How Is the Trade-off between Adverse Selection and Discrimination Risk Affected by Genetic Testing? Theory and Experiment[1]

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Abstract

We develop a theoretical analysis of two widely used regulations of genetic tests, Disclosure Duty and Consent Law, and we run an experiment 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 insurers, exposing them to a discrimination risk. Consent law allows them to hide any detrimental information, resulting in adverse selection. The experiment results in much lower genetic tests take-up rates with Disclosure Duty than with Consent Law, showing that subjects are very sensitive to the discrimination risk. Under Consent Law, take-up rates increase with the adverse selection intensity. A decrease in the test cost, and in adverse selection intensity, both make it more likely that Consent Law is preferred to Disclosure Duty.

    Keywords: Consent Law, Disclosure Duty, Personalized Medicine, Test take-up rate, pooling health insurance contracts.

    JEL Codes: C91, D82, I18.

1   Introduction

Health insurance regulation faces the following trade-off. Allow insurers to adjust the contracts offered to policyholders according to their individual health status, and individuals face a discrimination risk (or, in its dynamic version, a reclassification risk). Restrict the ability of insurers to price their contracts according to all relevant individuals' characteristics, and some adverse selection may emerge.

Our objective in this article is to study this trade-off in the context of the emergence of personalized medicine, defined as the use of an individual's genetic profile to guide prevention, diagnosis, or treatment decisions. The advent of ever cheaper and more informative genetic tests will drive the development of personalized medicine. These tests will 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.[1] With increasing medical benefits of testing, coupled with lower monetary costs, the prevalence of genetic testing will most probably increase in the foreseeable future.

In such a context, it becomes necessary to better understand how this genetic information should be regulated, and whether current regulations should be modified as the prevalence of genetic testing increases. More precisely, it is likely that in the next decades genetic testing will affect the trade-off between adverse selection and discrimination risk in two ways. First, these tests may convey more precise information on individuals' health risks. When tested agents are forced by law to reveal to insurers their genetic information, they then face a stronger discrimination risk. Second, in most countries

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[1]See Abrahams and Silver (2010) for a history of personalized medicine and also Anaya *et al.* (2016) for applications to autoimmune diseases. It is fair to say that, while the cost of sequencing a whole genome has decreased at a very impressive rate (see http://www.genome.gov/sequencingcosts, last accessed on October 26, 2018) and is likely to continue to do so, the amount of actionable health information gleaned from sequencing has not grown at the same pace. For instance, while knowing one's genome can bring more precise information as to the likelihood of developing a disease in the future, it does not always give much useful guidance for prevention. This is recognized by Snyder (2016), among others. The difficulty lies in the fact that genetic diseases are complex and affected by the environment. This being said, Snyder (2016) contains many examples where genetic testing already has medical value and claims that this will be the case even more in the not too distant future.

individuals decide whether they want to take a genetic test or not. This decision to acquire information then depends on whether this information has to be shared with insurers or not. If disclosure is mandatory, the ensuing discrimination risk may reduce incentives to take the test in the first place (Hirshleifer, 1971), resulting in the loss of precious health information. If disclosure is not mandatory, individuals may hide any bad information they have discovered, resulting in a stronger version of adverse selection than if they were uninformed of their genetic background. This last effect will likely increase as genetic testing becomes more widely used.

Regulations of the health information generated by genetic testing vary a lot across countries, as described by Otlowski, Taylor and Bombard (2012). While regulations labelled "Laissez-Faire" and "Disclosure Duty" mandate disclosure of genetic information to health insurers,[2] "Consent Law" and "Strict Prohibition" allow withholding of information.[3] The latter type of regulation generates adverse selection while the former type aims at avoiding this adverse selection but creates a discrimination risk. Moreover, the two types of regulation produce different incentives to take a genetic test.

In this article, we compare Consent Law and Disclosure Duty, as these two regulations best exemplify the trade-off between adverse selection and discrimination risk in a setting where individuals are left to decide whether to take a genetic test or not. We first develop a theoretical framework to compare those regulations, and we then devise an experiment to elicit which regulation individuals would selfishly prefer, and whether they would take a genetic test under each regulation. Moreover, we are interested in how preferences for testing and for regulations will evolve as testing costs decrease. An experimental setting is a natural first step to understand behavior and preferences with respect to both regulations, and how they change with test-

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[2]Laissez-Faire allows the health insurers to require testing from their customers, while Disclosure Duty does not. Laissez-Faire is applied in China, Japan, Korea, New Zealand, Russia, Singapore, Spain, and South Africa whereas Disclosure Duty is the regulatory regime in the UK.

[3]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 indirectly elicit information on individual risks. Australia, the Netherlands, and Switzerland are three of the countries applying a Consent Law regime whereas Austria, Belgium, Canada, Denmark, France, Germany (except for life insurances with significant premiums), Ireland, Israel, Italy, Norway, and Portugal apply a Strict Prohibition regime.

ing costs. Observe that, to obtain answers to those questions with empirical data, we would have to find a (quasi-)natural experiment where the regulation has changed at some point in time, and with discontinuities in genetic testing costs across groups. This is very unlikely because these regulations have been introduced quite recently in most countries, and have thus varied very little since their inception.[4]

Our theoretical set-up is as follows.[5] 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, and allows them to better tailor a prevention effort (*i.e.*, tests have medical value).[6] 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 perfectly competitive market.

Under Disclosure Duty (DD hereafter), equilibrium contracts are such that 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). As for Consent Law (CL hereafter), 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 with full (exogenous) coverage to all who pretend (truthfully or not) to be uninformed. At equilibrium, 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. The equilibrium (zero profit) premium attached to the pooling contract reflects the intensity of adverse selection at play (with a higher premium when more type H individuals falsely pretend to be uninformed).

Solving the analytical model allows us to obtain three hypotheses that

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[4]An important exception is studied in Miller and Tucker (2018), which we discuss at the end of this section.

[5]The model we develop here applies more generally to any kind of type-revealing tests (such as EKG, X-rays, HIV tests, IQ tests, *etc.*) that could be exploited by insurance companies, provided that agents tested positive can take some action in order to decrease their probability of damage. Genetic testing is an important leading example.

[6]See for instance Snyder (2016) for examples fitting our model, especially Figure 17 for how taking a genetic test gives more precise information as to the probability of developing several diseases, and page 76 for examples of prevention efforts for agents genetically more susceptible to develop certain diseases.

we then test with an experiment. First, test take-up rates decrease with the test cost under both regulations, and are higher under CL than under DD (since obtaining bad genetic news can be hidden from the insurer under CL). Second, the test take-up rate under CL increases with the amount of adverse selection (since agents test in order to escape the pooling contract, which is made less attractive by the higher equilibrium premium necessitated by a higher level of adverse selection). Third, agents prefer CL when the test cost is low, and DD when the test cost is large.

We design an experiment in a neutral framework in which subjects have to make several choices between a lottery and a sure payoff. The lottery (resp., the sure payoff) corresponds to the pay-off obtained when (resp., when not) testing. We have opted for a neutrally-framed (rather than for a health-framed) experiment because it is the most direct way to translate our model into an experiment, but also because this allows us to control directly for the heterogeneity in test costs (which, in our theoretical model, stands for both the financial and psychological costs of the genetic tests). More precisely, the payoffs offered to subjects correspond to the equilibrium contracts obtained in the analytical part of the paper, when considering four different costs of the genetic test, and five different intensities of adverse selection (for the CL regulation).

Our experimental results match the main theoretical predictions, but also allow us to go further and to shed light for instance on the intensity of the trade-off between adverse selection and discrimination risk. We refer the impatient reader to the concluding section for a more detailed summary of the main results of the paper. We find evidence of both discrimination risk and of adverse selection at equilibrium. Subjects seem very sensitive to the discrimination risk, since most of them do not test under DD, even when the test cost is low. Under Consent Law, take-up rates increase with the adverse selection intensity. A decrease in the test cost, and in adverse selection intensity, both make it more likely that Consent Law is preferred to Disclosure Duty.

We now turn to the related literature, starting with the articles closest to ours. Barigozzi and Henriet (2011) and Peter *et al.* (2017) compare DD and CL (among other regulations). Their result (that DD dominates CL) depends crucially on two simplifying assumptions that we are not making here: that genetic tests are costless, and that individuals are homogenous in their preference for information acquisition. These assumptions imply that

all individuals test under CL at equilibrium. 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. Hoel et *al.* (2006) study the consequences for the testing decisions of introducing heterogeneity in psychological preferences (repulsion from chance), in a setting with separating equilibria, but do not compare the properties of various regulations.[7]

Gemmo *et al.* (2017) develop a model where agents have access to a free technology (such as telemonitoring) that reveals their type to the insurers. This technology then plays a role similar to genetic testing in our consent law environment. Their model differs from ours in several important ways. First, they consider separating contracts. Second, all individuals are aware of their risk type, and the technology is only used to reveal this type to insurers (while in our setting agents who have not performed genetic tests are unaware of their type). Third, agents differ in their utility cost of revealing their risk type to the insurers (transparency aversion), so that low risk agents who are sufficiently transparency averse will not reveal their type to the insurers, in stark contrast with our setting.

