different payment schemes in a within design. We explore three pure payment schemes: fee-for-service (FFS), capitation payment (CAP) and payment-for-performance (P4P). CAP is designed as a payment per "treated" text. FFS is designed to reward the physician based on the quantity of services provided (number of words corrected in the text). Lastly, P4P is designed as a payment for a minimum number of appropriate corrections in priority sentences. Our empirical strategy involves a two-stage panel least-square estimation, used to compare the behavior of subjects who buy personalized medicine information with that of subjects who do not buy it, under the different payment schemes.

Our main results can be summarized as follows. First, as expected, our experiment reveals that P4P –a quality-oriented remuneration scheme– yields stronger incentives to prospective physicians to buy personalized medicine techniques than FFS or CAP. In line with this first result, it seems that our subjects are also sensitive to financial incentives in their patient-care activities: while they treat more patients when paid by CAP, they perform more medical interventions under an FFS payment scheme (already in Green (2014)). We also find that CAP and P4P tend to generate similar incentives regarding the number of interventions; however, P4P is less effective in transforming free access to personalized medicine into overall quality care. Interestingly, our results reveal that the impact of the information conveyed by personalized medicine crucially depends on whether access to it is free or paid. When access to personalized medicine comes at a cost, differences due to the informational input are magnified, greatly to the patient's benefit. We interpret this result as a "commitment device" effect. In fact, once

subjects buy information, they make much better use of it, compared to the situation where access to personalized medicine information is free for all the physicians.

Finally, using a simple quantification of our experimental results to study whether it is advantageous to generalize paid access to personalized medicine, we find that paid access for all is not recommendable. Thus, since the outcomes from personalized medicine information are better when it comes at a cost, our results convey a strong policy recommendation: instead of providing free access to personalized medicine, the regulator should partially subsidize it, opting for a P4P scheme to enhance the adoption of relevant tools.

Physician payment mechanisms is one of the central topics in health economics (Ellis and McGuire, 1986). As eloquently explained in McGuire, (2000), the incentives generated by different physician payment schemes may depend on institutional features such as the identity of the payer(s), the existence of market competition between physicians, or whether the health system is a gate-keeping one. Our main contribution to this literature is to study physicians' incentives in the context of personalized medicine. Howard et *al.* (2017) report on the interaction between financial incentives and medical decisions when physicians can use personalized medicine tests to choose between conventional radiotherapy and intensity-modulated radiation therapy (IMRT) for U.S breast cancer Medicare patients, so as to identify patients who are highly responsive to the IMRT option. Physicians work either in free-standing clinics (where their FFS payment plan also includes a monetary reward for treating patients with IMRT), or in hospital-based clinics (where they receive no additional benefits). Howard et *al.* (2017) find that physicians in free-standing clinics tend to under-use personalized medicine tests. Thanks to this original study design enabling comparison between physicians' behavior in two institutional settings, their finding strongly suggests the need to explore the interaction between payment schemes and the adoption of personalized medicine.

Counterfactual is not always available to evaluate the properties of different payment schemes at work in health systems, and this is especially true of their interaction with personalized medicine, which is relatively new. Our article therefore relies on the literature using experimental methods to study physician payments. Over the last decade, a burgeoning literature has used experimental economics to study physician payments: Hennig-Schmidt *et al.* (2011); Brosig-Koch *et al.* (2017, 2016, 2013); Green, (2014); Godager **et al.** (2016); Hafner *et al.*

(2017); Lagarde and Blaauw, (2017); Bejarano *et al.* (2017). The main messages of these articles can be summarized in four points. First, in terms of findings, there seems to be a consensus on the incentives from FFS (over-provision) and CAP (under-provision), as shown in theoretical and other empirical investigations. Second, there is growing evidence on the incentive role of pay-for-performance (P4P). Green (2014) reports for instance that P4P combined with FFS gives higher incentives for services than FFS alone, and P4P combined with CAP gives lower incentives for services than CAP alone. Third, recent papers in experimental health economics reveal that it is crucial to take into consideration physicians' altruism toward patients (see Brosig-Koch *et al.* [2013]; Hafner *et al.* [2017]). The behaviors that we have observed in our experiment corroborate what the fact that physicians are not exclusively sensitive to financial incentives.

Finally, Ahlert *et al.* (2012), Hennig-Schmidt and Wiesen (2014) and Hafner *et al.* (2017) warn the research community of the importance of the subject pool. Hennig-Schmidt and Wiesen (2014) find that a medical subject pool behaves differently from a non-medical subject pool, precisely, the former tends to be more "patient-oriented" than the latter.

In the light of this literature, we will opt for the recruitment of advanced medical students (prospective physicians) as our experimental subject pool. From a methodological point of view, we follow Green (2014), Bejarano *et al.* (2017) and, less directly, Lagarde and Blaauw, (2017), who design a real-effort task experiment rather than the 'declared-effort' used in earlier work on physician payment schemes. Equivalence between real and chosen effort is proven for altruistic behaviors in gift-exchange games (Brüggen and Strobel, 2007). However, a real-effort task might be a more appropriate way to elicit subjects' decisions, especially when studying complex tasks like medical interventions. We therefore build on Green (2014)'s task using proofreading of texts. There are, however, three differences between our experiment and Green (2014)'s. (i) Contrary to Green's between-subject design, we use a within-subject design: each prospective physician is observed under two different payment schemes. (ii) We introduce personalized medicine by offering the physician an informational advantage that may benefit the patient (this is the core of our contribution). (iii) We control for heterogeneity in patients' actions by giving them a more passive role. In Green's experiment, the optimal quantity of services depend on the interventions of a first set of subjects (the patients, hereafter subjects-1), while

we impose more standardized behavior on the first set of subjects.

2 Data and methodology

We imitate the physician-patient relationship by using an experimental game having two sequential phases: phase 1 organized for patients, and phase 2 for physicians. Before phase 1 and 2, we have selected 48 short texts, 36 of primary-school level and 12 of first-year secondary-school level. Each selected text contains words with errors (spelling, syntax, vocabulary).

2.1 Experimental design: Phase 1 of the game (passive patient role)

The aim of phase 1 is to "materialize" patients who will enter the experimentally-created physician-patient relationship. In experiments on physician behaviors, the physician should normally be able to identify the patient who will also be benefiting from his effort. In the first experiment on physician behavior for example, Hennig Schmidt *et al.* (2011) use abstracts patients in the lab, but their subjects know that gains generated for these abstract patients will benefit "real patients outside the lab". In these types of designs (this setting is also used by Brosig-Koch *et al.* [2013], Hennig-Schmidt and Wiesen (2014) among others), the total amount generated for "patients" is given to an entity outside the lab, a hospital for example. The advantage of this kind of experimental settings is that the experimenter can use abstract patients in the lab, therefore not rely on a "proper phase 1" with real patients. This procedure might however be at the cost of measuring "artificially" low levels of physician altruism.

We opt for a sequential game with patients playing phase 1. This is similar to the designs of Green, (2014) and Bejarano *et al.* (2017). In these designs, real subjects express their "symptoms" in a first phase, and in a second phase, physicians address these symptoms under different payment mechanisms. At the end of phase 2, the subject (patient) receives the experimentally-generated gains, which represents his health benefit.

