Adverse Selection *vs* Discrimination Risk with Genetic Testing. An Experimental Approach*

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November 1, 2014

Abstract

We develop a theoretical analysis of two widely used regulations of genetic tests, disclosure duty and consent law, and we run several experiments in order to shed light on both the take-up rate of genetic testing and on the comparison of policyholders' welfare under the two regulations. Disclosure Duty forces individuals to reveal their test results to their insurers, exposing them to the risk of having to pay a large premium in case they are discovered to have a high probability of developing a disease (a discrimination risk). Differently, Consent Law allows them to hide this detrimental information, creating asymmetric information and adverse selection. We obtain that the take-up rate of the genetic test is low under Disclosure Duty, larger and increasing with adverse selection under Consent Law. Also, the fraction of individuals who are prefer Disclosure Duty to Consent Law increases with the amount of adverse selection under the latter. These results are obtained for exogenous values of adverse selection under Consent Law, and the repeated interactions experiment devised has not resulted in convergence towards an equilibrium level of adverse selection.

JEL Codes: D82, I18, C91.
Keywords: disclosure duty, consent law, discrimination risk, informational value of test, personalized medicine, experiment.

*The authors gratefully acknowledge financial support by Health Chair – a joint initiative by PSL, Université ParisDauphine, ENSAE and MGEN under the aegis of the Fondation du Risque (FDR). The second author thanks University of Los Andes for its hospitality. The third author acknowledges support through ANR - Labex IAST. The usual disclaimer applies.

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1 Introduction

One of the major evolutions in medicine in the last decade has been the advent of so-called "personalized medicine", defined as the use of an individual's genetic profile to guide decisions made in regard to the prevention, diagnosis, and treatment of disease. For instance, in 2012 the FDA has approved a new drug for cystic fibrosis (a serious inherited disease impairing the lungs and digestive system) for patients with a specific genetic mutation – referred to as the G551D mutation – which is responsible for only 4% of cases in the United States. Personalized medicine also allows patients to initiate preventive treatments before the occurrence of the disease.

The development of ever cheaper and more informative genetic tests is behind the development of personalized medicine.[1] These tests allow individuals to obtain very detailed information on their genetic predisposition to several diseases, as well as on potential prevention strategies to decrease the probability of the disease occurring, and on the treatment to be followed if the disease occurs.[2] However, such tailored information on one's individual health risk may have two detrimental impacts on the health insurance market. On the one hand, if the tested agent is forced by law to disclose the information revealed by the test, he then faces the risk of a larger premium in case of a bad genetic background (rather than the "average" premium in case he does not acquire genetic information). If the individual is risk averse, this so-called discrimination risk (Hirshleifer, 1971) may prevent him from taking the test in the first place, resulting in the loss of precious health information. On the other hand, if regulation allows the tested individual to withhold information from the health insurer, we enter the realm of adverse selection, with agents revealing their genetic background to insurers only in the case of good news.

Policy makers then face a trade-off when choosing how to regulate the information obtained from genetic testing, with the obligation to disclose yielding to a discrimination risk while allowing withholding of information leads to adverse selection. Moreover, both types of regulation generate different incentives for taking a genetic test. Among the regulations currently in place,[3] those labelled *Laissez-faire* and Disclosure Duty prevent the tested agent from withholding genetic information from insurers,[4] while Consent Law and Strict Prohibition both generate asymmetric information and adverse

[1] See http://www.genome.gov/sequencingcosts

[2] See Abrahams and Silver (2010).

[3] See Otlowski et al. (2012) for a survey presenting the different regulations of genetic tests used throughout the world.

[4] *Laissez-faire* allows the health insurers to require testing from their customers, while disclosure duty does not. *Laissez-faire* is applied in Australia, Canada, China, Japan, Korea, Ireland, Portugal, Russia, Singapore, Spain and South Africa whereas disclosure duty is the regulatory regime in Germany, New Zealand, and the UK.

selection.[5]

Our objective in this article is to compare both types of regulations (more precisely, Consent Law and Disclosure Duty) in terms of their consequences on genetic tests' take-up rate and on the individuals' (*ex ante*) welfare. We first develop a theoretical framework to compare those regulations, and we then devise a series of experiments to elicit which regulation individuals would prefer, and whether they would take the genetic test under each regulation.

Our theoretical model is based on Bardey and De Donder (2013). Agents can be of two types depending on their genetic background: type L have a low probability of developing a disease while type H have a high probability. Agents are uninformed about their type, unless they take a genetic test which reveals their type without error. Genetic tests are costly to individuals, because of their monetary cost but also because some agents may dislike knowing with precision their genetic background. Agents are then heterogeneous in their testing cost. After deciding to test or not, individuals buy health insurance on a competitive market.

Under Disclosure Duty (DD hereafter), individuals pay an "average" premium if they do not test, but are faced with a discrimination risk if they test, in the form of a lottery (low premium if type L, high premium if type H). Under Consent Law (CC hereafter), agents show their test results to the insurers if they are revealed to be type L, and pretend to be uninformed (*i.e.*, not to have done the test) otherwise. In light of the current low take-up rate of genetic tests (see Hoy et al. (2014)), we assume that insurers offer a pooling contract to all who pretend (truthfully or not) to be uninformed. The (zero-profit) premium attached to this contract reflects the intensity of adverse selection at play (with a higher premium when more type H individuals falsely pretend to be uninformed).

The main theoretical results obtained are twofold. First, we establish that agents should test more often under CL than under DD or, more precisely, that they test under CL for higher values of the idiosyncratic test cost K than under DD. Second, we show that they should attain a higher utility level under DD when their test cost K is low enough that they test under both regulations, and a higher utility level under CL when their test cost is high enough that they do not test under either regulation. The comparison of utility levels for intermediate values of K (when agents should test under CL but not under DD) is ambiguous.

We then design a series of experiments in order to check the validity of these theo-

[5]Under Consent Law, agents choose whether they want to disclose genetic information, which can be used in their contracting with health insurers, while under Strict Prohibition no contract can be explicitly based on genetic information – which does not prevent insurers from offering menus of contracts that indirecty elicit information on individual risks. The Netherlands and Switzerland are two of the countries applying a consent law regime whereas Austria, Belgium, Denmark, France, Israel, Italy, Norway and USA (only for health insurance contract) apply a strict prohibition regime.

retical results, and also to resolve the ambiguity in the comparison of utility levels when the test cost is intermediate. We are especially interested in the role of the intensity of adverse selection under CL in these comparisons, as we surmise that this intensity will grow in the future as genetic tests become more commonplace. Observe that, to obtain answers to those questions with empirical data, we would have to find a (quasi-)natural experiment where the same subjects are exposed to both regulations at some point in time, which is very unlikely because these regulations have been introduced quite recently in most countries, and have thus varied very little since their inception.

We design an experiment which is neutrally framed, and divided in three stages. Stage A has the subjects choose between lotteries in order to estimate their individual degree of risk aversion. Stage B has them choose between a sure payoff (corresponding to not testing under DD) and several lotteries (corresponding to testing under CL) in order to assess the maximum (exogenous) degree of adverse selection under CL under which they prefer the latter (the lottery) to the former (the sure payoff). Stage C consists in 30 rounds in which subjects choose between a sure payoff (not testing under CL) and a lottery (testing under CL) where the lotteries are computed based on the population testing decisions in the previous round. Our objective there is to compute endogenously the amount of adverse selection under CL, and to see whether this amount converges towards an equilibrium value.

The main experimental results we obtain are as follows. The take-up rate of the genetic test under DD is low, at 10% of the population, while the take-up rate under CL is larger, and increases with adverse selection. The intuition for the latter result is that more adverse selection degrades the quality of the pooling contract for the insurer (since more agents buying this contract have the large risk associated to type H), forcing them to increase their premium and inducing more individuals to take the test to try and obtain the lower premium associated to being revealed of type L.[6] The individual degree of risk aversion seems to play little role in the testing decision under CL. As for the comparison of utilities, the proportion of subjects who prefer CL to DD when the testing decision varies across regulations decreases linearly (from 100% to 10%) as the amount of adverse selection under CL increases from its minimum amount (all individuals buying the pooling contract are truly uninformed) to its maximum amount (all who buy the pooling contract have taken the test). These results are obtained when the level of adverse selection under CL is set exogenously. When we compute this level endogenously in Stage C, we fail to obtain convergence. This non-convergence may be explained in part, but not exclusively, by agents differing in risk aversion. Consequently, we are able to comapre both regulations only for exogenous degree of the adverse selection under CL.

[6]This effect is not the only one at play when adverse selection increases, so that the theoretical impact of a higher level of adverse selection on the take-up rate is ambiguous.

Both Barigozzi and Henriet (2011) and Peter et al. (2014), in slightly different set-ups, obtain that disclosure duty weakly dominates the other regimes, including consent law. Their result is partly dependent on their joint assumption that genetic tests are costless and that individuals are homogenous in their preference for information acquisition, which induces *all* individuals to test under CL at equilibrium and, this being known by the insurers, results in everyone obtaining the contract designed for his type, L or H. By contrast, we obtain in our setting that not all individuals test under either CL or DD, because they vary in their (financial, but especially psychological) cost of taking the test. Also, to the best of our knowledge, our paper is the only one, with Crainich (2014), to assume that insurers offer a pooling contract under CL. We find this assumption to be much more in line with current practice than the separating contracts à la Rothschild-Stiglitz used by the rest of the literature. Finally, we are not aware of any experimental analyses comparing regulations for genetic testing.[7]

The paper is organized as follows. Section 2 develops the theoretical model, including the set-up and the analysis of the two regulations. Section 3 presents the experimental design while section 4 presents our experimental results. Section 5 concludes.

2 Theoretical Background

We develop a theoretical background that allows us to formulate predictions to be tested during the experiment. In a first section we provide a standard set-up of genetic testing where people may change their prevention decision according to the test result. Within this set-up, we present the feature of two current regulations of genetic testing: disclosure duty and consent law. We formulate some predictions in a third section which will be tested during the experiment.

2.1 Set-Up

The economy is composed of a unitary mass of individuals. We focus on a generic illness, for which each agent has a genetic background which either predisposes him to develop the disease (bad type, or type H, with a large probability of developing the illness) or a neutral/beneficial genetic background (good type, or type L, with a low probability of developing the disease). There is a fraction λ of type H in the population. Developing the disease is modeled as the occurrence of a monetary damage, d.