Few articles assume that insurers offer a pooling contract, an assumption much more in line with current practice than the separating contracts à la RS used by the rest of the literature. Hoy (2006) studies the equity-efficiency trade-off of regulatory adverse selection based on a pooling equilibrium. Bardey and De Donder (2019) analyzes which type of equilibrium (pooling or separating) emerges as a function of the genetic test take-up rate under Consent Law. A recent survey of the economic effects of risk classification bans, including in settings where insurers provide pooling equilibria, is provided by Dionne and Rothschild (2014). Other papers assuming pooling contracts under CL are Hoy *et al.* (2003) and Crainich (2017), but they do not compare regulations.[8]

Strohmenger and Wambach (2000) focus on health issues where the willingness to pay for treatment is lower than the treatment's cost. This simple twist to the assumptions underlying standard insurance models is enough to

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[7]Hoy *et al.* (2014) also depart from the traditional expected utility framework by studying the impact of ambiguity aversion on the acquisition of genetic information, but they do not consider heterogenous preferences.

[8]Furthermore, there is some recent interest in pooling equilibria, see Einav and Finkelstein (2011) for a general approach and Peter *et al.* (2016) for an application to guaranteed renewability.

generate strikingly different results. To start with, only agents with a low probability of getting sick wish to buy an actuarially fair insurance contract. Strohmenger and Wambach (2000) study the impact of genetic tests in two settings: with symmetric information (corresponding to the "laissez-faire" regulation allowing insurers to request genetic tests and use their results) and with asymmetric information (a "strict prohibition" regulation preventing insurers from making use of test results). They show that, in the case of symmetric information, genetic testing can enhance efficiency, in contrast to standard models. They obtain the opposite result in the strict prohibition setting, where the introduction of genetic testing can result in a complete market failure where no one buys insurance anymore. Note that these results are obtained for a large set of equilibrium contracts (pooling with full or partial coverage, separating with or without cross-subsidies across types).

All related articles mentioned so far are applied theory papers. Schudy and Utikal (2018) is the only paper we are aware of studying an experiment dealing with the acquisition and disclosure of personal health data in health care markets, but this paper does not study the trade-off between adverse selection and discrimination risk. Miller and Tucker (2018) studies how US States genetic privacy laws affect the diffusion of personalized medicine, using data on genetic testing for cancer risks. They focus on three aspects of the US regulations: the requirement of informed consent from tested individual, restrictions to discriminatory usages of genetic data by employers, health care providers or insurance companies, and limits to redisclosure of genetic information without the consent of the individual. Their obtain that "approaches to genetic and health privacy that give users control over redisclosure encourage the spread of genetic testing" (p. 1), which is in line with our result that agents test more under CL than under DD.

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 our experimental setting. Section 4 presents our experimental results. Section 5 concludes.

2   Analytical model and predictions

We develop a theoretical setting that allows us to formulate predictions to be tested during the experiment. We first introduce our analytical set-up where agents can take a genetic test allowing them to tailor their prevention effort.

We then introduce two regulations of the health insurance market, Disclosure Duty and Consent Law, and we finally compare the testing decisions and utility levels of agents across the two regulations.

2.1 Set-Up

The economy is composed of a unitary mass of individuals. We focus on a generic illness, for which agents have either a genetic background predisposing them to develop the disease (bad type, or type H, with a high 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.

Taking a genetic test is the only way for agents to know their type. The test reveals with certainty their true type.[9] Agents decide first to take the genetic test or not. With a slight abuse of language, we call those who do not take the test type U agents, as they remain uninformed about their type.

Learning about your genetic background has medical value. We assume that a (costly) prevention effort decreases the probability of developing the disease for type H agents, but has no effect for type L agents. We also assume that the cost/benefit ratio of this effort is low enough that even agents uninformed of their type find it worthwhile to 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.[10] We make the important simplifying assumption that the prevention effort is observable and contractible by the insurers. This assumption seems reasonable, since there is little empirical evidence of *ex ante* moral hazard in health insurance contracts (see Einav and Finkelstein, 2018). We refer the reader to the concluding section for a brief discussion of the consequences of this assumption.

We denote by p_H the probability that a type H agent who exerts a pre-

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[9]This simplification is often made in the economic literature on genetic testing: to the best of our knowledge, Hoy *et al.* (2014) is the only paper allowing genetic testing to generate errors of type I and II.

[10]Examples include all behavioral modifications that are not too costly (such as dietary requirements or physical exercise for instance). Our results would not be qualitatively affected if we were to assume that type U agents do not exert a prevention effort. Bardey and De Donder (2013) study which case arises at equilibrium as a function of the effort cost and impact on the probability of developing the disease when of type H.

vention effort becomes sick, and by p_L the probability that a low type agent (who does not exert the prevention effort) develops the disease, with $p_H > p_L$. The expected probability of developing the disease for an individual who does not take the test (but exerts the prevention effort) is

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

The monetary cost of the prevention effort is denoted by ϕ, and is the same for all agents undertaking the effort. The (monetary equivalent of the) cost of taking the genetic test is denoted by K. This cost includes the financial cost of the test plus the monetary equivalent of the psychological cost/disutility from knowing one's genetic background.[11] Agents differ according to K, allowing for different (unmodelled) attitudes towards (genetic) information acquisition. We denote by $G(K)$ the cumulative distribution of K.

The timing of decisions runs as follows. After having first decided whether to test and then whether to undertake the prevention effort, agents buy health insurance on the private market. The equilibrium contracts offered on the market depend on the regulation of this market, to which we now turn.

2.2 Health insurance market regulations: Disclosure Duty *vs* Consent Law

Throughout the paper, we study and contrast two well-known regulations of health insurance markets: Disclosure Duty and Consent Law. Under DD, agents are required to reveal to insurers the results of any genetic test they have chosen to take. Under CL, agents choose to reveal or not to the insurers whether they tested and the result of the genetic test. We study both regulations in turn.

2.2.1 Disclosure Duty

Insurers and policyholders have the same information when contracting, and know whether the agent has type L or H (if he has taken the test) or type U

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[11]This monetary equivalent K allows us to keep the simple expected utility framework and may capture different notions 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] and Barrigozi and Levaggi [2010]). We measure the cost K in monetary terms because we want to control for the individuals' value of K in the experiment.

(if he has not taken the test). 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 and an indemnity (net of the premium) in case of sickness, I_j. Competition induces profit-maximizing insurers to offer actuarially fair contracts with full insurance, so that $\pi_j = p_j d$ and $I_j = (1 - p_j)d$.[12] All agents have the same income y and the same preferences over consumption, which are represented by a classical Bernoulli utility function $v(.)$ (with $v'(.) > 0$ and $v''(.) < 0$).

An uninformed policyholder's expected utility 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 genetic testing".

Individuals who take the genetic test obtain a utility level equal to

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

if they are revealed to be of type H, and of

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

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 genetic test".

Let us denote by Ψ_{DD} the informational value of the genetic test under Disclosure Duty,

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

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[12] As mentioned above, we assume that the prevention effort is observable by the insurers, so that this effort is reflected in the equilibrium premium. As shown by Bardey and De Donder (2013), the non-observability of the prevention effort by insurers would result in contracts with partial coverage being offered to agents. Intuitively, agents need to have enough "skin in the game" in order to be induced to make a prevention effort whose result (a lower damage probability) is not observed by insurers. We adopt this assumption for simplicity reasons, as it would have been most difficult to elicit endogenous partial coverage rates in the experiment, and as our focus is rather on the adverse selection/ risk discrimination trade-off betwen regulations.

with agents doing the test if $\Psi_{DD} > 0$.

From (1), we see that the main drawback of DD 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. The more risk averse agents are, the less likely they are to take the test, as they suffer more from the discrimination risk. 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 a favorable genetic background. 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 DD–*i.e.*, the value of K such that $\Psi_{DD} = 0$.

2.2.2 Consent Law

Under CL, agents have an incentive to hide any bad genetic information, thereby creating adverse selection. The usual way to deal with adverse selection, in the Rothschild and Stiglitz (1976)'s tradition, is to assume that insurers offer 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. As pointed out by Hoy *et al.* (2003), there is no recorded instance of contracts offering a deductible in case the policyholder does not provide genetic tests results. We then rather assume that the insurers offer a pooling contract intended for all those who claim to be uninformed.[13] We further assume that insurers offer a pooling contract with an exogenous coverage level (as is the case in Switzerland[14] and in the Netherlands for instance, where the regulator imposes the coverage level), and for simplicity we consider full coverage.[15]

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[13]There exist both experimental and theoretical arguments in favor of the emergence of pooling (as opposed to separating) contracts: see for instance Posey and Yavas (2007) for the former, and Wilson (1977), Allard *et al.* (1997) and Newhouse (1996) for the latter.