48 short texts are selected prior to organizing phase 1. These texts are then given to a group of 8 subjects (a set of 6 texts per subject). Each of the 8 subjects has to highlight words. Those words are the ones displayed to prospective physicians playing phase 2. Health benefits are computed based only on corrections done on those highlighted words. The main difference between our design and Green (2014)'s one is that, rather than letting subjects choose the words,

we indicate those words to them. Proceeding this way allows to control "patient-heterogeneity" and we can better focus on the issue of personalized medicine. In Figure 1, we present the timeline of the main steps of the experiment.

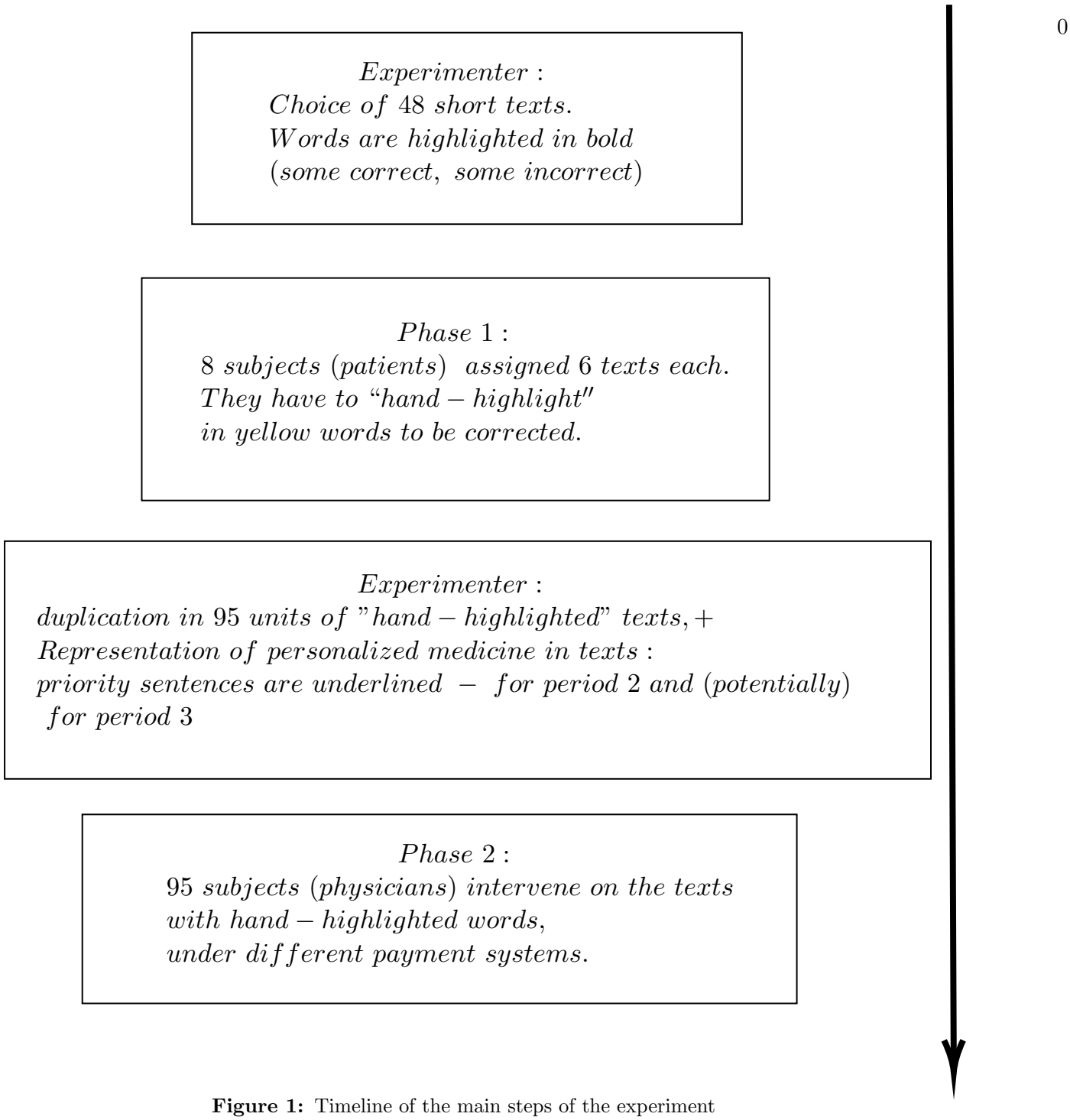

Figure 1: Timeline of the main steps of the experiment

Phase 1 is organized with 8 subjects, students from the department of economics of a French University. They receive a set of of 48 texts. Some words (both correct and incorrect) are in

bold in one set of texts, not in the other set. The task of each of the 8 subjects is to highlight manually, on the unmarked set of texts, words that are in bold on another set. They use a yellow highlighter for this task. They are told that they are participating in a 2-phase game in which they were playing the first phase. To further ensure incentive compatibility, we inform them that an additional payment is generated by other subjects playing phase 2 of the game. For this session, each of the 8 subjects is given a fixed endowment of €10. Each "bold-word" missed in the text incurs a penalty of €0.10.

Phase 1 took place in December 2016. All subjects behaved appropriately by "hand-highlighting" in yellow all the words found in bold in the other set of texts. Thereafter, in our instructions for the phase-2 game with physicians, we made it clear to the physicians that their actions would benefit a real subject elsewhere, called " subject-1" in the instructions.

2.2 Experimental design: Phase 2 of the game (physician role)

In phase 2, we have ran different experimental sessions with advanced medical students playing the role of physicians. We implement a within-subject design by "treating" each physician subject with two different payment mechanisms (part 1 and part 2 of the experiment). Such a design enhances statistical inference because each subject is his own control. We introduce a representation of personalized medicine by including access to information on priority sentences (underlined). The timeline of phase 2 is summarized in Figure 2.

Each treatment contains three successive periods of proofreading corresponding to three informational contexts:

- **Period 1:** 8 texts are presented without showing priority sentences, corresponding to a situation where personalized medicine is not available.
- **Period 2:** 8 texts are presented with priority sentences underlined, corresponding to a situation where personalized medicine is accessible free of charge.
- **Period 3:** the physician first has 1 minute to choose between a file of 8 texts with priority sentences underlined (personalized medicine) or a file of texts with no information. He then corrects the texts, playing the game either as in period 1 or 2. If he chooses to have access to priority sentences, he is charged a fixed €0.50 per treated text (a text