Agents can exert a costly effort to reduce their probability of being sick, where this effort reduces the risk of developing the disease only for agents with bad genetic

[7]Even though it does not really tackle the genetic testing issue, Schudy and Utikal (2012) perform an experimental approach in order to analyze the incentive to acquire personal health data in an environment where there is a risk of dissemination of such information.

backgrounds (type H). The probability of developing the disease is not affected by whether effort is exercised or not for agents of type L. Agents are uninformed about their type, except if they choose to take a genetic test, which reveals with certainty their true type.[8]

This setting has been studied by Bardey and De Donder (2013). They study the combination of effort cost and efficiency (measured as the decrease in sickness probability of type H agents when they exercise effort) under which effort is exercised at equilibrium. We assume from now on that effort is inexpensive and/or efficient enough that all agents who are either uninformed about their type, or who know that they are of type H, exert this effort. One reason to do the genetic test is then to forego the effort cost for agents who learn that they are of type L.[9]

We now introduce the minimum amount of additional notation used throughout this paper. Agents decide first to take the genetic test or not, and then exert the effort in case they do not take the test or if the test reveals that they are of type H. The monetary cost of the effort is denoted by ϕ. The probability of developing the illness is p_H for agents of type H and p_L for agents of type L. The probability p_H reflects the fact that agents do the effort, while p_L is not affected by effort (which is the reason why agents of type L do not exercise this costly effort). An agent not informed about his own type (*i.e.*, who does not take the genetic test) is denoted as type U, with the corresponding (expected) probability of getting sick,

$$p_U = \lambda p_H + (1 - \lambda) p_L.$$

Agents who take the genetic test may have to pay a financial cost.[10] The information generated by the test, by itself, may generate utility or disutility for agents (ambiguity preference). We denote by K the financial cost of the test, plus the (monetary equivalent) of the psychological cost/disutility from knowing one's genetic background.[11] Agents then differ according to K, since they have different (unmodelled) attitudes to-

[8] The fact that the genetic test allows people to obtain their true type for sure is obviously a simplifying assumption which is usual in the literature. To the best of our knowledge only Hoy et al. (2014) consider that genetic test may generate errors of type I and II which make individuals face second-order probabilities and consequently may be a plausible explanation for low take-up rates.

[9] Our results would no be affected under the alternative scenario under which only individuals informed about being of type H would undertake prevention.

[10] At the beginning of 2000s, the cost to decrypt human genome required an investment of several hundred millions of (US) dollars. Nowadays the cost is much lower, around 1,000 dollars. Roughly speaking, the cost has been divided by one hundred thousand, which represents a much faster improvement than the Gordon Moore Law applied to the microprocessor evolution.

[11] This financial equivalent K allows us to keep the simple expected utility framework and may capture different notions which have been introduced in the literature such as ambiguity aversion (Epstein, 1999), repulsion to chance (Hoel et al., 2006) and psychological expected utility (Caplin and Leahy, 2001; Barigozzi and Levaggi, 2010).

wards having more information on their genetic background, with individuals having a negative value of K if their (monetary equivalent) of their utility of knowing their genetic background is larger than the test's cost. We measure the cost K in monetary terms because we want to control for the individuals' value of K in the experiment. We assume that K follows a density $g(.)$ and a cumulative distribution[12] $G(.)$.

After having decided whether to test and do the effort, agents then buy health insurance on the private market. We consider two types of regulation of this market, starting with disclosure duty.

2.2 Disclosure Duty *versus* Consent Law: a theoretical approach

In this section, we compare two situations according to whether insurers can observe or not their policyholders' information status, *i.e.* if policyholders are more informed about their health risk than the average thanks to a genetic test. More precisely, on the one hand, we consider the situation under which policyholders have to disclose if they have made a genetic test. In practice, it corresponds to the **disclosure duty** regulation. On the other hand, we consider the opposite situation where policyholders are not obliged to reveal if they have done a genetic test. It corresponds to the regulation named **consent law**. In such a case, when policyholders have undertaken a test and that the test has revealed to them that they are low risk, then they may share the result of the test with insurers in order to benefit from a lower premium. On the contrary, when the test reveals that they are H-type, then they have the possibility to hide the result of the test in order to be insured as if they were of type U in a pooling contract. In such a case, the discrimination risk is smoothed but we may have adverse selection at play. We aim to compare the two situations for different levels of adverse selection.

2.2.1 Disclosure Duty

The insurance contract devised for an agent of type $j \in \{L, H, U\}$ is characterized by a premium in case of health, π_j, an indemnity (net of the premium) in case of sickness, I_j. Competition forces insurers to offer actuarially fair contracts with full insurance,[13] so that $\pi_j = p_j d$ and $I_j = (1 - p_j)d$. Agents who choose not to take the genetic test are uninformed about their type, and so are their insurers. Moreover, the disclosure duty regulation requires that the policyholders' informational status is observable from

[12] In the first stage of the experiment, we measure the subjects' risk aversion but we do not control for preferences toward ambiguity. Moreover, we have allocated different values of K over the population of participants in order to replicate the effect of ambiguity aversion heterogeneity which may have a crucial role in practice.

[13] See Bardey and De Donder (2013) for more details.

insurers. The policyholders' expected utility level is then

$$\begin{aligned} U_{DD}^0 &= (1-p_U)v(y-\pi_U-\phi)+p_U v(y-d+I_U-\phi) \\ &= v(y-p_U d-\phi), \end{aligned}$$

where the superscript 0 over U_{DD} stands for "no testing" and where $v(.)$ is a classical von Neumann Morgenstein utility function ($v'(.)>0$, $v''(.)<0$) with y the individual's exogenous income.

Individuals who take the genetic test receive a utility level

$$v(y-p_H d-K-\phi)=(1-p_H)v(y-K-\pi_H-\phi)+p_H v(y-K-d+I_H-\phi),$$

if they are revealed to be of type H, and

$$v(y-p_L d-K)=(1-p_L)v(y-K-\pi_L)+p_L v(y-K-d+I_L),$$

if they are revealed to be of type L. Their expected utility when taking the test is then given by

$$U_{DD}^1=\lambda v(y-p_H d-K-\phi)+(1-\lambda)\,v(y-p_L d-K),$$

where the superscript 1 over U_{DD} stands for "taking the test".

Let us denote by Ψ_{DD} the information value of the genetic test under disclosure duty, with agents doing the test if $\Psi_{DD}>0$. We have:

$$\begin{aligned} \Psi_{DD} &= U_{DD}^1-U_{DD}^0 \\ &= \lambda v(y-p_H d-K-\phi)+(1-\lambda)\,v(y-p_L d-K)-v(y-p_U d-\phi). \quad (1) \end{aligned}$$

From (1), we see that the main drawback of disclosure duty is that it exposes agents to a *discrimination risk*: rather than obtaining the sure payoff associated with remaining uninformed, they face a lottery when taking the test. Observe that agents may decide to take the test even if $K=0$, since taking the test allows them to save on the effort cost ϕ when they are revealed to have good genes. Besides, more risk averse agents are less likely to take the test, as they suffer more from the discrimination risk. Finally, a larger value of K (because, for instance, of a larger disutility from knowing one's own genetic background) renders genetic testing less attractive. We denote by K_{DD} the threshold value of K below (resp., above) which agents take (resp., do not take) the genetic test under disclosure duty–*i.e.*, the value of K such that $\Psi_{DD}=0$.

2.2.2 Consent Law

Under the consent law regulation, individuals reveal their information to the insurers only when they are of type L, and conceal the information that they are of type H,

claiming not to have done the test, in order to be pooled with the truly uninformed agents. The classical way for the insurers to solve this *adverse selection* problem is to issue separating contracts, with partial coverage (*i.e.*, a deductible) for the mimicked type (here, type U) in order to prevent the mimicking type (here, type H) from taking the contract intended for the former. We rather adopt the approach developed by Crainich (2014) in this context and assume that the insurers offer a pooling contract intended for all those who claim to be uninformed. This assumption of a pooling contract can be justified for instance by the existence of transaction costs generated by several contracts (see Newhouse (1996) and Allard et al. (1997)). As pointed by Hoy et al. (2003), it also better corresponds to the reality, as we are not aware of health insurance contracts offering a deductible in case the insured does not provide genetic tests results.

Anticipating that such a pooling contract will attract tested agents of type H, the insurers ask for a larger-than-p_U unitary premium in order to break-even. More precisely, if the pooling contract clientele is made of an (exogenous, for the moment) fraction f of truly uninformed agents (type U) and of a fraction $1-f$ of cheating agents (of type H), $0 \leq f \leq 1$, then the insurers have to set a premium

$$\pi_U = (p_U + x)\, d,$$

and an indemnity (net of the premium) in case of sickness,

$$I_U = (1 - (p_U + x))d,$$

where the zero-profit mark-up x satisfies

$$p_U + x = f p_U + (1-f) p_H.$$

Roughly speaking, both f and x are measures of the intensity of the adverse selection at play, with more adverse selection translating into a lower f and a larger x.