[14]Basic health insurance is mandatory with a 90% coverage rate (going to 100% above some expense threshold), but must be bought on the private market. See https://lenews.ch/2015/10/08/15-things-you-should-know-about-swiss-health-insurance/, last accessed on 5 November 2018.

[15]Alternatively, we could have used Wilson (1977)'s equilibrium concept, as in Crainich (2017) and Hoy *et al.* (2003), where the equilibrium contract is either a pooling one with partial coverage or the Rothschild and Stiglitz (1976) separating equilibrium. This

Tested agents of type L reveal their type to the insurers to benefit from a lower premium, while tested agents of type H claim to be uninformed to benefit from the pooling contract. The premium charged for the pooling contract reflects the composition of the pool. We assume that the pooling contract clientele is made of a fraction f of truly uninformed agents (type U) and of a fraction $1-f$ of cheating agents (tested agents of type H). Roughly speaking, $1-f$ measures the intensity of the adverse selection at play, with more adverse selection translating into a lower f.[16] The utility of an agent who does not test is then given by

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

while the expected utility of an agent who takes the genetic test is

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

We denote by Ψ_{CL} the informational value of genetic testing under CL, given by

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

Individuals who take the test obtain the same monetary payoff (minus the test cost 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. We then denote by K_{CL} the (positive) value of K such that $\Psi_{CL} = 0$, and below (resp., above) which agents (resp., do not) take the genetic test under Consent Law.

Increasing f (*i.e.*, decreasing adverse selection in the pool) has two impacts of opposite signs on K_{CL}. On the one hand, a larger value of f improves

alternative setting would increase type U's utility and decrease type H's utility, compared to our setting, resulting in a lower fraction of agents who take the test under CL, and who prefer CL to DD. Note that introducing endogenous coverage rate and endogenous move from pooling to separating contract, à la Wilson, would have been very difficult to translate into an experimental setting, since we would have had to first elicit the most-preferred coverage rate of uninformed subjects under CL, and whether they prefer this contract to a separating contract, before moving to the comparison between CL and DD.

[16]See also Peter *et al.* (2016) for a similar reasoning applied to guaranteed renewability.

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. The lower pooling premium generated by a larger value of f then increases more U_{CL}^1 than U_{CL}^0, thus increasing the incentive to test.[17]

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.*

Proof. Applying the implicit function theorem to (2), we obtain that:

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

∎

2.2.3 Comparisons between the two regulations

Figure 1 summarizes the payoff structure of the model we are studying. For each regulation, agents first choose whether to test or not, and nature determines their test result. They then buy the insurance contracts computed in the previous section, with the corresponding payoffs reported in the terminal nodes of Figure 1. In this section, we compare the testing decisions and utility levels across regulations.

Insert Figure 1 around here

We start by comparing utility levels across regulations, for given testing decisions.

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

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[17]This second effect occurs when an agent buys the pooling contract after having tested– *i.e.*, with probability λ.

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

For individuals who choose to test under both regulations, CL is *ex ante* (before the test reveals the agent's type) preferable to DD, because they obtain the same payoff under both regulations if they are revealed to be of type L, while they fare better under CL, by being pooled with type U, if they are revealed to be of type H. Conversely, for individuals who do not test under either regulation, DD is preferable to CL because the pooling contract offered under CL is more costly than the contract for uninformed agents offered under DD.

The previous sections have defined the test cost threshold levels below (resp., above) which agents take (resp., do not take) the test under each regulation. The following lemma compares these two thresholds.

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

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 CL than under DD. This result is intuitive, since individuals gain more by taking the test under CL than under DD ($\Psi_{CL} > \Psi_{DD}$), both because testing does not expose them to a discrimination risk under CL (since they obtain the same contract whether of type U or type H) and because the contract offered in case the test is not taken is more expensive under CL (because of adverse selection) than under DD.

The next proposition compares utility levels across regulations when agents choose optimally whether they test or not in each regulation (*i.e.*, it solves the game tree depicted in Figure 1 by backward induction).

Proposition 1 *All individuals with K low enough that they take the test under both regulations ($K < K_{DD} < K_{CL}$) are better off under Consent Law. All individuals with K large enough that they do not take the test under either regulation ($K > K_{CL} > K_{DD}$) are better off under Disclosure Duty. All individuals with intermediate values of K ($K_{CL} > K > K_{DD}$) take the test only under Consent Law, and their utility difference 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 CL (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 DD (by Lemma 2). In the intermediate case where $K_{DD} < K < K_{CL}$, the difference in utility levels between DD and CL is

$$
\begin{aligned}
U^0_{DD} - U^1_{CL} &= v(y - p_U d - \phi) \\
&\quad - \left[\lambda v(y - (f p_U + (1-f)p_H)d - K - \phi) + (1-\lambda)\, v(y - p_L d - K) \right],
\end{aligned}
$$

which is increasing in K and decreasing in f. ∎

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

Finally, we note for future reference that choosing to test under CL is a necessary, but not sufficient, condition for preferring CL to DD in the game depicted in Figure 1.

<center>Insert Figure 2 around here</center>

Solving our model reveals that the comparison of *ex ante* expected utilities under CL and DD is ambiguous when agents test under CL but not under DD and $0 < f < 1$. We now move to the presentation of the design of our experiment which will allow us, among other things, to shed light on this comparison.

<center>14</center>

3 Experimental Setting

In the first subsection, we prove that a simple contingent analysis consisting of two binary questions suffices to determine (i) whether agents test or not under each regulation and (ii) which of the two regulations they prefer. We then present the experiment we have devised to implement this contingent analysis. Finally, we formulate the three hypotheses we want to test using our experiment.

3.1 Task fundamentals

Our objective in the experiment is to elicit the preferences within regulation (*i.e.*, whether to test or not) and between regulations (*i.e.*, whether CL or DD is preferred, when agents choose optimally whether to test or not for each regulation separately). In other words, we aim at ranking with strict inequalities the following utility comparisons: $U_{CL}^1 \gtrless U_{CL}^0$, $U_{DD}^1 \gtrless U_{DD}^0$ and $U_{CL} \gtrless U_{DD}$. In terms of the tree diagram shown in Figure 1, we want to elicit the subjects' choices in each one of the three solid nodes.

Observe that both the choice of regulation and the choice of whether to test under CL depend both on the test cost K and on the intensity of adverse selection f, while the choice of whether to test under DD depends only on K. Since we are interested in testing decisions and regulation choices for several values of K and of f, it is important that we find a way to reduce the number of questions asked to the subjects for each pair (K, f).

We solve this problem by using a contingent analysis where, for each pair (K, f), we ask (at most) the following two questions.

- **Q1:** When faced with CL, does the subject prefer to test or not (*i.e.*, how does the subject rank U_{CL}^1 and U_{CL}^0)?

If the subject prefers not to test, no further questioning is required for this pair (K, f). If the subject prefers to test ($U_{CL}^1 > U_{CL}^0$), then we ask the second question:

- **Q2:** Does the subject prefer to "test under CL" or "not to test under DD" (*i.e.*, how does the subject rank U_{CL}^1 and U_{DD}^0)?

The following proposition shows that using this contingent analysis allows us to answer the two questions we are interested in.

Proposition 2 *The contingent analysis described above and composed of questions Q1 and Q2 asked for pairs (K, f) including $f = 0$ is sufficient to determine the preferences within and between regulations of the subjects for all pairs (K, f) studied.*

Proof. If the answer to Q1 is that $U_{CL}^0 > U_{CL}^1$, then using Lemma 2 allows us to infer the full ranking of utility levels of the subject: $U_{DD}^0 > U_{CL}^0 > U_{CL}^1 > U_{DD}^1$.

If the answer to Q1 is that $U_{CL}^0 < U_{CL}^1$, then we proceed to Q2. If the answer to Q2 is that $U_{DD}^0 > U_{CL}^1$, we know from Q1 and Q2 that $U_{DD}^0 > U_{CL}^1 > U_{CL}^0$ and from Q2 and Lemma 2 that $U_{DD}^0 > U_{CL}^1 > U_{DD}^1$. These two partials ranking are sufficient to determine the preferences within regulations and between regulations of the subject, even though we are not able to rank U_{CL}^0 and U_{DD}^1.