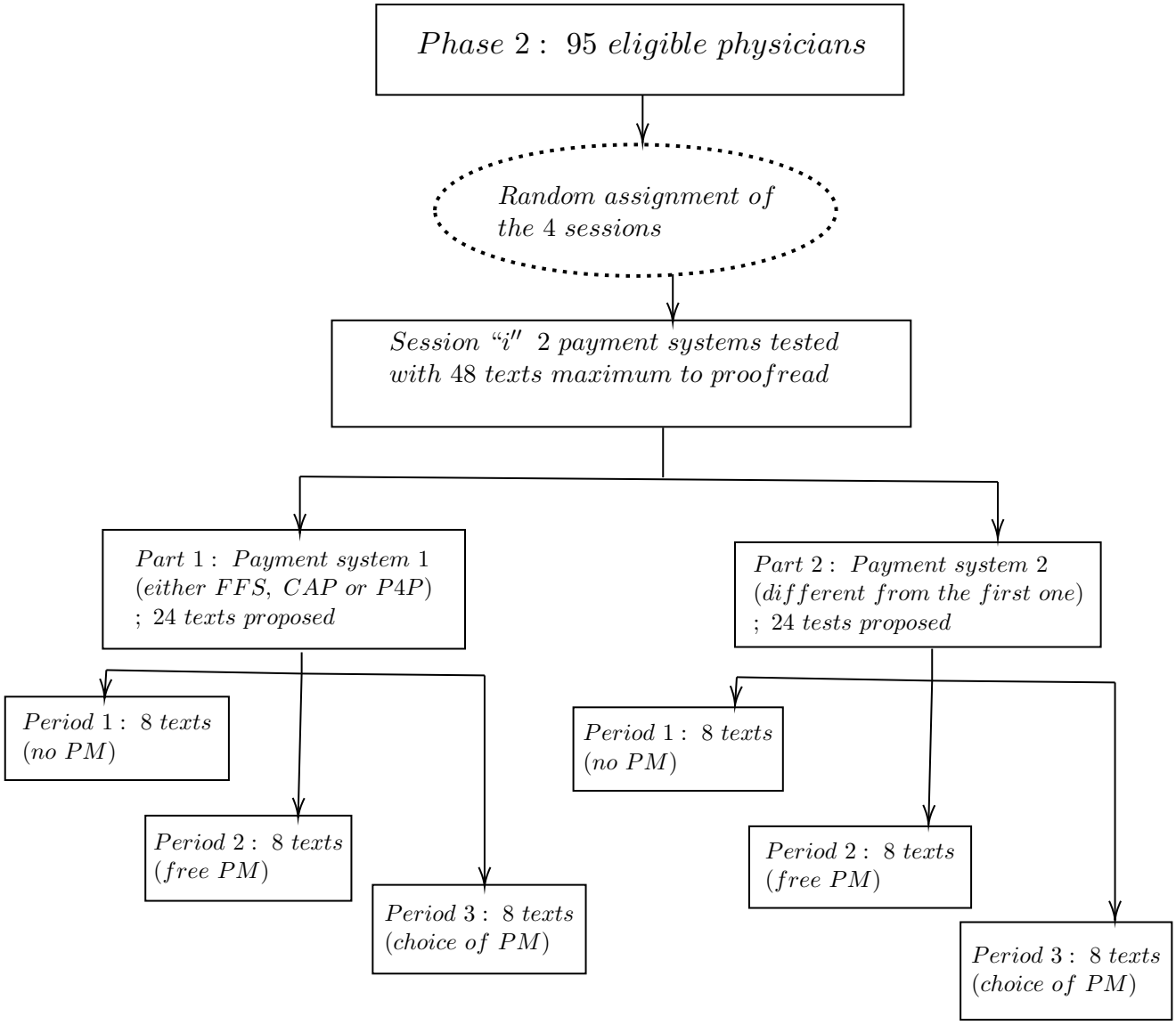

Figure 2: Timeline of phase 2

is considered treated if there is at least one correction). He is not charged otherwise. This last period captures a situation where the physician chooses whether or not to buy personalized medicine.

In Figure 3, we show an example of the texts given to physicians. The words in yellow are those to be proofread. Some of these words are correct, while others are not (in the Period 1 example above, only the words "vivant" and "culbuté" contain errors). The main difference between Period 1 and Period 2 is the fact that priority sentences are underlined in Period 2. In Period 3, depending on the physician's choice, the texts are either as in period 1 or in period 2.

Physicians have 5 minutes per period to correct 8 short texts. They are free to allocate

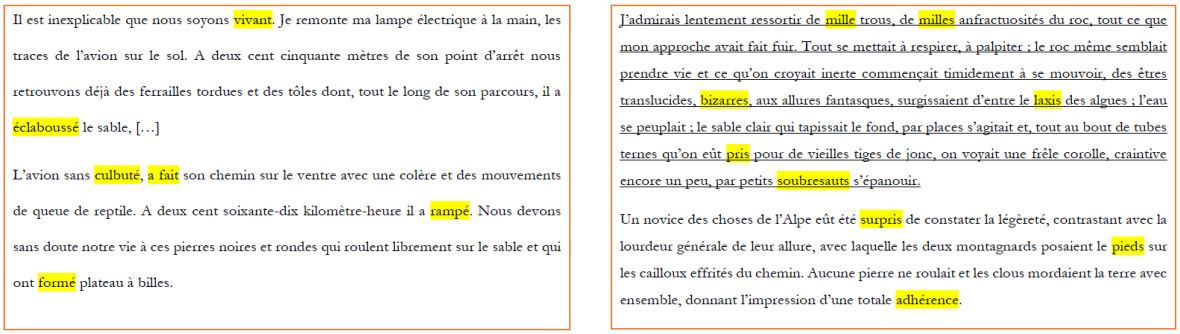

Figure 3: Examples of texts given to physicians in periods 1 and 2.

their time on the texts as they wish, including not altering some of them. For each treatment (payment mechanism), 24 texts are proposed (8 per period), so physicians can work on up to 48 texts per experimental session. Treatment variables are Capitation payment (CAP), Pay-For-Performance (P4P) and Fee-For-Service (FFS). Under CAP, the physician is paid €1.75 for each of the 8 texts showing at least one intervention on the highlighted words regardless of whether appropriate. Under FFS, physicians earn €0.30 per intervention, again regardless of appropriacy. Each text has a minimum of 6 highlighted words and a maximum of 12, thus the earnings range per text under FFS is between €1.80 and €3.60. Under P4P, the physician earns €2.50 per text if 80% of words in priority sentences are correctly written at the end of the proofreading, and nothing otherwise. The priority sentences contain between 5 and 9 words, and their positions in the texts vary.

To avoid portfolio strategies, we remunerate 2 periods chosen randomly (one period for the first treatment and one period for the second treatment). To ensure that physicians would earn approximately the same amounts, we ran a pilot experiment with different payment parameters. Based on these pilots, we chose the payment parameters described in Table 1. There is equivalence for example between either (1) doing one action per text on the 6 proposed texts in CAP; or (2) intervening on 80% of all the highlighted words in a given period (doing approximately 5 words per text); or (3) correcting appropriately 4 texts in P4P.

To implement the within-subject design, the game is presented to physicians as a game in two parts. They are informed of the payment system at the beginning of each part. We randomize the order of P4P.

* Cities are not displayed to maintain the anonymity of the paper.

The four sessions of Phase 2 have taken place between January and March 2017 in French

Table 1: Summary of the experimental payment mechanism parameters

Experimental condition	Payment parameter
CAP	€1.75 per subject-1 treated
FFS	€0.30 per intervention
P4P	€2.50 per subject-1 treated

Table 2: Different sessions of the experiment

Treatment for part 1 – Treatment for part 2	City*	Number of physicians	Date of the session
Session 1: P4P – FFS	French city 1	24	January 2017
Session 2: CAP – P4P	French city 1	21	February 2017
Session 3: P4P – CAP	French city 2	25	March 2017
Session 4: FFS – P4P	French city 2	25	March 2017

Universities. As mentioned in the introduction, medical students are chosen because there is evidence that they provide a better sample for testing healthcare supply behaviors (Hennig-Schmidt and Wiesen, 2014).