We denote by U^0_{CL} the (expected) utility of an agent who does not test under consent law, which is given by

$$U^0_{CL} = v(y - (f p_U + (1-f) p_H)d - \phi),$$

and by U^1_{CL} the (expected) utility of an agent who takes the genetic test, with

$$U^1_{CL} = \lambda v(y - (f p_U + (1-f) p_H)\, d - K - \phi) + (1-\lambda) v(y - p_L d - K).$$

We denote by Ψ_{CL} the information value of genetic testing under consent law, given by

$$\begin{aligned} \Psi_{CL} &= U^1_{CL} - U^0_{CL} \\ &= \lambda v(y - (f p_U + (1-f) p_H)\, d - K - \phi) + (1-\lambda) v(y - p_L d - K) \\ &\quad - v(y - (f p_U + (1-f) p_H)\, d - \phi). \end{aligned} \tag{2}$$

Individuals who take the test obtain the same payoff (minus K) than if they did not when they are unlucky (type H) and a better payoff if they are lucky (type L). It is then straightforward that they do take the test when $K = 0$, and that the incentives to take the test are reduced when K increases. The impact of variations in (exogenous) f on the incentives to take the test is more convoluted. On the one hand, a larger value of f improves the payoff associated to the pooling contract and thus reduces the amount to be gained by testing. On the other hand, if K is large, the marginal utility with the pooling contract is much higher if the agent has tested (and paid K) than if he did not, so that the increase in income with the pooling contract associated to a larger value of f increases more U^1_{CL} than U^0_{CL}. Denoting by K_{CL} the (positive) value of K such that $\Psi_{CL} = 0$ and applying the implicit function theorem to (2), we obtain:

$$\frac{dK_{CL}}{df} = \frac{(p_U - p_H)d\left[v'(y - (fp_U + (1-f)p_H)\,d - \phi) - \lambda v'(y - (fp_U + (1-f)p_H)\,d - K_{CL} - \phi)\right]}{\lambda v'(y - (fp_U + (1-f)p_H)d - K_{CL} - \phi) + (1-\lambda)v'(y - p_L - K_{CL})}, \tag{3}$$

so that

Lemma 1 *K_{CL} decreases with f if policyholders are not too risk averse ($v(.)$ is not too concave) and if λ is low enough.*

We have assumed up to now that f were exogenous, and we have computed the maximum value of K compatible with doing the test. The equilibrium value of f, if it exists, is given by

$$f^* = \frac{1 - G(K_{CL}(f^*))}{1 - (1-\lambda)G(K_{CL}(f^*))},$$

where the numerator denotes the fraction of individuals (in the overall population) who choose not to test and the denominator the fraction of the population who buys the pooling contract. In the experiment, we try to find the equilibrium value of f using a sequential procedure spanning several rounds of the same game. We construct the function $f_{t+1}(f_t)$ where t denotes the round agents are playing, such that

$$f_{t+1} = \frac{1 - G(K_{CL}(f_t))}{1 - (1-\lambda)G(K_{CL}(f_t))}, \tag{4}$$

where we compute K_{CL} from the answers given by the subjects in round t when the payoffs they are offered are based on f_t. We have an equilibrium (or steady state) when $f_{t+1} = f_t$. We assume that

$$G\left(K_{CL}\left(0\right)\right) < 1, \text{ and that } G\left(K_{CL}\left(1\right)\right) > 0$$

so that, respectively, $f_{t+1}(0) > 0$ and $f_{t+1}(1) < 1$.

Thanks to Lemma 1, we obtain that

$$\begin{aligned} \frac{\partial ft+1}{\partial f_t} &> 0 \text{ if } \frac{\partial K_{CL}(f)}{\partial f} < 0, \text{ and that} \\ \frac{\partial ft+1}{\partial f_t} &< 0 \text{ if } \frac{\partial K_{CL}(f)}{\partial f} > 0. \end{aligned}$$

Since the sign of the derivative of K_{CL} with respect to f is the same (either positive or negative) for all values of f and since the cdf $G(K)$ is continuous, we obtain the following result:

Proposition 1 *The sequential procedure developed above should converge towards an equilibrium value of f, so that for all $\varepsilon < 0$, there exists a value of t, denoted by t^*, such that $f_{t+1} - f_t < \varepsilon$,$\forall t \geq t^*$.*

In the next section, we compare the two regulations for exogenous values of K and of f. We will revert to endogenizing f when presenting and analyzing the experiments' Stage C.

2.2.3 Disclosure Duty *versus* Consent Law: Some Theoretical Predictions

The following lemma will prove to be very important in both the theoretical predictions and the design of the experiment.

Lemma 2 $U^1_{CL} \geq U^1_{DD}$ *and* $U^0_{DD} \geq U^0_{CL}$ $\forall K, f$.

Proof. Immediate from the definitions of the four utility levels. ■

For individuals who would test whatever the regulation at play, consent law is preferable to disclosure duty *ex ante*, because they would obtain the same payoff in both cases if they are revealed to be of type L, while they would fare better off under consent law, by being pooled with type U, if they are revealed to be of type H. Alternatively, for individuals who do not test whatever the regulation, disclosure duty is preferable to consent law because the pooling contract offered under consent law is more costly than the separating contract (based on p_U) offered under disclosure duty.

Lemma 2 has a direct consequence on the comparison of the threshold valus K_{DD} and K_{CL}.

Lemma 3 $K_{CL} \geq K_{DD}$ $\forall f \in [0, 1]$.

Proof. Follows from the facts that $\Psi_{CL} = U^1_{CL} - U^0_{CL} > \Psi_{DD} = U^1_{DD} - U^0_{DD}\ \forall f, K$ by Lemma 2, and that both Ψ_{CL} and Ψ_{DD} are decreasing in K, $\forall f, K$. ■

Lemma 3 says that, everything else equal, policyholders are more willing to take a genetic test under consent law than under disclosure duty. This result is intuitive, since individuals gain more by taking the test under consent law than under disclosure duty ($\Psi_{CL} > \Psi_{DD}$), both because consent law does not expose them to a discrimination risk (since they obtain the same contract whether of type U or type H) but degrades the contract offered in case the test is not taken, compared to the disclosure duty case (because of adverse selection).

Proposition 2 *Individuals are better off under disclosure duty if K is low enough that they take the test under both regulations ($K < K_{DD} < K_{CL}$) and under consent law if K is large enough that they do not take the test under either regulation ($K > K_{CL} > K_{DD}$). For intermediate values of K, they take the test only under consent law, and the utility gap between disclosure duty and consent law increases with K and decreases with f.*

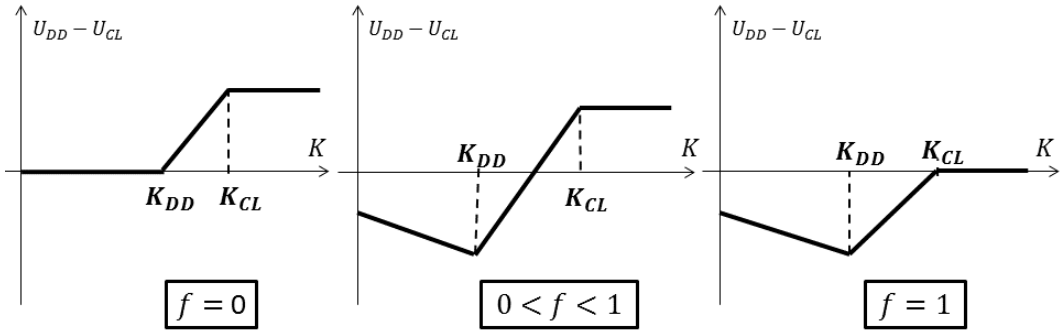
Proof. $K < K_{DD}$ implies that agents do the test under both regulations (by Lemma 3) in which case they are better off under disclosure duty (by Lemma 2). $K > K_{CL}$ implies that agents do not take the test under either regulation (by Lemma 3) in which case they are better off under consent law (by Lemma 2). In the intermediate case where $K_{DD} < K < K_{CL}$, the difference in utility levels between disclosure duty and consent law is

$$v(y - p_U d - \phi) - \left[\lambda v(y - (f p^1_U + (1-f)p^1_H)d - K - \phi) - (1-\lambda)\, v(y - p_L d - K)\right],$$

which is increasing in K and decreasing in f. ■

Proposition 2 can be summarized in Figure 1, which shows the utility differential between disclosure duty (U_{DD} =max(U^0_{DD}, U^1_{DD})) and consent law (U_{CL} =max(U^0_{CL}, U^1_{CL})) as a function of K, when $f = 0$ (panel a), $0 < f < 1$ (panel b) and $f = 1$ (panel c). When $f > 0$ (so that some agents who buy the pooling contract are uninformed about their own type), the utility level under disclosure duty decreases faster than under consent law when $K < K_{DD}$ because of the larger marginal utility under the former (due to the larger premium when revealed of type H). For intermediate values of K, the test cost K is paid only under consent law, so that the utility difference between disclosure duty an consent law increases with K. When $f < 1$ (so that some type H agents pretend to be uninformed), utility is strictly larger under disclosure duty because individuals suffer from adverse selection under consent law (in the guise of a larger premium in the pooling contract for those who do not test).

Figure 1: Utility differences between *disclosure duty* and *consent law*.



Theory shows that the comparison of utilities under CL and DD is ambiguous when agents test under CL but not under DD. We now present the design of the experiments which will allow us, among other things, to resolve this ambiguity.

3 Experimental design

Subjects were students at Universidad de los Andes (Bogotá). We conducted four sessions with 20 subjects each for a total of 80 participants. The experiment was programmed and conducted using the z-Tree software (Fischbacher, 2007).

Each session was divided into three stages. All decisions in all stages were neutrally framed – *i.e.,* were described in terms of lotteries, omitting all relationship to insurance contracts and genetic test taking. In **Stage A** we retrieve a measure of the participants' risk aversion, used as a control in further stages of the analysis. The novelty in our experimental analysis resides in **Stages B** and **C**, in which subjects with different and exogenously assigned test costs K take a series of testing decisions represented by gambles. In **Stage B,** the offered gambles represent a comparison between *disclosure duty* and *consent law*, whereas in **Stage C** these gambles focus on the *consent law* regulation.

The payoffs in Stages B and C were based on the following parameter values:[14] $y = 1.0$, $d = 0.7$, $\lambda = 0.5$, $p_L = 1/9$, $\phi = 0.1$ and $p_H = 5/9$. The monetary cost of the genetic test (including the monetary cost or benefit of having full information about one's own genetic background), denoted by K, follows a normal-like distribution such that K takes values 0.01, 0.05, 0.10, 0.15 and 0.20 with probabilities 0.10, 0.20, 0.40,

[14]Remember that we assume implicitly that the prevention effort decreases the probability of getting sick of a type H agent by at least $\phi/(\lambda d) = 2/7$, so that both uninformed and type H agents have an incentive to do the effort under both regulations. Payoffs are then calculated under the assumption that the effort is made by types H and U, but not by type L.

0.20 and 0.10, respectively. The heterogeneity of K intends to reflect, and control for, the expected heterogeneity among subjects despite having the same price of the test. These differences are derived from the psychological costs associated to take the test.

3.1 Stage A: Measuring risk aversion

Subjects were asked to select one out of six 50/50 gambles that were increasing in expected value and variance, in order to measure their risk aversion. The six gambles, adapted from Cárdenas and Carpenter (2013) are shown in Table 1. The second column reports the (range of) value(s) of the coefficient of relative risk aversion r an individual with utility function $U(x) = (x^{1-r})/(1-r)$ would need to exhibit in order to pick the corresponding gamble. Larger values of r represent higher risk aversion, since the concavity of the utility function is more pronounced as r increases. The protocol used was similar to Barr and Genicot (2008) and Eckel and Grossman (2008), and it intended to simplify the gamble choice.