If the answer to Q2 is that $U_{DD}^0 < U_{CL}^1$, we know from Q2 and Lemma 2 that $U_{CL}^1 > U_{DD}^0 > U_{CL}^0$ and that $U_{CL}^1 > U_{DD}^1$. We then know that the subject chooses to test under CL, and prefers CL to DD. In order to assess whether the subject chooses to test under DD, we need to compare U_{DD}^0 with U_{DD}^1. Observe that $U_{DD}^1 = U_{CL}^1$ when $f = 0$. We then know how the subject ranks U_{DD}^1 and U_{CL}^1 either from his answer to Q1 with $f = 0$ (when $U_{CL}^0 > U_{CL}^1$ with $f = 0$ so that $U_{DD}^0 > U_{DD}^1$) or to Q2 if $U_{CL}^0 < U_{CL}^1$ with $f = 0$. ∎

The proof of Proposition 2 makes use of the two utility rankings in Lemma 2 and of the fact that the expected payoffs when testing are identical under CL and DD when $f = 0$. Recall from Lemma 2 that agents most-prefer either CL and to test, or DD and not to test. The proof of Proposition 2 establishes that subjects prefer CL to DD if and only if they prefer to test in both Q1 and Q2. Alternatively, they prefer DD if they choose not to test in Q1 or in Q2. When subjects prefer to test in Q1 and Q2, their choice in Q2 when $f = 0$ determines whether they wish to test under DD or not. Their preference for testing or not under CL is of course obtained directly from Q1.[18]

We now turn to how we have implemented Q1 and Q2.

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[18]Our contingent analysis does not allow us to fully rank the four possible outcomes when agents choose to test in Q1 but not to test in Q2. In that case, we can only infer that $U_{DD}^0 > U_{CL}^1 > U_{CL}^0$ and that $U_{DD}^0 > U_{DD}^1$. We do not need the full ranking to be able to assess the preferences for testing within each regulation, and the most-preferred regulation.

3.2 Experimental Design

The experiment has been administered on paper. Subjects have received a set of stapled sheets with the instructions and the tasks (see Appendix A). On each page were displayed five tasks in consecutive rows. Each task consisted in answering Q1 and Q2, with K and f (and hence the subjects' payoffs) varying across tasks. We studied 4 different values of K and 5 values of f, for a total of 20 tasks. The tasks were applied on a within-subject basis, and the subjects were asked to perform the same twenty tasks.[19] Note that the ordering of the tasks differed between participants. More precisely, for all subjects, the value of K was held constant on each page, while the value of f was monotonic among tasks. We randomized across the participants the four possible orderings of tasks, corresponding to increasing and decreasing values of K (between pages) and f (within pages).

Q1 and Q2 were labeled as subtask A and subtask B, respectively. Both subtasks required that the subjects choose between the same lottery (corresponding to testing under CL) and a sure payoff (not testing under CL for subtask A, not testing under DD for subtask B). Proposition 2 has established that it is not necessary to ask the answer to subtask B when the subject prefers the sure payoff in subtask A (intuitively, subtask B improves the sure payoff compared to subtask A). We nevertheless chose to ask subjects to answer subtask B whatever their answer to subtask A in order to check the internal consistency of their answers (see section 4.1).

We have chosen a neutral framing because it permits to control for many characteristics of the experiment, such as the severity of the illness (which is common to all agents), the financial cost of the test, and the proportion of subjects of high-risk type. It has also the advantage of helping to secure the consistency between the multiple decisions elicited from the same participant. The repeated use of a health framing might have differential effects between

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[19]To have the closest fit with the model, subjects start the experiment with an endowment/income y, and tasks correspond to losses to be subtracted from that endowment. In all 20 tasks, the payoffs offered were computed from the following parameter values, with monetary values in €: $y = 36$, $d = 25.2$, $\phi = 3.6$, $p_H = 5/9$, $p_L = 1/9$ and $\lambda = 1/2$. The 20 tasks are obtained by crossing the 4 values of K ((2,4,6 and 8) corresponding to ($y/18$, $2y/18$, $3y/18$ and $4y/18$)) with the 5 values of f (0,0.25,0.5,0.75 and 1). Some of these parameters have more extreme values than in other insurance-motivated lab experiments (e.g., in Riahi *et al.* (2013) where the wealth at risk ratio d/y is 0.2 and the high-risk probability p_H is 3/10). Given the small values of ϕ and K, this is necessary to induce meaningful variations across choices within a task.

participants (for instance, according to their medical background) that would not have been observed by the researchers.

We now explain how we have implemented the lotteries in the experiment. At the beginning of the experiment, subjects were given at random a sealed envelope, and were told that one half of the envelopes distributed contained a green card, and the other half a red one. A green (resp., red) card was the equivalent to being of type L (resp., H) in our model, with $\lambda = 1/2$. Choices in both subtasks were framed as *opening* or *not opening* the envelope, corresponding to taking the test (and resolving the uncertainty as to one's type) or not. Participants were instructed to keep the envelope sealed until the payment stage.[20]

After having performed the twenty tasks, participants were also asked to answer an additional question in order to elicit their risk preferences using the procedure described in Eckel and Grossman (2008). Each subject had to choose one among six lotteries that were increasing in both expected value and variance. The risk elicitation procedure was framed as an extra task to decrease the protocol's complexity. The activity ended with a post-experimental survey aimed to measure the tolerance to ambiguity using a standardized and non-incentivized psychological test (Budner, 1962). The Budner test on ambiguity aversion includes sixteen items, all of them using a 7-point Likert scale. The ambiguity aversion score was computed according to Budner (1962)'s instructions: score reversing the indicated items, and then summing up all 16 items. The items from this test are reported in Appendix B. The post-experimental survey includes a final question to measure willingness to take risks in a more general domain. The question, which also uses a 7-point Likert scale and is adapted from Dohmen *et al.* (2011), says "I see myself as a person who is fully prepared to take risks, who rarely tries to avoid taking risks."

We now turn to the payment protocol. In order to preserve incentive compatibility (*i.e.*, to avoid portfolio strategies), participants were told from the outset that they would be paid according to one of the twenty one tasks they were asked to perform. Following Cox *et al.* (2015), participants were shown in advance all the tasks before any decision was made. Each partici-

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[20]We have framed the discovery (or not) of one's type as opening (or not) an envelope to bring to the decision problem a different notion of risk (*i.e.*, not knowing / not wanting to know what is inside the envelope). This framing's objective is to capture some psychological costs (or benefits) that are closer to the psychological costs of taking a genetic test than to its financial costs, helping the external validity of our experimental results.

pant was paid according to a different task number (1 to 21) and a different subtask (A or B, for the first 20 tasks).[21] Participants were allowed to open their envelope (and discover the color of the paper inside) only in the following two cases. The first case arises if they selected the lottery (described as "open the envelope") in the task (between 1 and 20) and subtask (A or B) chosen at random to be the basis of their payment. The second case occurs if they were paid according to task 21 (in which case the green and red cards were associated to the positive and negative outcomes of the lottery, respectively).[22]

Two sessions were conducted at the Toulouse School of Economics in December 2015 and February 2016. We had 33 participants in the first session and 34 participants in the second session. To minimize selection issues, both sessions were conducted during lecturing hours on two different courses from the Master in Economics (the first session in the elective "Behavioral and Experimental Economics" course and the second session in the mandatory "Microeconomics" course). Subjects were not informed in advance about the conduct of the experiment. Participants were, on average, 22 years old (standard deviation of 1.47). Sixty percent of them were male. We observe substantial variation in the ambiguity aversion score (the mean is 54.7, the standard deviation is 7.44, and the maximum and minimum achievable scores are 7 and 112) and in the non-incentivized risk aversion question (mean of 3.88, standard deviation of 1.39 in a 7-point Likert scale). Besides, the non-

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[21]The front of the envelope containing the colored paper exhibited a letter from A to U, with half of the envelopes showing a blue letter and the other half a black letter. Subjects were told from the outset that we would reveal at the end of the activity the bijections (i) between the letter printed on the envelope and the task number on which their payment would be based, and (ii) between the color of the letter and the subtask on which the payment would be based (except for task 21 for which this latter information was irrelevant). Each subject was paid according to a different combination of (K, f), corresponding to its unique letter. The color in which this unique letter was printed, blue or black, defined whether they were paid according to subtask A or B.

[22]With this particular feature we block anticipated regret. Suppose we allowed subjects to open the envelope, regardless of the experimental outcome, once the payment was made. A subject of type L would have felt regrets in case he chose not to test. We did not allow subjects to open their envelopes, unless the experimental outcome told them to do so, to prevent subjects from considering the hypothetical scenario described above. The use of envelopes with green and red cards representing L and H types, respectively, brings closer the experimental setting to the revelation of the type in a more realistic setting, compared to a die roll or a coin toss. This feature contributes to the "ecological validity" (Morton and Williams, 2010) of our design.

incentivized risk aversion question is positively correlated with the chosen lottery in task 21 (Pearson's ρ =0.33, p-value = 0.007). This evidence of consistency of risk preference across domains speaks well to the external validity of our experiment.[23] The activity lasted 45-50 minutes. The average earnings for the activity were 23 euros.