Patients' benefits from Phase 2: Physicians know that their actions can generate a financial gain for their subject-1 counterparts who has highlighted words in the texts in Phase-1 of the dual game. This represents the altruistic part of medical activity. Subject-1 counterparts receive €5 if 90% of the highlighted words in priority sentences are corrected appropriately, and nothing otherwise.

Recruitment procedure: To ensure anonymity of registrations, our advanced medical students were invited through the student's association. The invitation message contained the date of the experiment, its expected duration (one hour) and the earnings range (up to €40). A

dedicated website was constructed for registration, and all sessions took place in an auditorium. The auditorium was prepared prior to subjects' arrival with all the materials that was needed during the experiment: pens, sets of texts and instructions. There was enough space between subjects to avoid peer-influence in actions and decisions. 15 minutes was allowed to instructions' reading and completion of a comprehension test on instructions (results are available upon request). To ensure anonymity with respect to the experimenter and the students' association, subjects' earnings have been delivered to them by the university accountants.

At the end of each experimental session, we also collected personal information covering gender, age, other demographic features, attitudes toward risk, and declared altruism. The questionnaire also included a set of other questions capturing attitudes and practices related to the proofreading task that subjects had to perform in the experiment: their perceived writing skills, their performance in secondary school, and their appetite for medical decision technologies (categorical variable named *TECHNO* in the econometric analysis). Of this additional set, the first two variables are used as controls for the analysis, while *TECHNO* is also used as an instrumental variable.

The mean age in our sample is 22 years old. Our subject pool is made of 57% female and 58% of subjects are in year 4 of their medical school or above. The minimum and maximum earnings per physicians were respectively €6.20 and €35.40, with a mean and a median around €20. Out of the 95 subjects playing physicians' role, 5 did not collect their earnings. All subjects-1 collected their additionally-generated payments.

2.3 External validity of the experiment

Our experiment uses proofreading tasks to simulate situations in which the physician can benefit from personalized medicine. The patient declares his symptoms to the physicians (highlighted words in texts) and the physician intervenes to advise, diagnose and treat the patient (proofreading task). Periods 1 and 2 serve as initialization sessions, with access to personalized medicine information being free in period 2. The aim is to familiarize physicians with the game and help them understand the benefits of the information: the use of external technologies, yielding a more accurate and detailed patient profile. Thus, in period 3 of the experiment, we give the physician access to additional information on the patient's characteristics through the priority

sentences, which only generate payment for subject-1. In the context of this experiment, the cost to physicians and the benefit to patients are monetized in case of good corrections (Howard *et al.* 2017). Table 3 summarizes how our experimental settings correspond to real-life medical settings.

Table 3: Correspondence between experimental and real-life personalized medicine settings

	In experimental setting	**In real-life setting**
Period 1*	Crude declaration of wrong words by subject-1 & priority sentences not shown	Crude declaration of symptoms by patient & subset of relevant symptoms not shown
Period 2	Priority sentence shown, physician can target/focus interventions	Subset of relevant symptoms shown, physician can target/focus interventions
Period 3	Are you willing to buy the information on priority sentences?**	Are you willing to buy (/spend time on obtaining) PM information?
Payment schemes	-% quality of overall text -per intervention -per text	-P4P -FFS -Capitation

*Notes: * First yielding a free access to personalized medicine before the physician makes his choice in the costly setting captures real word situations where the physician first learns the benefits of the technology and then decides whether he wants to invest in it. This roll-out of the experiment has the advantage that the physician is arguably making an informed decision (what our experiment captures). This roll-out is however at the expense of not knowing what would have happened if the physician was first proposed access to personalized medicine, without knowing potential benefits for him. In such cases, we hypothesize that physician's attitude towards risk might be at play in physician's decision to invest in personalized medicine. These cases are left for future research.*
*** This "monetization" of the decision is, in our view, the first limitation to the external validity of the experiment: in the real word, the reward to the patient is a health benefit and the penalty to the physician a time loss (although this could actually become a monetary loss in many payment systems). The second limitation that we see is the fact that our P4P is defined as a remuneration system on its own. This choice enabled us to keep experimental instructions readable*

The main attribute of personalized medicine is that it gives physicians the opportunity to focus on the relevant subset of symptoms, thereby achieving more effective selection of medical interventions. Adopting personalized medicine techniques usually has a cost, requiring doctors to leave their office for training in particular, but it increases the efficacy of their patient care. Our experiment aims to capture this fixed cost/variable cost trade-off. Our prospective

physicians (in period 3) have to pay a price, intended to capture this opportunity cost of time. Our priority sentences, on the other hand, are intended to capture the potential efficiency gain for physicians from "buying" personalized medicine. Our prospective physicians can allocate this efficiency gain to treat more texts, or to increase the quality of their intervention on each text treated. It is well documented that personalized medicine techniques enable physicians to focus on the subset of symptoms that will allow them to choose the most appropriate therapeutic alternative for their patients' characteristics. Our experimental setting works in a similar way: instead of a badly informed doctor seeing various sentences in the text as alternatives for action, the well-informed doctor uses the information related to the priority sentence to choose the best course of action.

3 Results

We focus on two issues to study the role of physicians' incentives. First, we look at their *decision to invest in personalized medicine information* through the decision in period 3 and we describe the main determinants of this choice, mainly in relation to the payment schemes. Second, we look at the *quality of services*. For this second issue, the main variable is having access to the information allowing "personalization" and its correlation with some key quality indicators; this correlation is also examined in interaction with the payment schemes. There are two sub-questions related to the issue of quality: Do the physicians' qualitative outcomes change when they obtain personalized medicine information free of charge? Do they change when this information is accessible but has to be paid for?

3.1 Result 1: Decision to invest in personalized medicine information

Our first results deal with the decision to acquire information allowing the practice of personalized medicine. In the table 4, we report the decision to buy the information on priority sentences by payment mechanism.

Table 4 shows that the number of physicians choosing to buy personalized medicine information, *i.e.* paying for information on which sentences are priority, is greater in the P4P scheme (58% of subjects) than in the CAP (28% of all CAP subjects) and the FFS (19% of FFS subjects). Thus, at first glance the decision to buy personalized medicine information is

Table 4: Decision to buy information and payment mechanisms

Decisions and Payment systems	P4P	FFS	CAP	**Total decisions**
Buy	55	9	13	77
Not buy	40	40	33	113
Total number of subjects	95	49	46	190

p-value = 4.236e-06 from a Khi-2 independence test.

not independent of the proposed payment scheme (p-value< 0.05).

The decision to invest in such information is further investigated using a Probit model. We hypothesize that the decision to purchase information on priority sentences might be influenced not only by the payment scheme but also by a set of other explanatory variables: the physicians' self-declared preference for innovative technologies (*TECHNO* variable, as determined from the questionnaire at the end of each session), their declared writing skills, their gender and their secondary school performance.

Our estimation results summarized in Table 5 reveal that there is a positive and statistically significant association between the purchase decision and the preference of physicians for innovative technologies (Reference for interpretation: very likely). Other variables are used as controls for regressions (coefficients not shown). When it comes to payment methods, the Probit estimation corroborates the descriptive analysis: compared to the P4P, the FFS and CAP are less likely to be associated with personalized medicine purchase.