Table 1: Gambles offered in Stage A of the experiment

Gambles	Parameter from the CRRA utility function
Lottery 1: \$33—\$33	$r > 1.77$
Lottery 2: \$25—\$47	$0.82 \leq r \leq 1.77$
Lottery 3: \$18—\$62	$0.48 \leq r \leq 0.82$
Lottery 4: \$11—\$67	$0.27 \leq r \leq 0.48$
Lottery 5: \$4—\$91	$0.00 \leq r \leq 0.028$
Lottery 6: \$0—\$95	$r \leq 0.00$

We compare on Figure 2 the cumulative distribution of the subjects' decisions in Cárdenas and Carpenter (2013) and in our experiment. The cumulative distribution in Cárdenas and Carpenter (2013) is always above ours, which means that we have a *less* risk averse sample of subjects than theirs.[15] At least two elements could explain this difference. First, Cárdenas and Carpenter (2013)'s subjects are 567 non-students (also in Bogotá), while ours are 80 students. Second, the stakes for this task are slightly larger in Cárdenas and Carpenter (2013): although the average payoffs in both experiments are similar (12 USD), the share of Stage A decisions in the total payoff of the experiment is on average 25% for Cárdenas and Carpenter (2013) but only 17% in our study.[16]

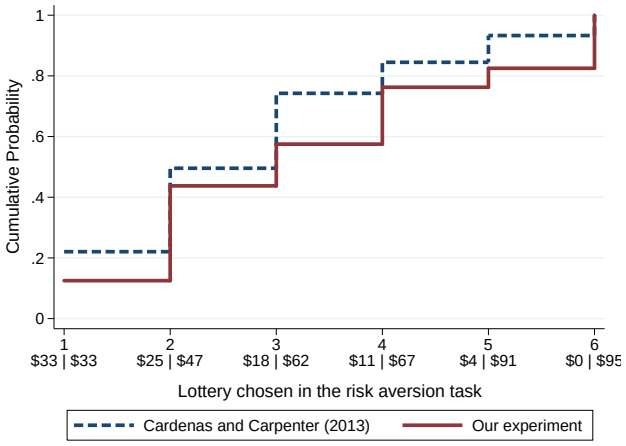
In addition to the measure of risk preferences we also measure subjects' tolerance to ambiguity using a non-incentivized test (Budner, 1962) during the post-experimental survey. An index measuring tolerance to ambiguity[17] was constructed from a set of

[15]The two distributions are statistically different according to a Kruskal-Wallis equality of populations rank test (chi-squared 5.967 and p-value =0.0146).

[16]A Wilcoxon-Mann-Whitney test applied to our Stage A results shows that women are more risk averse (p-value of 0.0014).

[17]Budner (1962) defines the intolerance for ambiguity as the "tendency to perceive ambiguous situ-

Figure 2: Cumulative distribution of lotteries chosen with respect to Cárdenas and Carpenter (2013)



sixteen questions. Each question uses a Likert scale from 1 to 7, whose score was added to the index. Higher values of the index represent more intolerance to ambiguity. The average index in our sample was 49.6, with a minimum of 28 points and a maximum of 68 points.[18]

3.2 Stage B: Simultaneous choice between regulation type and genetic testing

The aim of Stage B is to elicit when individuals prefer consent law to disclosure duty, as a function of their idiosyncratic test cost K and of the exogenous value of f, taken as a measure of the extent of adverse selection under consent law. The decisions offered to participants in this Stage mimic a setting where individuals choose *simultaneously* the type of regulation (disclosure duty or consent law) and whether they take the genetic test or not. Lemma 2 has shown that disclosure duty dominates consent law for individuals who take the genetic test, while consent law dominates disclosure duty when individuals do not take the genetic test. In other words, individuals faced with a simultaneous choice of regulation type and testing decisions never choose the two combinations "testing under disclosure duty" and "not testing under consent law", so that we can restrict their

ations as sources of threat". Budner's scale measures four different factors related to the tolerance for ambiguity: predictability, variety and originality, clarity, and regularity (Benjamin et al., 1996).

[18]We find gender differences in the average tolerance for ambiguity, with women scoring on average 51.9 points compared to the 47.9 points scored by men. This difference, of 4.0 points, is statistically significant at the 5% level.

choice to the two options "not testing under disclosure duty" and "testing under consent law". We now explain how we have framed this choice neutrally, without mention to genetic testing and health insurance.[19]

Subjects were presented with seven binary *decisions*. In each *decision,* participants had to choose between a 50/50 gamble, corresponding to the payoff they would have obtained under consent law when the genetic test is taken, and a fixed amount of money, representing the payoff under disclosure duty when the genetic test is not taken. For each *decision,* we then have the following set of payoffs:

Fixed amount (Not testing under DD)	**Gamble (Testing under CL)**	
	If $H-$type	If $L-$type
$y - p_U d - \phi$	$y - (fp_U + (1-f)p_H)d - K - \phi$	$y - p_L d - K$

From one decision to the next, we increase the value of f (from -0.2 to 1, by steps of 0.2), making the gamble (testing under consent law) more attractive (since a larger f means less adverse selection and thus a better payoff), while not impacting the sure payoff corresponding to not testing under disclosure duty. We ask participants for the first *decision* in which they prefer to gamble instead of keeping the fixed amount of money.[20]

3.3 Stage C: Repeated decisions under *consent law* when f is made endogenous

Stage C concentrates on the testing decision by subjects within the consent law regulation. Its aim is to endogenize the extent of adverse selection (as measured by f) based on the decisions of the subjects. We then have the subjects choose between taking the test (*i.e.*, playing a gamble) and not taking the test (*i.e.*, receiving a sure payoff) for

[19]We could rather have modeled a *sequential* decision, where agents choose first whether they prefer disclosure duty or consent law, and then whether they take the genetic test or not, for each regulation. This more ambitious scenario would have allowed us to assess and compare directly the testing decisions across regulations. After much thinking about this alternative model, our opinion is that it would have involved too many choices by subjects to offer reliable results. In other words, our experimental design is the result of a trade-off between the simplicity of the task for the respondents and the richness and simplicity of interpretation of the results obtained. We show in the Result 2 below how our simple experimental design allows us to infer indirectly whether the test would have been taken by the subjects under disclosure duty, and to give both a lower- and upper-bound on the value of f, for each individual value of K, between which genetic tests would have been taken under consent law. More importantly, this design also allows us to rank unambiguously U_{DD} and U_{CL} when the testing decision is allowed to vary across regulations (see Result 3).

[20]We start with a negative value of f in order to detect an interior switching point.

thirty consecutive rounds, with the payoffs based on the consent law regulation and given by at each round by[21]

Fixed amount (Not testing under CL)	**Gamble (Testing under CL)**	
	If $H-$type	If $L-$type
$y-(fp_U+(1-f)p_H)d-\phi$	$y-(fp_U+(1-f)p_H)d-\phi-K$	$y-p_Ld-K$

The value of f was recomputed after every round using formula (4). In words, the payoffs offered to subjects in round $t+1$ are obtained using a value of f which reflects the choices of the subjects in the previous period t –*i.e.*, the fraction of subjects who know they were of type H among all the subjects who ended up buying the pooling contract in period t. Exogenous values of $f = 0.10$ and $f = 0.90$ were set in rounds 1 and 16.

Subjects were informed of their type at the end of each period, independently of whether they chose to take the test or not. Our aim with this feature is to block the inter-temporal effects of different information sets between subjects. Subjects were not informed on how the payoffs were computed at each round. Therefore, it was unnecessary to give them information about the proportion of U-types and H-types in the population and we did not give them this information to avoid imitation behaviors.

3.4 Timing and payoffs

In all sessions, subjects started playing Stage A. In order to control for the potential order effects, we randomize the sequence in which Stage B and Stage C were played. We also randomize the sequence of the exogenous values of f in Stage C, with the same purpose. At the end of the experiment, three random draws defined the subjects' earnings from each stage. A first draw decided the outcome of the lottery chosen in Stage A. A second draw defined the decision to be paid from Stage B, and the low/high prize was simultaneously chosen. A third draw was used to determine which one of the thirty rounds in Stage C was paid. We decided to pay to subjects for only one of their decisions in Stage C in order to avoid strategies involving inter-temporal computations that would be out of the scope of this paper. Average earnings were approximately \$25,000 Colombian pesos (cop).[22]

[21] More precisely, we told the subjects that a random letter, X or Y, was assigned to them in each round. They had to decide whether they wanted to learn the letter assigned to them (equivalent to playing the gamble, with the larger payoff for letter X), or not (receiving then the sure payoff).

[22] \$2,500 cop are equivalent to €1.00 at the time of the experiment.

4 Experimental results

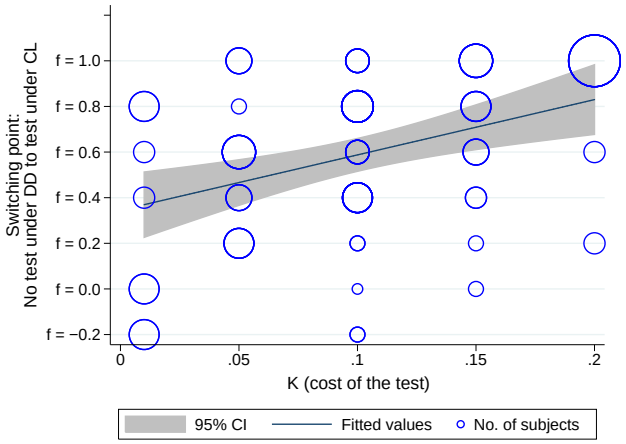
4.1 Stage B: Comparison between *consent law* and *disclosure duty*

We obtain the following three results. The first result compares no testing under disclosure duty and testing under consent law, while the two subsequent results compare testing behavior (Result 2) and utilities (Result 3) across regulations.

Result 1: **The value of f required to switch from *not testing under DD* to *testing under CL* is increasing in K and in the level of ambiguity aversion, whereas risk aversion plays a minor role.**

Figure 3 shows that the value of f (denoted henceforth by $\hat{f}$) such that individuals switch from the sure payoff (under DD) to the lottery (under CL) increases with the cost of taking the test K. The correlation between $\hat{f}$ and K is 0.373 (p-value 0.001), represented by the upward slope. This positive relationship between $\hat{f}$ and K can be interpreted as a mere confirmation of rationality: a larger value of K decreases the payoff obtained with the lottery, so that agents prefer the sure payoff for larger values of f (recall that the payoff with the lottery improves when f increases).[23] The regression analysis reported in Table 2 allows us to identify which individual factors, above and beyond the cost K, affect the preferences for testing under CL *vs* not testing under DD.