3.3 Experimental hypotheses

Our main objective in this article is to shed light first on the decisions by agents to take a genetic test or not for a given regulation (CL or DD), and then on their preferences for these regulations, given their testing decision under each regulation. More formally, we now describe the three hypotheses we want to test. These hypotheses, summarized in Table 1, are informed by our analytical results (Lemmas 1 to 3 and Proposition 1 above).[24]

Table 1: Summary of hypotheses to be tested

Hypothesis	Derived from	What do we test?	Description
H1(a)	Lemma 3	$K_{CL} > K_{DD} \, \forall f \in [0,1]$	Higher test take-up rates under CL than under DD.
H1(b)	Equations (1) and (2)	$\frac{\partial \Psi_{DD}}{\partial K} < 0$, and $\frac{\partial \Psi_{CL}}{\partial K} < 0$	Take-up rates decrease with K for CL and DD.
H2(a)	Lemma 1	$\frac{\partial \Psi_{CL}}{\partial f} < 0$	Take-up rates decrease with f under CL.
H2(b)	Lemma 1	$\left\| \frac{\partial \Psi_{CL}}{\partial f} \right\|$ smaller for more risk averse agents	For large K, the effect of f on the probability of testing under CL is smaller for risk averse subjects.
H3	Proposition 2	$U_{CL} > U_{DD}$ if K low, and $U_{CL} < U_{DD}$ if K large	CL is preferred to DD for low K. DD is preferred to CL for high K.

Starting with the within-regulation decisions, we formulate the following hypothesis.

Hypothesis 1 *(a) Test take-up rates are higher under CL than under DD for any value of the parameters (K, f). (b) Take-up rates decrease with test cost K both for CL and for DD.*

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[23]Similarly, Dohmen *et al.* (2011) write that their "results suggest that risk attitudes are strongly but not perfectly correlated across contexts."

[24]We show in section 4.1 that the number of inconsistent choices made by subjects is very low. We are thus confident that subjects have well understood the experiment, and that we can base the hypotheses to be tested on the theoretical results obtained above.

Part (a) of Hypothesis 1 derives from Lemma 3. Part (b) is straightforward from the definitions of the information value of genetic tests (see (1) and (2)).

The next hypothesis concentrates on the testing decisions under CL, and on how they are affected by the value of f and by the preferences of the agents.

Hypothesis 2 *(a) Take-up rates under CL are decreasing with f (i.e., increasing with the intensity of adverse selection). (b) For a large test cost K, the marginal effect of f on the probability of testing under CL is smaller (i.e., less negative) for risk averse subjects (with respect to more risk tolerant subjects).*

Part (a) constitutes a test of whether the conditions under which K_{CL} decreases with f (see Lemma 1) are satisfied in the experiment. Part (b) further builds on Lemma 1, and looks at how risk aversion affects the impact of adverse selection (as measured by $1 - f$) on the probability of testing when K is large (so that the marginal utility with the pooling contract is much higher if the agent has tested than if he has not, reducing the incentive to take the test when f is increased).

Moving now to the between-regulation decision, the following hypothesis is obtained from Proposition 1:

Hypothesis 3 *CL is preferred to DD for low levels of K. DD is preferred to CL for high levels of K.*

Section 4 tests these three hypotheses using all twenty exogenous pairs (K, f) studied in the experiment.

4 Results from the experiment

We start by showing in the first subsection that the number of inconsistent choices across tasks and subtasks is very low. This result gives us confidence that the subjects have well understood the protocol,[25] so we proceed to the second subsection, where we study the testing decisions of the subjects. In the last subsection we analyze their preferences over regulations.

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[25] For instance, they seem to have well understood that the subtasks were framed as losses to be subtracted from the endowment of €36.

4.1 Inconsistent choices

We perform two exercises to detect inconsistent choices made by subjects. First, we perform a within-task comparison. Remember from section 3.1 that, for any given (K, f) with $f < 1$, agents who prefer the sure payoff in subtask A (so that $U_{CL}^0 > U_{CL}^1$) should also prefer the sure payoff in subtask B (so that $U_{DD}^0 > U_{CL}^1$) since both subtasks differ only in the sure payoff amount, which is larger in subtask B than in subtask A (with $U_{DD}^0 > U_{CL}^0$). Hence, we tag a choice as inconsistent when, for any of the four values of K, any of the subjects choose not to test in Q1 and then to test in Q2. Out of 268 cases (4 values of K times 67 subjects), we found 3 within-task (1.1%) inconsistencies.[26] We use a Mann-Whitney test to confirm that these differences are not associated to particular sessions, and neither to the use of decreasing or increasing values of f or K in the way that tasks were presented (p-values are 0.2675, 0.315 and 0.188, respectively).[27]

Second, we perform a between-task comparison. A simple inspection of the protocol in Appendix A shows that, for K constant (same question sheet), moving down the list of tasks improves the worst payoff among the two offered in subtask B's lottery, but keeps the other payoffs in this subtask unaffected. Hence, we tag a choice as inconsistent when the subject tests in Subtask B for a given task number, and does not test for a larger (resp. smaller) task number, associated to a larger (resp. larger) f, where the worst outcome from testing improved (resp. decreased). Out of 268 cases, we found 9 between-task (3.4%) inconsistencies. Mann-Whitney tests reveal that inconsistencies are not systematically associated to a session, and neither to the use of decreasing or increasing values of K (p-values are 0.769 and 0.119, respectively). However, inconsistencies across tasks are more likely to appear when f decreases from one task to the next within the same sheet (p-value 0.012).

In the light of the low proportion inconsistencies, we feel confident that subjects have well understood the experiment protocol, and we move to the

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[26]Note that the frequency of inconsistencies would be even lower if we were to take the unit of observation to be the task when $f < 1$, in which case we only have 4 inconsistencies out of 4 (values of K) times 4 (values of $f < 1$) times 67 (subjects) = 1072 observations.

[27]We also obtain 8 cases out of the 268 answers to tasks involving $f = 1$ where subjects make different choices in subtasks A and B, even though the payoffs are the same in both subtasks. Different choices may not correspond to inconsistencies, but rather to indifference between the two payoffs, since we do not allow subjects to register indifferences in the experiment. So we obtain *at most* 3% of inconsistencies of that type.

study of its results, starting with the testing decisions.

4.2 Testing decisions within regulations

Figure 3 reports the observed test take-up rates within CL and DD for the different levels of K and f considered in our experiment. We first observe that take-up rates are higher under CL than under DD, as predicted in Hypothesis 1 (a). Actually, the take-up rates under DD are very small (varying from 7.5% for the lowest value of K, to 0 for its two highest values). This means that subjects are very sensitive to the discrimination risk associated with this regulation. By contrast, take-up rates under CL are very close to 100%, for any value of f, when K is low. This is intuitive since section 2.2.2 has shown that take-up would be 100% with $K = 0$, and thus would remain by continuity close to 100% for K small. We then observe that take-up rates decrease with the cost of the test under both regulations, in accordance with Hypothesis 1 (b).

We now study more closely the testing decisions under CL. Figure 3 shows that take-up rates under CL are decreasing with f, confirming Hypothesis 2 (a).[28] Recall from Lemma 1 that increasing f improves the pooling contract offered to agents (pretending to be) uninformed, which has two effects of opposite signs on the incentives to take the test. On the one hand, a better pool decreases incentives to test since agents test in order to move away from this pooling contract. On the other hand, if utilities are very concave, marginal utility is especially large when agents take the test (and pay its cost), and the lower premium associated to a larger f especially benefits those who take the test, inducing more agents to do so. Figure 3 shows that the former effect is larger than the latter.

Insert Figure 3 here

Hypothesis 2 (b) claims that the least risk averse participants should be more sensitive to changes in f in their testing decision under CL. We compute a probit model for Q1 to examine this hypothesis, paying special attention to

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[28]The only exception in Figure 3 seems to be the increase in take-up rate for $K = y/9$ when moving from $f = 3/4$ to $f = 1$, but both a chi-squared test (p-value 0.71) and a t-test (same p-value) show that the difference in take-up rates between those two points is not significant.

the heterogeneous effects of subjects' risk aversion. We measure risk aversion by asking participants to choose one from the six lotteries shown in Task 21 in Appendix A. The lotteries are ordered by increasing expected payoff going hand in hand with increasing variance. Less risk averse agents then should choose a lottery with both a higher expected payoff and a higher variance. For the computation of the probit model we classify as "least risk averse" the respondents who have chosen one of the two least risky lotteries (43% of respondents), and as "most risk averse" those respondents who have chosen one of the two most risky lotteries (27% of respondents).