The fact that P4P is associated with a higher probability of buying personalized medicine information can be explained by the opening for double motivation under P4P in physicians' preferences: expectation of financial return and altruism. Unlike P4P, buying information on priority sentences under CAP and FFS would stem from altruism alone, since these schemes do not provide physicians with any financial incentive to do so.

To describe quality outcomes, our identification strategy is twofold. We compare physicians' behaviors with and without free personalized medicine information, and we perform the same analysis when such information has to be paid for.

Table 5: Variables affecting the decision to buy information on priority sentences

	Decision to invest in the information on priority sentences
	Probit model
FFS (Ref: P4P)	-1.072^{***} (0.254)
CAP (Ref: P4P)	-0.919^{***} (0.247)
TECHNO *Strongly*	0.606^{**} (0.266)
TECHNO *Weakly*	0.838^{*} (0.450)
Controls included	*Yes*
Constant	−2.526 (1.610)
Observations	190
Log Likelihood	-110.488
Akaike Inf. Crit.	238.976

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

3.2 Result 2: Access to personalized medicine information and physicians' qualitative outcomes

Before describing our results on qualitative outcomes, a natural transition would have been to look at physicians' quantitative outcomes (number of interventions and number of texts). However, since our results are comparable to those in the literature, *i.e.* more interventions (words proofread) in FFS, more patients (texts treated) in CAP, these results are relegated to appendices. Interestingly, it is worth noting that CAP and P4P generate similar outcomes in terms of number of interventions, while FFS and P4P yield similar outcomes in terms of number of patients (indicators not statistically different across payment schemes). As our focus here is on the impact of personalized medicine techniques on patients' health, we select the variables involved in quality outcomes, with direct implications for patients' health. We first introduce our results on the setting where access to information was free.

3.2.1 Free access to personalized medicine information and physicians' qualitative outcomes

The design of the experiment allows us to compare results in period 1 with those in period 2, *i.e.* to compare behaviors in a "no information" setting with those in a "free information" setting.

As it is common, we first report descriptive statistics and complement these by estimating an econometric model to provide further evidence. The econometric model is the following:

$$y_{itT} = c + \alpha_i + \beta_i Pay_{iT} + \gamma_i INFO_{it} + \theta_i Pay_{iT} * INFO_{it} + \Theta_i X_i + \epsilon_{itT} \quad (1)$$

In equation (1):

- y_{itT} is the outcome of i, ($i \in [1-95]$) physician; period t ($t \in$ no info, free info) in treatment T. We consider three outcome variables: the degree of focus of actions, the number of well-treated (appropriately corrected) texts and the rate of well-treated texts.
- c is the constant and α_i is the individual specific effect.
- Pay_{iT} is the payment mechanism in treatment T. This is a categorical variable with three modalities: P4P, FFS and CAP. Our reference is P4P. β is a vector of parameters that identifies the pure effect of the payment method on the outcome.
- $INFO_{it}$ is a binary variable equal to 1 in period 2 ("free information"), and to 0 in period 1 ("no information"). Our reference is "no information" (period 1). γ is a vector that captures the effect of information on the outcome.
- θ captures the interaction effect between free information and payment method. When significant, results are reported.
- X is the fixed set of objective time invariant control variables.
- ϵ is an idiosyncratic error term.

Due to the repetition of observations on the same subject (through our within-subject design), our dataset is a panel. Our three dependent variables are the physician's degree of focus, the number and the rate of well-treated texts. Given the fact that our design uses a task involving specific skills (proofreading of texts), we seek to control the average effects by time-invariant individual characteristics such as performance at secondary school, self-declared writing skills and gender.

Estimation results presented below are from a random effect model, applied to control and identify the effect of time-invariant regressors. The implicit assumption is that there are no unobserved individual characteristics influencing our dependent variable. This assumption is valid if the control questions, such as self-declared writing skills and gender, capture a sizable part of the inter-individual heterogeneity. The Hausman test is performed to challenge this intuition. Running a fixed and a random effect model, we do not reject the null hypothesis that the preferred model is the random-effect model.

3.2.2 Free access to personalized medicine information and physicians' lack of focus (degree)

The focus variable allows us to capture how physicians orient their intervention with the informational tool at their disposal. We measure focus by looking at the rate of interventions outside priority sentences (number of interventions outside priority sentences divided by the total number of interventions). The degree of focus captures the proportion of actions with no impact on the final benefit to subjects-1 (patients). This criterion is a measure of quality, as it captures the extent to which the physician focuses on the patient's problem. Figure 4 and Table 6 present both descriptive statistics and results of our estimation.

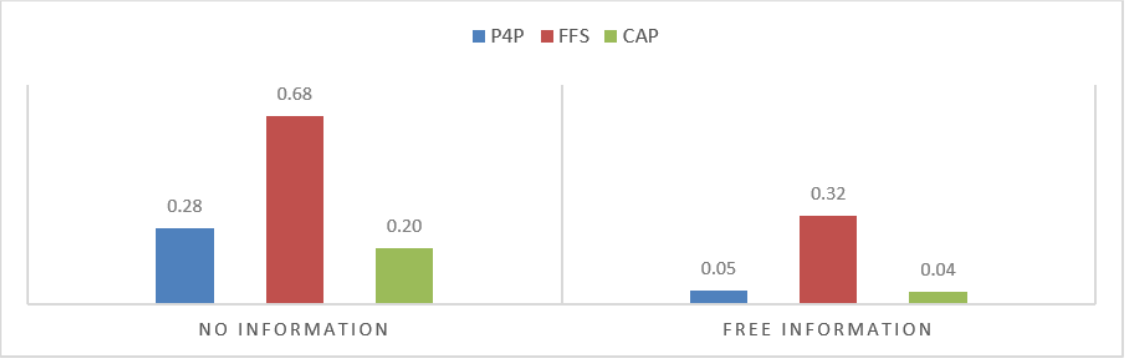

Figure 4: Free access to information and physicians' degree of focus.

Remember that correcting words outside priority sentences is not of any benefit to patients (while it could be costly for the society, depending on the payment scheme). When information is available, the degree of focus as measured by the intervention rate outside priority sentences is lower whatever the payment scheme (columns 1 and 2 of Table 6, variable '*INFO*'; and Figure-

Table 6: Impact of free information and payment mechanisms on degree of focus

	Focus (rate of interventions outside priority sentences)		
	Panel linear		
FFS (Ref: P4P)	0.341*** (0.036)	0.303*** (0.047)	0.371*** (0.056)
CAP (Ref: P4P)	−0.039 (0.036)	−0.048 (0.036)	−0.081* (0.047)
INFO (Ref: No info)	−0.244*** (0.025)	−0.244*** (0.025)	−0.227*** (0.035)
Controls included?	*No*	*Yes*	*Yes*
INFO in the FFS payment system			−0.136** (0.060)
INFO in the CAP payment system			0.067 (0.059)
Constant	0.284*** (0.025)	0.511* (0.293)	0.503* (0.294)
Observations	190	190	190
R^2	0.522	0.527	0.549
Adjusted R^2	0.514	0.509	0.527
F Statistic	67.603*** (df = 3; 186)	29.022*** (df = 7; 182)	24.388*** (df = 9; 180)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4-histogram bars in "No information" *vs* bars in "Free information"). From Figure 4, we can see that, when information is made available in period 2, the rate of intervention outside priority sentences is halved in the FFS system, while it becomes five times lower in CAP and P4P. FFS is, in any case, always associated with the highest degree of focus. When access to information is free, P4P and CAP are not significantly different from one another (Table 6 and Figure 4). Thus, we can conclude that physicians really used information to focus their interventions on the priority sentences.