Figure 3: Switching point ($\hat{f}$) from *not testing* to *testing* as function of K.



[23] We should stress that $\hat{f}$ is not related to K_{CL}, since the latter is obtained when comparing U^1_{CL} and U^0_{CL} (rather than U^0_{DD} for $\hat{f}$). The sign of the relationship between K_{CL} and f is ambiguous (see (3)) because f affects both U^0_{CL} and U^1_{CL}, while here the sign of the relationship between $\hat{f}$ and K is unambiguous since f and K do not affect U^0_{DD}.

We run two OLS models whose coefficients are reported in columns (1) and (2) of Table 2, and where the dependent variable is the number of decisions in which the participant prefers not to test (*i.e.*, the sure payoff under DD). The switching point $\hat{f}$ is obtained by a linear transformation of this variable: each additional *decision* in which the subject decided not to test represents an increase of $\hat{f}$ by 0.2 units. The coefficients show the positive and robust effect of K: according to model (1), an increase in K of 0.1 will increase the number of decisions in which the participants will not test by 1.175, or equivalently, will increase $\hat{f}$ by 0.235. This explanatory power of K is a reason for the difficulty in retrieving the effects of risk aversion and intolerance to ambiguity. The effect of intolerance to ambiguity becomes significant only after being interacted with K. According to model (2), an additional point in Budner's scale (see footnote 17) increases the number of decisions in which the test is not taken by 0.096, or equivalently increases the value of $\hat{f}$ by 0.019. This effect decreases as the value of K increases, as shown in the corresponding interaction coefficient.

Table 2: OLS regressions. Dependent variable is the switching point, *i.e.*, the number of decisions in which the test was not taken

Dependent variable:	OLS regression	
switching point $\hat{f}$	(1)	(2)
K	11.75***	46.67**
	(3.552)	(22.20)
Intolerance to ambiguity	0.0085	0.0959*
	(0.0221)	(0.0537)
K × Intolerance to ambiguity		-0.804*
		(0.448)
Gender (Male = 1)	-0.219	-0.557
	(0.421)	(0.902)
K × Gender		3.167
		(7.974)
Lottery 2: \$25—\$47	0.597	0.928
	(0.637)	(0.664)
Lottery 3: \$18—\$62	0.237	0.470
	(0.748)	(0.753)
Lottery 4: \$11—\$67	0.641	0.999
	(0.717)	(0.745)
Lottery 5: \$4—\$91	-0.157	0.176
	(0.930)	(0.961)
Lottery 6: \$0—\$95	1.235	1.482*
	(0.745)	(0.761)
Constant	2.923**	-1.140
	(1.305)	(2.877)
Observations	79	79
R-squared	0.186	0.226

The omitted category in the risk aversion measure is Lottery 1: \$33—\$33.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We now turn to the impact of risk aversion. We measure risk aversion using the subjects' answers to Stage A. More precisely, we use a dummy variable that indicates

which of the six lotteries proposed in Stage A has been chosen by the subject. Recall that these lotteries are increasing in both expected value and variance (we indicate in Table 2, for each lottery from 2 to 6, the two payoffs that were proposed, with a 50% probability attached to each payoff). The effect of risk aversion is significant only when comparing the most risk averse subjects (who chose lottery 6 in Stage A) with the least risk averse subjects (who chose the first lottery, namely the sure payoff), in model (2). One may think that the lack of explanatory power of risk aversion is due to the potential collinearity with ambiguity aversion. However, in our experimental sample the correlation between these variables is 0.189, with a p-value of 0.095. This moderate but significant correlation is consistent with the literature in neuroscience and economics (Hsu et al., 2005; Bossaerts et al., 2010; Potamites and Zhang, 2012).

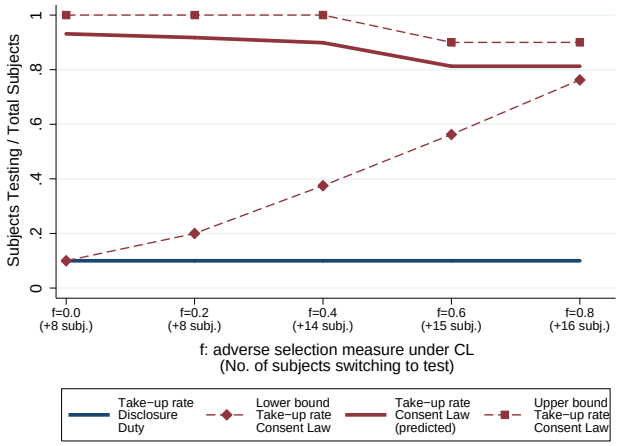
Result 2: **The take-up rate under DD is low, while the take-up rate under CL is more precisely identified when f is large. The take-up rate predicted for CL on the basis of answers to Stage A is very large and close to the take up rate of risk neutral agents.**

Even though Stage B does not ask subjects directly whether they would test under each regulation separately, the setting offered to subjects allows to indirectly gather some information about their testing behavior with each regulation. We start with disclosure duty. Observe that the payoffs offered under both regulations are equivalent when testing and when $f = 0$ –*i.e.*, $U^1_{DD} = U^1_{CL}$. Hence, when $f = 0$, comparing "no testing under DD" and "testing under CL" is equivalent to comparing "no testing under DD" and "testing under DD". We can then infer from the choice of subjects when $f = 0$ whether they would take the genetic or not under the DD regulation. We report in Figure 4 the fraction of subjects (using the "discrete-normal" distribution of test costs K) who choose to test under DD.[24]

We then move to consent law. We know of two categories of individuals who should prefer testing to no testing, under CL. The first category is composed of those who prefer to test (rather than not testing) under DD, since Lemma 3 shows that all individuals who test under DD (*i.e.*, with $K < K_{DD}$) should also test under CL (*i.e.*, are such that $K < K_{CL}$ since $K_{DD} < K_{CL}$). The second category is made of those who prefer not testing under DD ($U^0_{DD} > U^1_{DD}$) but who prefer the lottery under CL to the sure payoff under DD (*i.e.*, $U^1_{CL} > U^0_{DD}$), since in that case we obtain the following ranking of utilities: $U^1_{CL} > U^0_{DD} > U^0_{CL}$, with the latter inequality proved in Lemma 2. Hence, we can compute the lower-bound on the take-up rate under CL, which consists, for each value of $0 \leq \tilde{f} \leq 1$, in the fraction of individuals who prefer the lottery under CL to the

[24]The preference for testing or not under DD (and thus the aggregate take-up rate of the test under DD) does not change with f, since f does not impact the payoffs under DD, even though we use the subjects' decision when $f = 0$ to assess this preference as both regulations are equivalent in such a case.

Figure 4: Take-up rates for *disclosure duty* and *consent law*



sure payoff under DD for a value of f at most equal to $\tilde{f}$. We report this lower-bound on the take-up rate on Figure 4.[25] This lower-bound is of course increasing in f.

As for the upper-bound on take-up under CL, we see from the definition of K_{CL} (as the value of K such that Ψ_{CL} defined in (2) is zero) that increasing risk aversion decreases the value of K_{CL}, all other things kept unchanged.[26] The maximum value of K_{CL} (corresponding to the upper-bound on the take-up rate) is then obtained when agents are risk neutral –*i.e.*, with linear utilities. We report on Figure 4 the upper-bound on take-up rate as $G(K_{CL}(f))$ with linear utilities. It is straightforward from (3) that K_{CL} decreases with f in that case.

We see from Figure 4 that the take-up rate of genetic testing under DD is low, at 10%. Individuals then dislike so much the discrimination risk associated to taking the test under DD that most of them prefer not taking the test. As for CL, we do not observe the actual take-up rate but rather construct both a lower- and an upper-bound. We obtain that the interval gets more precise as f increases (*i.e.*, as the intensity of adverse selection decreases), since the lower-bound increases while the upper-bound decreases. We obtain a quite precise estimate of the take-up rate as f becomes large, with around 80% of subjects who should take the test if $f = 0.8$. Also, recall from Lemma 3 that the take-up rate need not be increasing in f, especially if agents are very risk averse.

[25] This is a lower-bound because individuals with $U^1_{DD} < U^0_{DD}$ and $U^1_{CL} < U^0_{DD}$ can either be such that $U^1_{CL} > U^0_{CL}$ or $U^0_{CL} > U^1_{CL}$. For the lower bound, we assume that $U^1_{CL} > U^0_{CL}$.

[26] This is intuitive, since the test cost K is paid when the test is chosen, in which case the agent is faced with a lottery. A larger risk aversion then decreases the certainty equivalent of this lottery, other things equal, and induces the more risk averse individuals to favor the sure payoff associated with not taking the test for a lower value of K.

We then construct a prediction of take-up rates under CL by using the estimated degree of risk aversion of subjects obtained in Stage A. More precisely, for each subject preferring lotteries 2 to 5, we use the middle value of the corresponding range of the relative risk aversion parameter (for instance, when a subject chooses lottery 3, we assume that his value of r is 0.65). For very risk averse subjects who prefer lottery 1 (the sure payoff), we use the lower-bound value of their estimated relative risk aversion parameter ($r = 1.77$) while, for the very risk averse subjects who prefer lottery 6, we use the upper-bound value of 0. We then compute the take-up rate of our population as a function of f, given the discrete-normal distribution of K, assuming that individual preferences exhibit this constant relative risk aversion parameter. The result is reported on Figure 4.

We obtain that this measure is very close to the upper-bound value, and is (weakly) decreasing with f. Both phenomena are due to the fact that our population is made of a large proportion of agents exhibiting little risk aversion in Stage A (see section 3.1). Interestingly, our predicted take-up rate is, for all values of f, larger than the lower-bound we have computed. This was not a foregone conclusion, since the lower-bound is computed using responses to Stage B, while our prediction is based on Stage A alone. We have tested the robustness of this characteristic to the degree of risk aversion retained for the most risk averse agents. As long as the value of the coefficient of relative risk aversion of those subjects is lower than 3.23, the predicted curve remains the same. Agents with $r \geq 3.23$ prefer not to test when $f = 0.8$, bringing down the predicted take-up rate of the population. When more than 40% of subjects choosing lottery 1 in Stage A exhibit $r \geq 3.23$, then our predicted take-up rate decreases below the lower-bound computed from responses to Stage B.