Figure 4 shows the predicted marginal effects for different values of f, ranging from 0 to 1, for the "least risk averse" (hollow diamonds) and "most risk averse" (circles with dashed line) participants, separately, for the largest value of K ($= 2y/9$). The initial difference in the marginal effects on the probability of testing between risk aversion types is about 50 percentage points for $f = 0$ (*i.e.*, maximum adverse selection). This difference vanishes as f gets closer to one (*i.e.*, no adverse selection). This supports Hypothesis 2 (b).

Insert Figure 4 here

4.3 Preferences over regulations

We now move to the preferences over regulations. The left panel of Figure 5 displays the observed preferences for CL over DD as a function of the cost of the test (K) and of the intensity of adverse selection (f). Recall from Proposition 3 that, given the sequence of the choices presented in Figure 1, if agents most prefer DD they also prefer not to test, and that if they most prefer CL, they then prefer to test. Also, agents prefer CL to DD if they choose to test in both Q1 and Q2, and DD otherwise.

We obtain that the proportion of subjects preferring CL to DD decreases with K, for any given value of f. This is intuitive, since a larger value of K discourages testing, and since CL is preferred to DD only when it is optimal to test under CL. When K is large, most subjects prefer DD to CL, in accordance with Hypothesis 3.

For K sufficiently low, $y/18$ and $y/9$ in our experiment, where y is the endowment of the subject when the experiment starts, the proportion of subjects preferring CL increases when the intensity of adverse selection decreases

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(*i.e.*, when the proportion f of truly uninformed agents increases). This is intuitive, since a larger value of f makes the pooling contract under CL more attractive. Recall from Figure 3 that, for low values of K, the test take-up rate under CL remains large for all values of f.

For higher levels of K, $y/6$ and $2y/9$, the preferences between regulations are less affected by the intensity of adverse selection, even though Figure 3 shows that the test take-up rate under CL decreases rapidly as f increases. Recall the observation made after Proposition 1 that taking the test under CL is a necessary, but not sufficient, condition to prefer CL over DD. One can then infer that many of those subjects who change their decision to not testing under CL as f increases already preferred DD to CL anyhow. Observe that, for high levels of K, the amount of adverse selection needs to be minimal (f close to 1) for some subjects to prefer CL over DD (7.5% for $K = y/6$ and 4.5% for $K = 2y/9$). Figure 3 shows that most agents do not take the test under CL for these parameter values.

Insert Figure 5 around here

We complement this analysis by jointly estimating the testing decisions in subtasks A and B. We employ a bivariate probit regression to model the two binary choices as dependent from each other.[29] As is explained in Proposition 2, choosing to test under Subtask A (Q1) corresponds to choosing to test under CL, while choosing to test under Subtask B (Q2) corresponds to preferring CL to DD. We show in section 3.1 that these testing decisions are expected to be positively correlated because, conditional on not testing in Subtask A, it is rational to not test in Subtask B: the sure payoff associated to not testing is higher in Subtask A than in Subtask B, while both subtasks offer the same lottery. An additional implication is that subjects testing in Q2 also test in Q1. The choices in Q1 and Q2 are expected to be different only for those willing to test within CL but prefer (not to test under) the DD regulation (in which case they prefer the lottery in Q1, and the sure payoff in Q2).

We report the results from the bivariate probit in Table 2. The table includes, for all the listed variables, the coefficients corresponding to changes

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[29]See Appendix C for more details on how the bivariate probit captures the relationship between testing decisions.

in the random utility model describing the testing decisions in Q1 and Q2. For the main variables of interest, f and K, we also report their marginal effects on the probabilities of testing in Q1 and Q2 (see coefficients in bold and in brackets, and their standard errors in brackets). Marginal effects allow us to assess how the intensity of adverse selection, captured by f, and the cost of the test as a proportion of income, K, affect the probability of testing in each task.[30]

We start with the sparsest specification in model (1), in which the only covariates are f and K. Model (2) adds as covariates some participants' characteristics (risk aversion, ambiguity aversion and gender), in addition to categorical variables to control for order effects and session fixed effects. Model (3) adds an interaction between the cost of the test K and our measures of risk aversion and ambiguity aversion. Model (4) adds participants' fixed effects (at the expense of dropping participants' characteristics that are time invariant).

Model (1) shows that increasing the value of f by 0.1 (*i.e.*, a decrease of 10 percentage points in the intensity of adverse selection) decreases the probability of testing in Q1 (*i.e.*, testing under CL) by 5.7 percentage points, and increases the probability of testing in Q2 (*i.e.*, preferring CL to DD) by 2.6 percentage points. Regarding K, the marginal effects are large and highly non-linear, so we list the effects for every increase in K that occurred in our experimental setting. Computations following model (1) reveal that increasing K from €2 to €4 decreases the probability of testing in Q1 and Q2 by 17.4 and 36.4 percentage points, respectively; increasing K from €4 to €6 decreases the probability of testing in Q1 and Q2 by 39.7 and 12.6 percentage points, respectively; and increasing K from €6 to €8 decreases the probability of testing in Q1 and Q2 by 31.1 and 1.48 percentage points, respectively.

The negative, and large, effect that an increase in K has on the probability of testing under CL provides additional evidence supporting Hypothesis 1

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[30]We do not report the marginal probabilities for the other covariates listed in Table 2 because the coefficients capturing the associated changes in the random utility model are small, and therefore the computed marginal effects are statistically not different from zero for risk aversion, ambiguity aversion and gender. Besides, marginal effects for f and K are computed at the mean of the other covariates, and therefore it is not straightforward to obtain the marginal effects for the interaction terms in model (3). Additional computations of such heterogeneous effects do not exhibit differences in the effect of K between low *versus* high levels of risk aversion or ambiguity aversion.

(b). Similarly, the negative effect of K on the probability of testing in Q2 supports Hypothesis 3, since a larger cost of the test increases the probability of preferring DD over CL. Also, the negative effect of f on the probability of testing under CL provides additional evidence in favor of Hypothesis 2 (a).

Results from models (2) and (3) show that the marginal effects are robust to the addition of participants' characteristics, session and order fixed effects. As for model (3), the coefficients for the added interaction terms reveal the absence of heterogeneous effects of the cost of the test driven by preferences for (financial) risk or by ambiguity. Unreported heterogeneous marginal effects are also not significant.

The most noticeable differences in the computed marginal effects emerge in model (4). However, these differences are partly a consequence of how marginal effects are computed. Usually, marginal effects are computed assuming the mean value of covariates. This is not possible in model (4), since we have 66 dichotomous variables that capture participants' fixed effects.[31] Hence, we compute the marginal effects for each participant and report in Table 2 the average marginal effect of f and K on the probability of testing in Q1 and Q2.

We obtain that the magnitudes of the marginal effects in model (4) are smaller for Q1 and larger for Q2, compared with models (1) to (3). After taking account of the within-subject variation in testing decisions between tasks, the probability of testing under CL (measured with Q1) is less sensitive to the values of f and K; whereas the probability of preferring CL to DD is more sensitive to the values of f and K.

Going back to Figure 5, the right panel displays the predicted preferences for CL over DD, corresponding to the marginal effects of the probit regression estimating the probability of testing for each value of f and K in the experiment, instead of assuming a linear or quadratic relationship for each parameter. The comparison of the two panels of Figure 5 shows that our probit regression makes a good job at fitting the experimental data.

Both the good fit and the highly significant coefficients in Table 2 make us confident that we can build on these regression results to shed additional light on the subjects' preferences. In Figure 6, we report the probability of testing under CL (left panel) and of preferring CL to DD (right panel), as a function of K and f, obtained from the probit regression coefficients in model

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[31]We have in total 67 participants, but one of them chose to not test in the two subtasks for all 20 tasks.