This stronger impact on focus in FFS can be quantified by the '*INFO * FFS*' interaction variable, which is significant, and adds an additional negative effect equal to *-0.136* (Table 6, column 3). Despite their financial incentives, when physicians have access to personalized medicine information, they reduce their interventions outside priority sentences even though their income is increasing in the number of interventions. In the context of FFS, this result clearly reveals that our physicians have a more complex objective than mere profit maximization: they are behaving altruistically. This finding on altruism is not new. Many previous works have established that physicians can demonstrate altruistic behaviors (most recently, Godager and Weisen, 2013; Green, 2014, among others).

3.2.3 Free access to personalized medicine information and physician' well-treated texts

The number and rate of well-treated texts are other quality indicators that we use to describe physicians' performance. The first variable simply captures whether the physician's actions generated €5 for subject 1, while the second describes the ratio of well-treated to treated texts. The first variable provides insights into how personalized medicine and physicians' payment affect the number of patients effectively treated. The second is a more refined indicator that controls for the number of patients encountered (the denominator), which could differ across payment schemes and/or periods. We summarize our results in Table 7 and Figure 5. Table 7 only presents estimation results for the ratio of well-treated to treated texts. Econometric results on the well-treated texts are very similar.

Figure 5: Free information and physicians' number and rate of well-treated texts

As expected, the FFS system shows poor results when this second quality indicator is considered. More surprisingly, CAP and P4P still generate similar incentives, although 'in theory' P4P should be associated with a stronger incentive for quality interventions. The intermediary position of CAP may illustrate the fact that, without stressing the purely quantitative criterion of number of interventions performed (like the FFS), a remuneration scheme rewarding the number of patients treated incites toward a neutral quality/quantity trade-off, and therefore a middling level of quality. However, when we correct for total number of treated texts (as a

denominator), CAP actually appears to lead to a lower rate of well-treated texts than P4P. In other words, we easily come back to the expected -and intuitive- result of better quality under P4P, after correcting for the quantitative effect of payment schemes (CAP incites physicians to treat more patients).

Last, as Table 7 shows, we do not find any significant effect of (free) information on quality. Interestingly, we will observe that this result is different when personalized medicine comes at a cost.

Table 7: Impact of free information and payment mechanisms on number of well-treated texts

	Rate of well-treated texts	
	Panel linear	
FFS (Ref: P4P)	-0.297^{***} (0.048)	-0.263^{***} (0.063)
CAP (Ref: P4P)	-0.083^{*} (0.047)	-0.073 (0.048)
INFO (Ref: No info)	0.003 (0.027)	0.003 (0.027)
Controls included?	*No*	*Yes*
Constant	0.536^{***} (0.031)	0.130 (0.389)
Observations	190	190
R^2	0.172	0.183
Adjusted R^2	0.159	0.151
F Statistic	12.912^{***} (df = 3; 186)	5.811^{***} (df = 7; 182)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

3.3 Paid access to personalized medicine information and physicians' qualitative outcomes

Access to information on priority sentences is available but has to be paid for in period 3. Due to the impact on benefits that we introduce, many factors might have played a role in physicians'

decisions: expectations of "returns on investment", altruism, perceived writing skills, intrinsic "appetite" for information, and the payment scheme. All these factors are potential sources of endogeneity. We model the physician's decision by the binary variable "BUYINFO". Our estimation strategy therefore has to consider the endogenous nature of BUYINFO and propose a consistent method to examine its impact on physicians' behaviors. Having estimated a Probit model for the decision to buy information, we use estimation results in this subsection.

To compare information buyers and non-buyers, we provide estimates of a 2-stage Instrumental Variable Probit model. The Probit model estimated in the "first step" to predict the probability of investing in priority sentences under different payment schemes and with the set of available individual characteristics is used here (TECHNO is our "instrument"). In this "second step" estimation, we use a two-stage panel least-square estimator, where the predicted value of the first-step model is included as an extra exogenous variable for our regressions. All the results presented in the tables below are second-step regression results and corrected for the endogeneity of the decision to buy information on priority sentences. For the 95 subjects, we have a total of 190 decisions observed. Using a panel technology in the second-step estimation preserves the longitudinal dimension of the model.

Formally, we estimate the following set of equations:

$$BUYINFO_{iT} = c + \mu_i Pay_{iT} + \eta_i TECHNO_i + \rho_i X_i + v_{iT} \tag{2.3.3}$$

$$y_{i,T} = c + \alpha_i + \beta_i Pay_{i,T} + \gamma_i \widehat{BUYINFO}_{iT} + \theta_i Pay_{iT} * \widehat{BUYINFO}_{iT} + \Theta_i X_i + \epsilon_{itT} \tag{2.3}$$

Equation (2.3.3) was previously estimated and results provided in Table 4. In equation (2.3) :

- y is the outcome of individual i, ($i \in [1-95]$) in period 3, for treatment T. We use the same dependent variables as in the free information case.
- $\widehat{BUYINFO}_{iT}$ is the predicted value of the first-step regression (buyers/non buyers). γ is a vector that captures the pure effect of information on the outcome.

- $TECHNO_i$ captures the physician's appetite for new technologies. This is our IV-variable.

- All other variables are defined as previously.

As usual, to avoid the endogeneity problem, the second-step regression (3) does not include the raw variable BUYINFO, the "choice" made in period 3 *per se*, but rather ($\widehat{BUYINFO}_{iT}$), the predicted probability. The $TECHNO$ variable provides a strong instrument for modeling the decision to buy priority sentences, as $TECHNO$ appears independent of all our dependent variables and correlated to the decision to buy personalized medicine. Three independent indicators are used to confirm that the instrument predicts the decision to invest in priority sentences. First, we verify that there is not independence between preference for innovative technologies and decision to invest in personalized medicine (Fisher test on the contingency table describing the two variables, pvalue $< 10\%$). Second, comparing our regressions with and without the correction for endogeneity, we reject the null hypothesis that the instrument is weak (p-value < 0.05). Third, in the regression analysis that models the decision to purchase personalized medicine, we observe that the appetite for innovative technologies is correlated with the likelihood of buying personalized medicine (See Table 5). Our second argument for using this instrument is the fact that it does not affect directly our outcome variables (focus of actions, rate of well-treated patients). We also check that we do not have potential confounding factors that could affect both the instrument and the outcome variables to be sure that the exclusion restriction is verified. We have checked for risk aversion and we have also used a proxy of self-confidence. Both are not linked neither to our instrument nor to our dependent variables.

3.3.1 Paid access to personalized medicine information and physicians' lack of focus (degree)

We summarize our results on focus in Figure 6 and Table 8.