Result 3: **The proportion of subjects who prefer CL to DD when the testing decision varies across regulation increases linearly (from 10% to 100%) as f increases from 0 (maximum adverse selection under CL) to 1 (no adverse selection under CL)**

Stage B allows us to compute the fraction of subjects who prefer DD to CL when testing can vary across regulations–*i.e.*, to compare $U_{DD} = \max(U^0_{DD}, U^1_{DD})$ and $U_{CL} = \max(U^0_{CL}, U^1_{CL})$. As explained in Result 2, looking at the subjects' decision when $f = 0$ allows us to compare U^0_{DD} and U^1_{DD}. Subjects' decisions also allow us to compare U^0_{DD} with U^1_{CL} as a function of f. Finally, recall that we always have that $U^0_{DD} > U^0_{CL}$ and that $U^1_{CL} > U^1_{DD}$, for any value of $0 < f < 1$. We can then put subjects in three groups, for each value[27] of f:

(i) Members of group 1 are such that $U^0_{DD} < U^1_{DD}$. Putting together this inequation with $U^0_{DD} > U^0_{CL}$ and $U^1_{CL} > U^1_{DD}$, we obtain that $U^1_{CL} > U^1_{DD} > U^0_{DD} > U^0_{CL}$, so

[27]The composition of groups does vary as we change exogenously f.

that subjects in group 3 prefer the CL regulation. Observe that $U^0_{DD} < U^1_{DD}$, so that $K < K_{DD}$, and that $K < K_{CL}$ since $U^1_{CL} > U^0_{CL}$.

(ii) Members of group 2 are such that $U^0_{DD} > U^1_{DD}$ and that $U^0_{DD} < U^1_{CL}$. Putting together these two inequations with $U^0_{DD} > U^0_{CL}$ and $U^1_{CL} > U^1_{DD}$, we obtain that $U^1_{CL} > U^0_{DD} > U^1_{DD}$ and that $U^0_{DD} > U^0_{CL}$, so that subjects in group 2 prefer the CL regulation. Observe that $U^0_{DD} > U^1_{DD}$, so that $K > K_{DD}$, and that $K < K_{CL}$ since $U^1_{CL} > U^0_{CL}$.

(iii) Members of group 3 are such that $U^0_{DD} > U^1_{DD}$ and that $U^0_{DD} > U^1_{CL}$. Putting together these two inequations with $U^0_{DD} > U^0_{CL}$ and $U^1_{CL} > U^1_{DD}$, we obtain that $U^0_{DD} > U^1_{CL} > U^1_{DD}$ and that $U^0_{DD} > U^0_{CL}$, so that subjects in group 1 prefer the DD regulation. Observe that $U^0_{DD} > U^1_{DD}$, so that $K > K_{DD}$, but that we cannot compare U^1_{CL} with U^0_{CL}, so that we do not know whether K is larger or smaller than K_{CL}.

We can reconcile these results with Proposition 2 by looking at Figure 5, which reproduces Figure 1 (b) and adds the three groups of subjects just identified.

Figure 5: Utility differences between *disclosure duty* and *consent law* and preferences between regulations

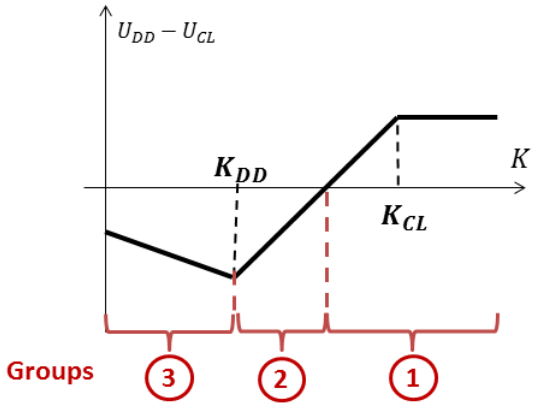
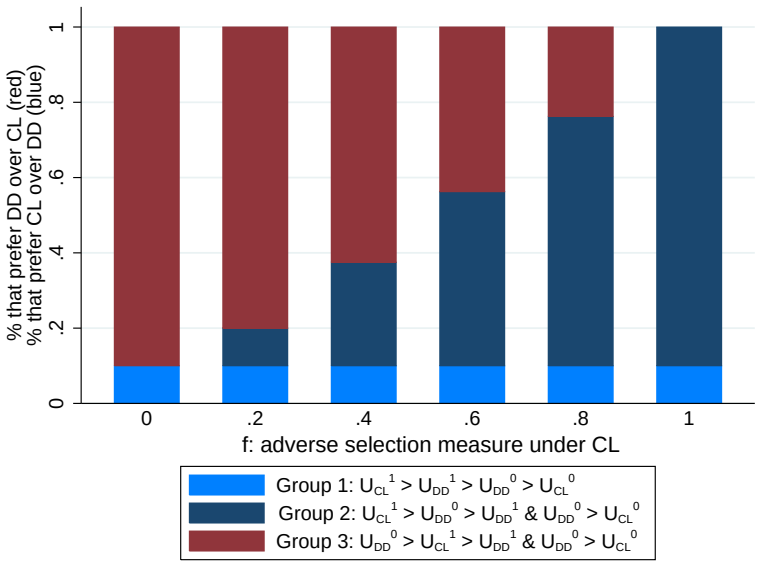


Figure 6 reports the fraction of subjects belonging to group 1 (in blue), group 2 (dark blue) and group 3 (red) for the values of f, from 0 to 1, corresponding to the lotteries offered to subjects in Stage B. In the absence of adverse selection under CL ($f = 1$), all subjects prefer CL to DD. As adverse selection increases, the proportion of subjects preferring DD increases monotonically, to reach 90% when $f = 0$. More subjects favor CL than DD when f is larger than (roughly) 0.5. Also, we have regressed the proportion of subjects preferring CL on the value of f, and we obtain that the intercept is not statistically significant, while the slope is not statistically different from one. In other words, an increase in f by 0.1 increases the fraction of our population

favoring CL by 0.1.

Figure 6: Proportion of subjects that prefer *disclosure duty* and *consent law* as function of f



We now turn to the results obtained from Stage C, where subjects choose whether to test or not (*i.e.*, choose between a sure payoff and a lottery) when we vary f from one round to the next, based on the subsjects' answers in the previous round.

4.2 Stage C: Take-up rates under *consent law*

Result 4: **The quality of the pool f has a negative impact on the probability of taking the test under CL. The degree of risk aversion plays little role in the testing decision.**

Lemma 1 has shown that the impact of increasing f on the decision to test under a CL regulation is ambiguous. We now use the experiments' results to resolve this ambiguity.

We estimate a logistic model (where the dependent variable takes the value one when the test is taken–*i.e.*, when the subject prefers the lottery to the sure payoff) using a discrete panel with random effects, *i.e.*, assuming that covariates are independent of

Table 3: Discrete panel regressions with random effects. The dependent variable indicates if subject i tests (1) or not (0) in period t.

Dependent variable:	Full sample		High risk aversion		Low risk aversion	
Test was taken (1) or not (0)	(1)	(2)	(3)	(4)	(5)	(6)
K	-21.70***	-64.28***	-25.55***	-76.99***	-18.71***	-74.99**
	(3.128)	(19.23)	(5.477)	(26.24)	(4.017)	(30.92)
f (quality of the pool)	-1.693***	-1.694***	-1.785***	-1.783***	-1.640***	-1.649***
	(0.339)	(0.339)	(0.512)	(0.511)	(0.454)	(0.454)
Intolerance to ambiguity	0.0010	-0.0952**	-0.0280	-0.160**	0.0189	-0.0880
	(0.0178)	(0.0438)	(0.0306)	(0.0662)	(0.0221)	(0.0613)
K × Intolerance to ambiguity		0.874**		1.159**		1.001*
		(0.361)		(0.516)		(0.534)
Gender (Male = 1)	0.557*	0.524	0.823	1.932	0.625	-0.493
	(0.339)	(0.757)	(0.590)	(1.178)	(0.406)	(1.254)
K × Gender		1.093		-9.004		10.36
		(6.624)		(9.831)		(11.89)
Health (L-type = 1)	-0.103	-0.105	-0.245	-0.239	-0.00801	-0.0126
	(0.106)	(0.106)	(0.165)	(0.165)	(0.138)	(0.138)
Health_{t-1}	0.232**	0.229**	0.350**	0.353**	0.162	0.158
	(0.106)	(0.106)	(0.165)	(0.165)	(0.138)	(0.139)
Health_{t-2}	0.202*	0.199*	0.120	0.121	0.256*	0.254*
	(0.106)	(0.106)	(0.164)	(0.164)	(0.138)	(0.138)
Period	-0.0061	-0.0061	-0.0036	-0.0036	-0.0078	-0.0077
	(0.0065)	(0.0065)	(0.0102)	(0.0102)	(0.0085)	(0.0085)
Constant	3.366***	8.249***	5.548***	11.35***	2.169*	8.105**
	(1.148)	(2.527)	(1.901)	(3.496)	(1.245)	(3.445)
Observations	2,212	2,212	980	980	1,232	1,232
Number of ID	79	79	35	35	44	44

Lotteries from Stage A to measure risk aversion were included in models (1) and (2) as indicator variables, none of them were statistically significant. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

the unobserved characteristics of each subject. The estimations for the full sample are reported in columns (1) and (2) on Table 3.

We interpret the coefficients of the regression using the concept of odds ratio. The coefficients then represent the expected change in the log odds ratio ($log(p/(1-p))$ where p is the probability to test under CL) for a one-unit increase in the dependent variable. According to results reported in Table 3, the effect of f on the log odds ratio of testing is negative and significant. An increase of 0.1 in the value of f decreases the odds ratio by 16% (since $e^{-0.169} = 0.844$ where -0.169 is 0.1 times the estimated coefficient for f). This result shows that subjects do not exhibit enough risk aversion (*i.e.*, concavity in their utility function) to counteract the fact that a larger f, by improving the payoff with the pooling contract, reduces the (monetary) incentive to test (recall the discussion before equation (3)).[28]

Table 3 shows that increasing the test cost K by 0.05 decreases the odds ratio of

[28]This of course does not contradict Result 2, since increasing f when the choice is between "no testing under DD" and "testing under CL" unambiguously encourages testing by increasing U^1_{CL} without impacting U^0_{DD}.

taking the test by 67%.[29] This confirms the raw exploitation of the subjects' decisions, where we obtain that when $K = 0.01$ subjects test 97.5% of the times, whereas subjects with $K = 0.20$ test 29.3% of the times. So, as in Stage B, increasing the test cost K has a very sizeable impact on the testing decision.