Table 2: Coefficients from the bivariate probit estimation. The reported coefficients correspond to changes in the utility of testing in Q1 and Q2, respectively. For the variables f and K, the marginal probabilities of testing are reported in brackets and in bold (with the respective standard errors also in brackets). The ρ coefficient corresponds to the covariance of the error terms of testing decisions captured in **Q1** and **Q2.**

VARIABLES	(1) Q1: Test	(1) Q2: Test	(2) Q1: Test	(2) Q2: Test	(3) Q1: Test	(3) Q2: Test	(4) Q1: Test	(4) Q2: Test
f	-1.49*** (0.17) **[-0.568]** [(0.057)]	2.39*** (0.25) **[0.258]** [(0.045)]	-1.56*** (0.18) **[-0.597]** [(0.061)]	2.47*** (0.26) **[0.228]** [(0.041)]	-1.58*** (0.17) **[-0.603]** [(0.060)]	2.47*** (0.26) **[0.222]** [(0.040)]	-2.01*** (0.17) **[-0.338]**	3.43*** (0.25) **[0.376]**
K	-19.6*** (1.85) **[-7.483]** [(0.628)]	-19.6*** (1.93) **[-2.115]** [(0.374)]	-19.9*** (1.92) **[-7.593]** [(0.655)]	-20.3*** (2.06) **[-1.874]** [(0.330)]	-14.8 (10.7) **[-7.735]** [(0.642)]	-6.00 (8.67) **[-1.849]** [(0.335)]	-25.4*** (1.23) **[-4.280]**	-27.5*** (1.71) **[-3.015]**
Risk aversion (lottery)			-0.015 (0.043)	-0.028 (0.053)	0.23 (0.20)	0.012 (0.12)		
$K \times$ Risk aversion					-1.66 (1.30)	-0.23 (1.18)		
Amb. Aversion Score			-0.0037 (0.012)	0.0030 (0.012)	-0.0041 (0.034)	0.027 (0.018)		
$K \times$ Amb. Aversion Score					-0.0023 (0.19)	-0.25* (0.14)		
Gender (=1 male)			0.030 (0.16)	0.19 (0.18)	0.031 (0.16)	0.19 (0.18)		
Constant	3.76*** (0.37)	-0.095 (0.19)	3.92*** (0.63)	-0.56 (0.77)	3.24* (1.82)	-2.00* (1.12)	5.51*** (0.74)	1.68* (0.88)
Rho (Corr. between decisions)	0.781*** (0.078)		0.760*** (0.077)		0.761*** (0.076)		0.931*** (0.052)	
Fixed Effects	No		Session level		Session level		Participant level	
Observations	1,340		1,260		1,260		1,260	

Standard errors clustered at the participant level shown in parentheses (models 1-4). *** p¡0.01, ** p¡0.05, * p¡0.1

Coefficients for between-subjects variation of order effects (increasing/decreasing f, increasing/decreasing K) included but not reported.

(2) of Table 2. In line with our theoretical analysis, we find that a decrease in the test cost K makes it more likely that CL be preferred to DD, and that subjects take the test within CL. Less adverse selection in the pooling contract under CL (*i.e.*, a higher f) makes CL more likely to be preferred to DD, but decreases the test take-up rate under CL.

Insert Figure 6 around here

Figure 6 also shows that the sensitivity of the testing decision to adverse selection depends non-linearly on the value of K. When the cost of the test is high (resp. low), this sensitivity to adverse selection is small, due to the low (resp. high) probability of testing estimated with the bivariate probit. For intermediate values the bivariate probit model is more sensitive to adverse selection.

5 Conclusion

Our main results from the experiment run as follows. We have spotted very few inconsistencies in the subjects answers, and we thus feel confident that they have well understood the experiment's protocol. We obtain that test take-up rates decrease with the genetic test cost under both regulations, and that they are larger under CL than under DD. This result is intuitive and due to the lack of discrimination risk under CL, unlike under DD. The test take-up rate is very small under DD, even when the test cost is small: this shows that subjects in the experiment are extremely sensitive to the discrimination risk embedded in the DD regulation. The test take-up rate increases with the amount of adverse selection in the pooling contract under CL (since more agents try to escape this more expensive contract by obtaining the cheaper contract associated with good genetic information), although the impact of adverse selection is smaller for the more risk averse agents.

As for the preference for regulations (when individuals choose optimally whether to test or not, under each regulation), the support for CL over DD increases when the genetic test cost decreases. Recall that agents fare better under DD than under CL if they choose (in both cases) not to test, because the (pooling) contract under CL is costlier due to the presence of adverse selection. Preferring to test under CL is thus a prerequisite to favor CL over

29

DD, and a lower test cost (inducing more testing, especially under CL) then increases the fraction of agents who prefer CL (and test) to DD. A lower adverse selection intensity increases the support for CL over DD.

We obtain that less than one half of agents prefer CL to DD, whatever the value of the test cost K. This equilibrium with DD and very little testing seems pretty bleak from a normative perspective, as it is impossible to reap the benefits from personalized medicine when genetic testing is shunned by the public.

Which policy recommendations can we draw from these results? Authorities bent on favoring the emergence of personalized medicine should prefer CL to DD, as the genetic test take-up rate is larger under the former than under the latter. But this preference may not be shared by a majority of the electorate, as we show above. The *Laissez-Faire* regulation would probably make policyholders worse off than under DD in our framework, since it allows insurers to demand from agents that they perform the genetic tests, while very few agents voluntarily test under DD even when the test cost is low.

Our results of course have to be taken with caution. We have chosen to run an experiment with neutral framing and with simple choices, mainly to be able to remain as close as possible to the analytical model developed, and to be able to better control all relevant aspects of the experiment and to help secure the consistency of the respondents' answers. The reality is of course more complex, has higher stakes and relates to health decisions. We thus take our results as indicative of what could happen in the realm of personalized medicine within the next decade.

We would like to come back to two important assumptions made in the analytical model. First, our results are based on the simplifying assumption of a pooling contract with full coverage under CL. As we explain in footnote 15, this assumption biases our results in the direction of a larger fraction of agents testing under CL, and preferring CL to DD, than with Wilson (1977)'s approach resulting in endogenous partial coverage. This is an important reminder that our results depend crucially on the type of equilibrium contract offered in both regulations.

Second, we have assumed that the prevention effort (which is the source of the health benefit generated by genetic tests) is observable by the insurers, and that agents perform this effort if and only if it is efficient. Relaxing either assumption would likely modify our experimental results. Unobservable prevention would induce insurers to offer contracts with partial coverage rates, to control for the *ex ante* moral hazard problem. Allowing agents in the ex-

periment to choose whether they want to exert this prevention effort would probably have generated a different pattern of prevention, which would have affected their pay-offs. For instance, if agents procrastinate when considering the prevention effort, then a test which makes this effort non necessary (when revealed to have a good genetic background) has higher value than in our setting, potentially leading to larger take-up rates.

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Appendix A: The protocol

Welcome!

Thank you for your participation. You will receive a payment at the end of the activity, which will be based on the answers you are about to provide. These answers are totally anonymous, do not have a correct or incorrect response, and will remain unrelated to your grade in the course. If you'd prefer not to participate in the activity, you are welcome to leave the room now, without any earnings, and come back in 45 minutes. From now on we will ask you to turn off your mobile phone and to remain silent until the end of the activity.

Please DO NOT open the envelope you received with this form until the supervisor announces that you are allowed to, at the very end of the activity. The envelope contains a colored piece of paper, GREEN or RED. Half of the participants in this room have received an envelope with a GREEN paper. The other half of participants has received an envelope with a RED paper. This color is not related with being seated on the left or the right side of the room.

You will find several tasks that we ask you to complete. They all have in common that you start with an amount of 36€ (your endowment), and that you have to choose one out of several options. Each option may decrease your final earnings by some amount. Whatever your choice, you will end up with a non-negative amount of money at the end of the activity. Please answer ALL questions so that we can compute how much you will be paid at the end of the activity.

PART ONE: TASKS 1 TO 20

In the **first twenty (20) tasks**, you will be asked to decide which of the following two choices you would prefer:
- to OPEN the envelope and face a lottery in which your endowment of 36€ decreases by the amount in euros corresponding to the colored paper it contains, with the GREEN paper offering a smaller loss than the RED paper,

or
- NOT TO OPEN the envelope and face a sure payoff deduction from your endowment of 36€. The sure loss falls in-between the amount deducted with the GREEN paper and the amount deducted with the RED paper.

More precisely, you will be presented with TWENTY (20) different combinations of payoffs deductions, in euros, for the GREEN and RED colored papers. For each one of these tasks we will ask you to decide whether you would prefer to OPEN or NOT TO OPEN the envelope for **two different subtasks**, differing only in the amount deducted if you choose NOT TO OPEN. Please answer both subtasks A and B before moving to the next task.

Here is how each one of these tasks will look like:

Example:

Please indicate, **for both subtasks A and B**, whether you prefer to OPEN the envelope (by putting an "X" next to OPEN) or NOT TO OPEN the envelope (by putting an "X" next to NOT TO OPEN).

Consider the example above. In subtask A, you will receive a payoff of 36€-25€ = 11€ if you choose NOT TO OPEN, a payoff of 36€-15€=21€ if you choose to OPEN the envelope and it contains a green slip of paper, and a payoff of 36-30€=6€ if you choose to OPEN the envelope and it contains a red slip of paper.

PART TWO: TASK 21

In the **21st and last task**, you will be asked to choose **one** among six different lotteries. As for the first twenty (20) tasks, the GREEN and the RED colored papers indicate your payoff deduction in euros from the selected lottery, with the GREEN paper always giving a smaller payoff deduction than the RED paper.

Example:

Please select which one of the lotteries shown here you would like to play. Payoff deductions depend on the color of your slip of paper.