When considering the effect of information, the intervention rate outside priority sentences is much higher in the non-buyers group than in the buyers group. Even though the rate of intervention outside priority sentences is still higher under FFS, Table 8 reveals that the net effect of the information (purged of selection bias) is stronger under FFS than under the other

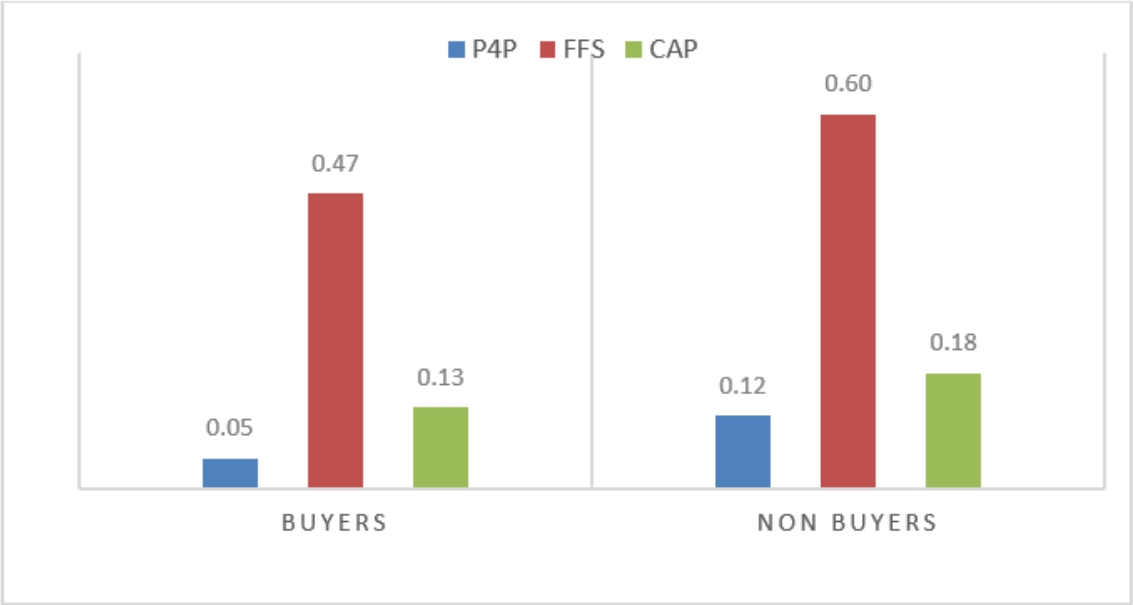

Figure 6: Free information and physicians' rate of actions outside of priority sentences

Table 8: Impact of buying information and payment mechanisms on the degree of lack focus

	Focus (rate of interventions outside priority sentences)		
FFS (Ref: P4P)	0.338*** (0.068)	0.292*** (0.077)	0.653*** (0.123)
CAP (Ref: P4P)	−0.038 (0.057)	−0.078 (0.069)	0.130 (0.144)
BUYINFO (Ref: Non-buyers)	−0.280* (0.143)	−0.403** (0.179)	−0.146 (0.194)
Control included	*No*	*Yes*	*Yes*
BUYINFO in the FFS payment system			−1.414*** (0.386)
BUYINFO in the CAP payment system			−0.477 (0.376)
Constant	0.269*** (0.086)	0.152 (0.242)	−0.100 (0.245)
Observations	190	190	190
R^2	0.468	0.487	0.523
Adjusted R^2	0.460	0.467	0.500
Residual Std. Error	0.208 (df = 186)	0.207 (df = 182)	0.200 (df = 180)
F Statistic	54.637*** (df = 3; 186)	24.686*** (df = 7; 182)	21.970*** (df = 9; 180)

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

two payment schemes. This result can be interpreted as a commitment device effect that appears to operate on physicians deciding to buy personalized medicine information despite being paid by a non-incentivizing scheme like FFS. A commitment device effect is consistent

with the fact that the rate of intervention outside priority sentences decreases by 0.14% when access to personalized medicine is free (column 3 of Table 6), whereas under paid access to information, we observe a decrease of 1.4%. It appears that our physicians tend to make better use of information when they had to pay for it.

3.3.2 Paid access to personalized medicine information and physicians' treatment of texts

Results on the two other indicators of quality are summarized in Figure 7 and Table 9. In Table 9, an interesting difference appears for the percentage of well-treated texts: acquiring information is not only associated with a decrease in the degree of focus, but this time the focus is "effective". It results in a significant effect on the quality criteria (slope equal to +0.395, Table 9). This is probably due to the commitment device already mentioned. When physicians decided to invest in acquiring information, they actually used it, improving their percentage of appropriately corrected texts.

Table 9: Impact of buying information and payment mechanisms on ratio of well-treated to treated texts

	Ratio of well-treated to treated texts
	OLS
FFS (Ref: P4P)	0.001 (0.089)
CAP (Ref: P4P)	0.121 (0.079)
BUYINFO (Ref: Non-buyers)	0.391* (0.206)
Constant	−0.187 (0.278)
Observations	190
R^2	0.147
Adjusted R^2	0.114
Residual Std. Error	0.237 (df = 182)
F Statistic	4.482*** (df = 7; 182)
Notes:	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

To compare the payment schemes, Table 10 summarizes all our descriptive results on the qualitative variables.

This last table compares the three payment schemes in terms of our two quality outcome

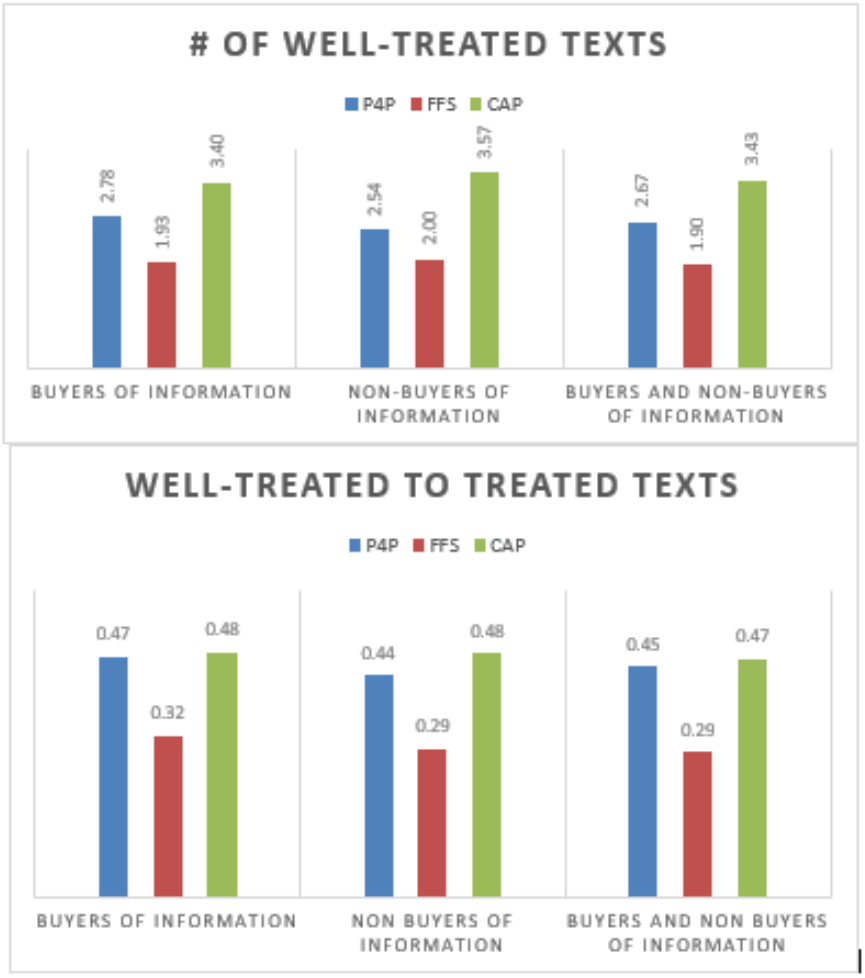

Figure 7: Paid access to information and number and rate of well-treated texts

Table 10: Payment scheme ranking according to information structure

	No info	With free info	With bought info (comparison of buyers)	With bought info (comparison of non-buyers)
degree of focus	CAP >P4P >FFS	P4P=CAP >FFS	P4P >CAP >FFS	P4P >CAP >FFS
% of well-treated texts	–	P4P = CAP >FFS	CAP = P4P >FFS	P4P = CAP>FFS