The first two columns of Table 3 also show that the type assigned in a previous round does influence the likelihood to test in the current round, even though types are reassigned at random to each subject at the beginning of each round. Having been assigned a type L (in the form of letter X, see footnote 21) in the previous round increases the odds of taking the test in the current round by 26%, and in the next round by 23%.[30] This is reminiscent of Jessup et al. (2008), who show that positive feedback increases the likelihood to pick a gamble instead of a fixed payment when the odds of achieving the high payoff outcome are not too small.

According to model (2) in Table 3, an additional point in the ambiguity score (meaning less tolerance to ambiguity) reduces the likelihood to take the test by nearly 10% when K is very small. However, this impact decreases as the test cost increases, as it also did in Stage B.

We do not observe any effect of risk aversion, as measured in Stage A, on the testing decision under consent law. An indicator variable for each one of the lotteries in Stage A was introduced in the regression models (1) and (2), but none of the coefficients proved to be statistically significant.

We then compute again the regressions with two separate sub-samples based on the levels of risk aversion measured in Stage A. One sub-sample includes the subjects who picked lotteries 1 or 2 in Stage A -*i.e.*, the 43.75% of the population with the highest risk aversion levels. Results with this sub-sample are reported in models (3) and (4) in Table 3. The other sub-sample includes the remaining 56.25% subjects, a population with moderate to low levels of risk aversion. Results for this population are to be found in Models (5) and (6) in Table 3. Negative coefficients are larger, in magnitude, for the sub-sample with high risk aversion. However, the differences across sub-samples for the coefficients of f and K are not substantive and the coefficients remain significant at the one percent level. Note that the intolerance to ambiguity is significant only for subjects with high risk aversion, a result related to the positive correlation of risk aversion and ambiguity aversion mentioned before. The two subsamples also differ in how they react to past information regarding their type. In the sub-sample with high risk aversion, only information from the previous round (Health_{t-1}) is significant, whereas for the sub-sample with lower risk aversion, only the information from two previous rounds (Health_{t-2}) is statistically significant.

[29] Dividing the coefficient of K by 20 (so that $\Delta K = 0.05$) and using the exponential function to obtain $e^{-1.085} = 0.338$.

[30] Additional regressions, not reported in the paper but available upon request, show that this effect disappears after two rounds.

Up to this point, we find little empirical support for the relevance of risk aversion on the testing decision. One explanation for this limited impact is that the exposure to repeated testing decisions makes risk averse subjects more willing to choose the gamble. Benartzi and Thaler (1999), inspired by the work of Samuelson (1963), call this phenomenon "myopic loss aversion," claiming that subjects are more sensitive to the losses in a gamble if they are exposed to a single trial than to multiple trials.

Result 5: **Experience in the game reduces the effect of f in the most risk averse participants and increases its effect in the less risk averse participants.**

Logit coefficients from the discrete panel with random effects are reported in Table 4, where we run again the regressions for the sub-sample of high and low risk averse subjects, but splitting the sample into an early part in which subjects do not have too much experience (rounds 1-15), and a late part in which subjects have gained more experience in the decision task (rounds 16-30). We observe strong differences across risk preferences across time in the individual responsiveness to the quality of the pool f. For the most risk averse participants, a comparison of the coefficients between models (1) and (2) shows that the coefficient of f decreases by more than half from the early to the late part of the game. For this sub-sample of subjects, the average testing rate is 60.4% in the first fifteen rounds and 59.8% in the last fifteen rounds. The difference in testing rate is negligible, meaning that subjects are less sensitive to f although they are not testing more.

Table 4: Discrete panel regressions with sub-samples. Full sample splitted by risk aversion level and by early part (rounds 1-15) and late part (rounds 16-30) of the game.

Dependent variable:	High risk aversion		Low risk aversion	
Test was taken (1) or not (0)	Rounds 1-15	Rounds 16-30	Rounds 1-15	Rounds 16-30
	(1)	(2)	(3)	(4)
K	-80.74***	-67.33**	-59.70***	-59.22**
	(24.67)	(28.95)	(22.05)	(27.73)
f (quality of the pool)	-2.485***	-1.210*	-0.832	-2.103***
	(0.856)	(0.666)	(0.729)	(0.596)
Intolerance to ambiguity	-0.173***	-0.116	-0.0890*	-0.0619
	(0.0626)	(0.0734)	(0.0538)	(0.0659)
K × Intolerance to ambiguity	1.264***	0.839	0.923**	0.836
	(0.482)	(0.573)	(0.454)	(0.570)
Gender (Male = 1)	1.067**	0.669	0.731**	0.340
	(0.511)	(0.619)	(0.336)	(0.440)
Constant	12.50***	9.178**	6.793**	5.573*
	(3.382)	(3.912)	(2.684)	(3.299)
Observations	455	525	572	660
Number of ID	35	35	44	44

Additional covariates omitted in the table: Period, Health, Health_{t-1} and Health_{t-2}.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

For the less risk averse subjects we observe the opposite pattern. The coefficient of f in model (3) is not statistically significant, suggesting that these subjects are not very responsive to f in the early part of the game. However, model (4) shows that for the late part of Stage C the coefficient of f becomes significant at the one percent level. In this case, the increase in sensitivity to the quality of the pool was accompanied by a decrease in the testing rate of five percentage points, from 66.5% to 61.5%. This difference in testing rates suggests that the less risk averse subjects are becoming more selective to the offered contracts as they gain experience in the game.

The repeated exposure to the decision is also dampening the effects of gender and ambiguity aversion. In models (1) and (3), the coefficients of these two variables are statistically significant, but they become insignificant in models (2) and (4). In addition, the effects of gender and ambiguity aversion are larger for the most risk averse subjects. The higher likelihood to test of men compared to women in models (1) and (3) is reminiscent of the well established experimental result that women are more risk averse than men (Borghans et al., 2009; Croson and Gneezy, 2009).[31] However, the gender difference becomes insignificant in the late part of the game.

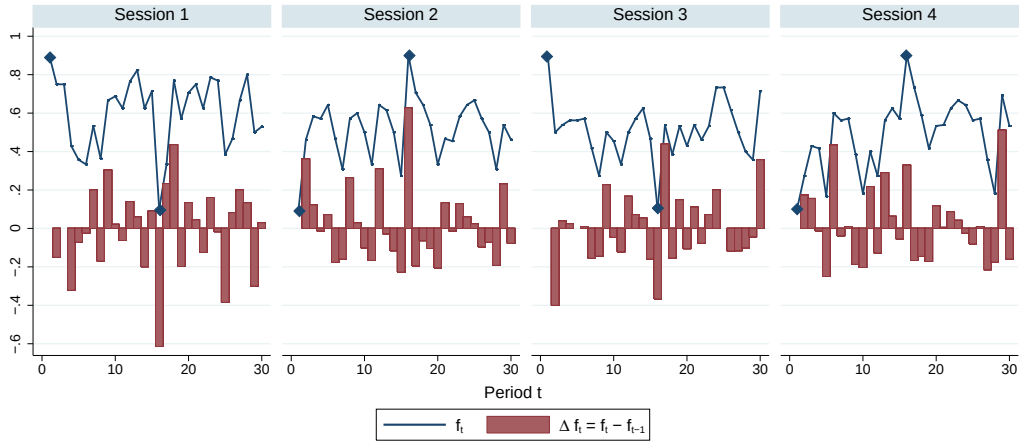
We also observe that the effect of ambiguity aversion reported in Result 4 is driven by the early interactions in the game. One explanation for the decreasing effect of ambiguity aversion over time is that subjects learn from previous realizations of the game and therefore become more tolerant to uncertainty. This interpretation goes in line with the "comparative ignorance hypothesis" (Fox and Tversky, 1995), according to which ambiguity aversion is driven by comparisons of states of knowledge. The results we obtain are compatible with assuming that subjects compare their own states of knowledge over time, which are enriched by previous experiences in the game.

Result 6: **We do not observe convergence over time to an equilibrium value of f.**

According to Proposition 1, we should expect convergence to an equilibrium value of f. Such a convergence would allow us to compare again the two regulations, but with the equilibrium value of f for consent law rather than with an exogenous value. Unfortunately, we do not obtain convergence, as evidenced in Figure 7. The red bars, representing the difference $f_t - f_{t-1}$ in each period, should be shrinking over time if f were reaching a steady state. Setting $\varepsilon = 0.05$ (resp., $\varepsilon = 0.1$) and excluding rounds 1 and 16, we find that $f_t - f_{t-1} < \varepsilon$ in 21.4% (resp., 39.3%) of the 30 rounds. Moreover, as Figure 7 shows, there is no downward trend in $f_t - f_{t-1}$, with low (absolute) values dispersed along the time line in each session. The correlation between $f_t - f_{t-1}$ and the period is not significant either.

[31] This is also the case with our subjects: see footnote 16.

Figure 7: Evolution of f and Δf over the 30 rounds



Interestingly, Figure 7 shows an alternation of positive and negative values of Δf_t, while theory would predict that $f^* > f_{t+1} > f_t$ as long as $f_t < f^*$ (so that $\Delta f_t > 0$), and $f^* < f_{t+1} < f_t$ as long as $f_t > f^*$ (so that $\Delta f_t < 0$).[32] It is thus as if subjects were over-reacting to variations in f_t, generating endogenous values of f which alternate between values larger and smaller than the equilibrium value, without exhibiting any convergence.

One reason for this non-convergence may be that our convergence result (Proposition 1) assumes that all agents share the same utility function, while in reality they of course differ in, among other things, their degree of risk aversion. With heterogeneous utility functions, some subjects may be such that a larger value of f reduces their incentive to test under CL (*i.e.*, $\partial K_{CL}/\partial f < 0$) while for others the opposite relationship would hold ($\partial K_{CL}/\partial f > 0$). We want to stress that this is not the (only) mechanism at play in the experiment to prevent convergence. Whatever their utility function, the impact of a larger f on the incentive to take the test under CL should have the same sign, for any given subject, whatever the value of f, since we have that the sign of $\partial K_{CL}/\partial f$ does not change with f (see equation (3)). Unfortunately, this is not what we observe in the experiment. We call "consistent" a testing behavior characterized by a threshold value of f, above (resp., below) which a subject always takes the same testing decision. For instance, an inconsistent testing behavior consists in a subject testing when f is low, not testing when f is medium, and testing again when f is large. We find repeated violations of consistency for 82.5% of the participants. The few exceptions are subjects who always test (10 in total, 6 of them with $K = 0.01$), those who always test except

[32] Proof available upon request.

when $f = 0.9$ (3 in total, 1 of them with $K = 0.01$ and another two subjects with $K = 0.10$) and a subject who never tests (with $K = 0.20$).

The subjects' inconsistencies may have at least two explanations. One is that the sensitivity to the quality of the pool is changing with the experience in the game, and that the change is heterogeneous with respect to the risk aversion level. Another explanation, not mutually exclusive, is an inherent sampling behavior that is likely to appear when subjects are unable to construct a full action profile, and instead directly build a correspondence between actions and rewards (Osborne and Rubinstein, 1998). Since, in our experimental setting, subjects are not informed of the exact procedure used to recompute payoffs after each round, this lack of information may induce a sampling behavior.

Another reason why we do not observe convergence is that the required time horizon may be longer than fifteen periods. We have two arguments against this possibility. First, the time correlations for $f_t - f_{t-1}$ within each session are not statistically significant, and this lack of statistical correlation hold also when the time horizon is split into rounds 1-15 and 16-30. Second, the sensitivity of the testing decision to the variable f is decreasing over time for the most risk averse subjects. We then have no reason to think that extending the time horizon would have resulted into convergence.

5 Conclusion

In this paper, we develop a theoretical analysis of two regulations of genetic tests, disclosure duty and consent law, and we run several experiments in order to shed light on both the take-up rate of genetic testing and on the comparison of utilities under the two regulations. We obtain that the take-up rate is low under DD, larger under CL and is increasing with adverse selection under CL. Also, the fraction of individuals who prefer DD to CL increases with the amount of adverse selection under CL, measured as the fraction of agents informed of their (bad) type among those who buy the pooling contracts devised for uninformed agents. As long as this proportion is lower than (roughly) one half, a majority of subjects prefer CL to DD. These results are obtained for exogenous values of adverse selection under CL, and the 30-round experiment devised in Stage C has not resulted in convergence towards an equilibrium level of adverse selection.

Our setting is well adapted to the current situation where most people do not test, and where insurers offer pooling contracts to agents who are (or pretend to be) uninformed about their genetic type. As long as few people test, the CL regulation offers higher utility to a majority of individuals, compared to DD.[33] As personalized medicine

[33]This stands in stark contrast with other papers such as Barigozzi and Henriet (2011) and, as ex-

develops, with cheaper tests and more options offered to agents who discover their detrimental genetic background, more people can be expected to test, and a majority of individuals may then benefit from DD rather than CL.

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plained in the introduction, is due to our very reasonable assumptions that agents face different financial and psychological costs of testing, and that insurers offer pooling rather than separating contracts.

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Experimental Instructions

You will find below the experimental instructions. All the text inside a box was displayed in a single screen to the participants. When the text appears in brackets [ ] it corresponds to a button displayed in the screen. Amounts of money displayed inside the boxes are provided as an example, as they depend on the test cost which is different across subjects.

Welcome!

This activity is part of a study about how individuals take economic decisions.
The decisions you will take today are divided in three stages.

First Stage:
In the first stage a total of six (6) lotteries will be shown to you. You will have to decide which one you prefer to play.

Second Stage:
In the second stage a total of seven (7) lotteries will be shown to you. You will have to decide in which ones of them you would prefer to play and in which ones you would prefer to receive a compensation for not playing.

Third Stage:
In the third stage you will play for several rounds.
In each round of the third stage a given letter, X or Y, will be assigned to you. Each one of these letters will represent an amount of money.
You will not know which letter was assigned to you. But you know that each letter has a 50% chance to be assigned.
You will have to decide if you want to reveal the assigned letter, and receive the corresponding amount of money, or receive a fixed amount of money for not revealing the assigned letter.
The amount received for not revealing the assigned letter is a value in-between the money received for having the letter X and the money received for having the letter Y.
These three values, the amount received for having the letter X, the amount received for having the letter Y, and the amount received if you prefer to not reveal the letter, will be displayed simultaneously before you have to take a decision of each round.

[Continue]

Earnings in the activity:

After playing the three stages we will proceed to make the raffles that will define your earnings from each one of the stages.
At the end of the activity you will receive the following earnings:

Raffle No. 1: The payment of the lottery chosen in the first stage, according to the result obtained in the draw.

Raffle No. 2: One of the lotteries from the second stage will be randomly drawn. If you decided to play the selected lottery you will receive the payment corresponding to the raffle's outcome. Otherwise, you will receive the compensation for not playing the lottery.

Raffle No. 3: One round of the third stage will be randomly chosen. You will receive the corresponding earnings.

Do you have any questions?

If the instructions have been understood and you do not have any question you can click on "Continue."
In the next screen you will find the informed consent. If you agree with the conditions exposed in this document we ask you to please click on "I accept the conditions of the activity."

[Continue]

FIRST STAGE:

Now six (6) lotteries will be shown to you. You have to choose which one you want to play.
In each lottery will be randomly drawn a color between **BLUE** and **BLACK** as outcome.
The probabilities of drawing **BLUE** and **BLACK** are the same.
The raffle, which defines the random choice of one of the two colors, will be done at the end of the activity.

[Continue]

FIRST STAGE:

Now you have the six lotteries.
You can pick the one you prefer most. At the end you will receive the lottery's earnings according to the randomly chosen color, **BLUE** or **BLACK**.
Remember for every lottery the two outcomes are equally likely to occur. In other words, each color has a 50% chance to be randomly chosen.

Option A:	\$3,300	or	**\$3,300**	[Lottery A]
Option B:	\$2,500	or	**\$4,700**	[Lottery B]
Option C:	\$1,800	or	**\$6,200**	[Lottery C]
Option D:	\$1,100	or	**\$7,700**	[Lottery D]
Option E:	\$ 400	or	**\$9,100**	[Lottery E]
Option F:	\$ 0	or	**\$9,500**	[Lottery F]

SECOND STAGE:

In the next screen you will see **seven (7)** lotteries. In each one of them you may receive a **HIGH PRIZE** or a **LOW PRIZE**.
The lotteries are ordered according to the value of the **LOW PRIZE**, in increasing order.
You will have to choose from which of these lotteries you prefer to play instead of receiving a fixed amount of money for not playing.
At the end of the activity a raffle will decide which one of the lotteries will be chosen. If you decided to play this lottery, the raffle will also define if you receive the **HIGH PRIZE** or the **LOW PRIZE**.
You will only play the chosen lottery if it is one of the lotteries in which you accepted to gamble instead of receiving the fixed payment.
Consider the following example. You decided to play from lottery No.4 to lottery No. 7 and the randomly chosen lottery is lottery No. 2. In this case you will not play and instead will receive the fixed payment.

[Continue]

SECOND STAGE:

You will find now seven (7) lotteries.
In each one of them you can decide whether to PLAY or to NOT PLAY.
In case you decide to NOT PLAY you will receive $10,000.
In case you decide to PLAY you may receive the HIGH PRIZE or the LOW PRIZE.
The HIGH PRIZE is $13,000.
The LOW PRIZE increases with each one of the lotteries.
You will have to decide from which lottery you would prefer to PLAY.
In other words, you will have to decide which is the minimum LOW PRIZE you are willing to accept in order to choose PLAY.

	PLAY			**NOT PLAY**
	LOW PRIZE	**HIGH PRIZE**		
Lot. 1	You receive $6,400	You receive $13,100	[I PLAY this lottery and the following 6]	You receive $10,000
Lot. 2	You receive $6,900	You receive $13,100	[I PLAY this lottery and the following 5]	You receive $10,000
Lot. 3	You receive $7,400	You receive $13,100	[I PLAY this lottery and the following 4]	You receive $10,000
Lot. 4	You receive $7,900	You receive $13,100	[I PLAY this lottery and the following 3]	You receive $10,000
Lot. 5	You receive $8,300	You receive $13,100	[I PLAY this lottery and the following 2]	You receive $10,000
Lot. 6	You receive $8,800	You receive $13,100	[I PLAY this lottery and the following 1]	You receive $10,000
Lot. 7	You receive $9,200	You receive $13,100	[I PLAY this lottery]	You receive $10,000

THIRD STAGE:

A letter, X or Y, will be assigned to you in each round of the game. The probability that the letters X or Y will be assigned to you are the same.
Your task, before being informed which letter was assigned to you, is to decide if you want to reveal the assigned letter.
Before you take this decision, a payment will be offered for the letter X, another payment will be offered for the letter Y, and another payment if you prefer not to reveal the assigned letter. The payment for having the letter X is larger than the payment for not revealing the letter, which at the same time is larger than the payment for having the letter Y.
You will repeat this procedure for a total of 30 rounds.
At the end of the activity a raffle will be made to randomly select which of the 30 rounds will be paid and added to your total earnings.

[Continue]

Round 1:

You may receive $9,800 if you decide not to reveal the letter.

If you decide to reveal the letter you may receive:
$13,100 if the letter is an X
$ 9,000 if the latter is a Y

[Reveal the letter]
[Not reveal the letter]

Round 1:

You decided to not reveal the letter.
The assigned letter was:

Y

Your earnings, if this round is selected, will be $9,800

[Continue]

RAFFLES

Now the three raffles will be realized, one for each stage in the activity.
For each random draw you will find a gray button and a red button.
The gray button's purpose is to practice the random draw. You can click on it for practice all the times you want.
The red button's purpose is to make the decisive draw. You can click on the red button just once per raffle.

Raffle No. 1: By clicking you will choose if the outcome of the lottery is BLUE or BLACK.

Raffle No. 2: By clicking you will choose one of the seven lotteries and whether the lottery's outcome is the HIGH PRIZE or the LOW PRIZE. If you decided not to play the randomly selected lottery you will receive a fixed payment.

Raffle No. 3: By clicking you will choose the round from the third stage that will be paid.

[Continue]

FINAL EARNINGS

Your earnings in the first stage were $4,700
Your earnings in the second stage were $10,000
Your earnings in the third stage were $9,800
After rounding to the nearest thousand your final earnings were $25,000

Please click on "Continue" when you are done. We will ask you to complete a short survey before leaving the room.

Thank you for your participation.

[Continue]