variables. We use *t-tests* to compare the different means across payment methods. We consider whether personalized medicine information is accessible, and whether this access is free or has to be bought. This table shows that P4P and CAP generate very similar incentives, except

for the focus variable, where P4P does better than CAP for both buyers and non-buyers. In the next section, we provide a quantification framework that enables us to address a potential policy issue: should the access to personalized medicine be free of charge or paid?

4 Quantification exercise: should access to personalized medicine information be free or paid for?

One of our main results is that pricing the information conveyed by personalized medicine can yield a social benefit: physicians better exploit information they had to pay for. As we have shown, this is not a self-selection effect, as in principle the selection is controlled for by the IV-method. However, a thorough policy recommendation should consider both the advantages and the disadvantages of any policy option. Here, charging for access to personalized medicine has the advantage of improving the effectiveness of information (because of the commitment-device effect described earlier), but the drawback of limiting access to information to those physicians who are not willing to pay for it. We provide a simple framework that highlights this trade-off for the policy-maker. Our key variable will be the degree of lack focus, as it is the only variable for which interactions with payment schemes often appeared significant. We will also limit our simple analysis to P4P and FFS. Capitation does not allow for comparisons, because there is not enough variation between free and paid access to information.

We suppose that we have a community made of N physicians (N = 95 in our case). Depending on the payment scheme (FFS or P4P), physicians jointly produce an outcome H^P (P stands for the payment scheme). Aggregate outcome for each payment option is the weighted sum of individuals' performances h^P, realized by B^P buyers and $(N - B^P)$ non-buyers:

$$H^P = B^P.h^P(Info = 1) + (N - B^P).h^P(Info = 0).$$

We are interested in variations of H depending on whether or not there is a price for information. Decomposition of equation 1 and simple differentiation give:

$$\Delta H^P = B^P.\Delta h^P(Info = 1) + \Delta B^P * \Delta h^P(Info = 1) - h^P(Info = 0)]. \quad (2)$$

The complete effect of charging for information is given by equation (2). The quantity Δh^P is the positive effect of the commitment-device (from free to paid info), as measured by the econometric estimation for"focus" as a dependent variable. The quantity ΔB^P is the variation in the number of buyers between period 2 and period 3, for payment scheme P; this number is always negative. In the FFS system, our experiment showed a decrease from 49 (100% of beneficiaries in period 2) to 9, $\Delta B^{FFS} = -40$. In the P4P system, the decrease was from 95 (100% of beneficiaries in period 2) to 55 in period 3, $\Delta B^{P4P} = -40$.

Using the simple calculation framework provided above, we can derive the full impact of charging for access to personalized medicine on the degree of focus of physicians' interventions. The aggregate variation of H in FFS would be given by:

$$== B^{FFS} * (\text{slopes in Table 8}) + \Delta B^{FFS} * \text{ (slope in Table 6 for the var. Info)}$$
$$== 9 * (-1.414) - 40 * (-0.227 + -0.136)$$
$$= +1.794.$$

In the same way, the aggregate variation of H in P4P would be given by:

$$== B^{P4P} * (\text{slopes in Table 8}) \ + \Delta B^{P4P} * (\text{slope in Table 6 for the var. Info})$$
$$== 55 * (0) - 40 * (-0.227)$$
$$= +9,08.$$

A positive value implies that the quantity of useless interventions increases when physicians have access to information. In FFS, the full effect of charging for info is +1.794 more useless interventions. In the experiment, 9 physicians did better (-1.414 useless interventions per physician buying info). But charging a price increased the number of physicians without info to 40,

leading to +0.363 (0.227+0.136) useless interventions per physician. In the same way, in P4P, the full effect of charging a price for info is +9.08 more interventions outside priority sentences.

Overall, our results show that, despite the existence of a commitment-device effect on the subset of buyers, it is still undesirable to organize paid access to personalized medicine for all physicians. This finding relies on the focus criterion and the set of incentives proposed in this experiment. It would have been interesting to perform the same analysis with other indicators. However, we did not find significant effects for the interaction between access to personalized medicine and the payment mechanism.

5 Concluding remarks

This article reports results from an experiment on physicians' incentives to use personalized medicine techniques. Our experimental design uses the same task as Green (2014), where proofreading stood for medical services. Green (2014) and Lagarde and Blaauw (2017) demonstrated the feasibility of mimicking the physician-patient relationship using a real-effort task. We modify Green's experiment to consider the new context of personalized medicine, enriching the assessment of physicians' payment schemes to include physicians' choices on the use of personalized medicine tools, both free and paid. We thus recreate the fundamental trade-offs of an agent (the physician) deciding on access to an informational technology like personalized medicine. This framework not only allows us to complement the abundant literature on the incentive properties of physicians' payment schemes, but also to contribute to the economic analysis of a newly-relevant behavior: buying information (/technology) that can enhance an expert's service provision. There may even be room for generalization to other contexts (other types of expertise, like law or education) where the provider has to make an (unobserved) informational procurement effort, enhancing the quality of services.

Two questions have been answered in this article:

What determines the decision to adopt personalized medicine? We find that, compared to capitation and fee-for-service, pay-for-performance is associated with a higher probability of deciding to have access to information on priority sentences. Pay-for-performance is designed to reward the physician based on the number of well-treated patients. Investing in personalized medicine under a P4P scheme can stem both from altruism toward the patient

and from expectation of higher financial returns. In CAP and FFS, only the altruistic motive plays a role in the decision, which is probably why these two payments schemes are less likely to incite physicians to pay to adopt personalized medicine.

What is the impact of personalized medicine on the quality of services? We find that information allows physicians to better focus their interventions, regardless of the payment mechanism. This focus effect is greater in FFS (probably because physicians were performing too many interventions in the no-information regime, which left more room for improvement). This result suggests the need to address the use of personalized medicine as related to the current payment mechanisms governing physician activities.

Last, information for personalized medicine, when it is accessible at a cost, is positively associated with the rate of well-treated patients. Physicians tend to better use the information when they have to pay for it (all things being equal, including the selection bias). We conclude that this is consistent with a "commitment device". Using a simple quantification framework to assess the consequences of a generalized paid access to personalized medicine, we find that charging for information is not desirable in P4P and FFS. While the experiment provides evidence that physicians better employ information they have paid for, charging for access will necessarily reduce the adoption of personalized medicine, which could be detrimental for patients. This trade-off must be taken into account when determining the best policy.

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