	-10.0		-8.0		-6.0		-4.0		-2.0		0.0
	-10.0		-11.0		-12.0		-13.0		-14.0		-15.0
THIS LOTTERY		THIS LOTTERY		THIS LOTTERY		THIS LOTTERY		THIS LOTTERY		THIS LOTTERY	

You then have a total of TWENTY ONE tasks to perform: TWENTY tasks where you indicate whether you would prefer to OPEN or NOT TO OPEN the envelope, plus one final task where you SELECT THE LOTTERY you prefer.

HOW DO YOU GET PAID?

Please do not open the envelope until you are instructed to, at the payment stage, or we won't be able to pay you.

You will be paid the amount you have chosen in ONLY ONE of the 21 tasks according to the following procedure.

There is a letter, from A to U, on the outside of the envelope. This letter differs across envelopes. Each letter is randomly matched with a task number. After we have collected the filled forms, we will reveal the correspondence between letter and task number.

If the letter on your individual envelope corresponds to task 21, you will be paid according to the lottery you have chosen: you will open the envelope and get 36€ minus the lower payoff deduction if there is a GREEN paper slip in the envelope, and 36€ minus the larger payoff deduction if there is a RED paper slip.

If the letter on your individual envelope corresponds to a task between 1 and 20, we will toss a coin to determine whether you will be paid according to subtask A or to subtask B. If, for the subtask determined by the toss outcome, you have indicated that you prefer NOT TO OPEN the envelope, the corresponding amount will be deducted from your endowment of 36€. If you have indicated that you prefer to OPEN the envelope, you will be asked to open it and you will get 36€ minus the smaller payoff deduction if there is a GREEN paper slip in the envelope, and 36€ minus the larger payoff deduction if there is a RED paper slip.

Finally, we will ask you to fill a questionnaire. The collected information will be treated anonymously and will be used only with scientific purposes. Once you fill the questionnaire, please remain seated and silent until this form is collected.

If you have any question, please raise your hand and we will respond individually.

If all the instructions are clear and you agree to take part in this activity please sign the accompanying informed consent form. We also ask you to fill the accompanying receipt with your name, we will ask you to sign it when we pay you.

Thank you for your participation!

PLEASE DO NOT TURN THE PAGE UNTIL YOU ARE INSTRUCTED TO DO IT

Task	Subtask A	Subtask B

1

Subtask A: Would you like to open the envelope? -5.0 / -20.0 — OPEN. Or leave it closed? -18.0 — NOT OPEN

Subtask B: Would you like to open the envelope? -5.0 / -20.0 — OPEN. Or leave it closed? -12.0 — NOT OPEN

2

Subtask A: Would you like to open the envelope? -5.0 / -18.5 — OPEN. Or leave it closed? -16.5 — NOT OPEN

Subtask B: Would you like to open the envelope? -5.0 / -18.5 — OPEN. Or leave it closed? -12.0 — NOT OPEN

3

Subtask A: Would you like to open the envelope? -5.0 / -17.0 — OPEN. Or leave it closed? -15.0 — NOT OPEN

Subtask B: Would you like to open the envelope? -5.0 / -17.0 — OPEN. Or leave it closed? -12.0 — NOT OPEN

4

Subtask A: Would you like to open the envelope? -5.0 / -15.5 — OPEN. Or leave it closed? -13.5 — NOT OPEN

Subtask B: Would you like to open the envelope? -5.0 / -15.5 — OPEN. Or leave it closed? -12.0 — NOT OPEN

5

Subtask A: Would you like to open the envelope? -5.0 / -14.0 — OPEN. Or leave it closed? -12.0 — NOT OPEN

Subtask B: Would you like to open the envelope? -5.0 / -14.0 — OPEN. Or leave it closed? -12.0 — NOT OPEN

Task	Subtask A	Subtask B

6

Subtask A: Would you like to open the envelope? **-7.0** / **-22.0** — OPEN. Or leave it closed? **-18.0** — NOT OPEN

Subtask B: Would you like to open the envelope? **-7.0** / **-22.0** — OPEN. Or leave it closed? **-12.0** — NOT OPEN

7

Subtask A: Would you like to open the envelope? **-7.0** / **-20.5** — OPEN. Or leave it closed? **-16.5** — NOT OPEN

Subtask B: Would you like to open the envelope? **-7.0** / **-20.5** — OPEN. Or leave it closed? **-12.0** — NOT OPEN

8

Subtask A: Would you like to open the envelope? **-7.0** / **-19.0** — OPEN. Or leave it closed? **-15.0** — NOT OPEN

Subtask B: Would you like to open the envelope? **-7.0** / **-19.0** — OPEN. Or leave it closed? **-12.0** — NOT OPEN

9

Subtask A: Would you like to open the envelope? **-7.0** / **-17.5** — OPEN. Or leave it closed? **-13.5** — NOT OPEN

Subtask B: Would you like to open the envelope? **-7.0** / **-17.5** — OPEN. Or leave it closed? **-12.0** — NOT OPEN

10

Subtask A: Would you like to open the envelope? **-7.0** / **-16.0** — OPEN. Or leave it closed? **-12.0** — NOT OPEN

Subtask B: Would you like to open the envelope? **-7.0** / **-16.0** — OPEN. Or leave it closed? **-12.0** — NOT OPEN

Task	Subtask A	Subtask B

11

Would you like to open the envelope? | -9.0 / -24.0 | Or leave it closed? -18.0
OPEN | NOT OPEN

Would you like to open the envelope? | -9.0 / -24.0 | Or leave it closed? -12.0
OPEN | NOT OPEN

12

Would you like to open the envelope? | -9.0 / -22.5 | Or leave it closed? -16.5
OPEN | NOT OPEN

Would you like to open the envelope? | -9.0 / -22.5 | Or leave it closed? -12.0
OPEN | NOT OPEN

13

Would you like to open the envelope? | -9.0 / -21.0 | Or leave it closed? -15.0
OPEN | NOT OPEN

Would you like to open the envelope? | -9.0 / -21.0 | Or leave it closed? -12.0
OPEN | NOT OPEN

14

Would you like to open the envelope? | -9.0 / -19.5 | Or leave it closed? -13.5
OPEN | NOT OPEN

Would you like to open the envelope? | -9.0 / -19.5 | Or leave it closed? -12.0
OPEN | NOT OPEN

15

Would you like to open the envelope? | -9.0 / -18.0 | Or leave it closed? -12.0
OPEN | NOT OPEN

Would you like to open the envelope? | -9.0 / -18.0 | Or leave it closed? -12.0
OPEN | NOT OPEN

Task	Subtask A		Subtask B	

16

Would you like to open the envelope? | **-11.0** / **-26.0** | Or leave it closed? | **-18.0**
OPEN | NOT OPEN

Would you like to open the envelope? | **-11.0** / **-26.0** | Or leave it closed? | **-12.0**
OPEN | NOT OPEN

17

Would you like to open the envelope? | **-11.0** / **-24.5** | Or leave it closed? | **-16.5**
OPEN | NOT OPEN

Would you like to open the envelope? | **-11.0** / **-24.5** | Or leave it closed? | **-12.0**
OPEN | NOT OPEN

18

Would you like to open the envelope? | **-11.0** / **-23.0** | Or leave it closed? | **-15.0**
OPEN | NOT OPEN

Would you like to open the envelope? | **-11.0** / **-23.0** | Or leave it closed? | **-12.0**
OPEN | NOT OPEN

19

Would you like to open the envelope? | **-11.0** / **-21.5** | Or leave it closed? | **-13.5**
OPEN | NOT OPEN

Would you like to open the envelope? | **-11.0** / **-21.5** | Or leave it closed? | **-12.0**
OPEN | NOT OPEN

20

Would you like to open the envelope? | **-11.0** / **-20.0** | Or leave it closed? | **-12.0**
OPEN | NOT OPEN

Would you like to open the envelope? | **-11.0** / **-20.0** | Or leave it closed? | **-12.0**
OPEN | NOT OPEN

21

Please select which one of the lotteries shown here you would like to play. Payoff deductions depend on the color of your slip of paper.

| **-23.5** / **-23.5** | **-18.0** / **-26.5** | **-12.5** / **-29.0** | **-7.0** / **-32.0** | **-1.5** / **-34.5** | **0.0** / **-36.0** |
| THIS LOTTERY | THIS LOTTERY | THIS LOTTERY | THIS LOTTERY | THIS LOTTERY | THIS LOTTERY |

40

Appendix B: Questionnaire for measuring ambiguity aversion

Each one of the following sixteen statements was evaluated by the participants using a Likert scale from 7 (strongly agree with the statement) to 1 (strongly disagree with the statement). To compute the ambiguity aversion score, odd-numbered items must be summed directly and even-numbered items must be reverse-scored (a "7" scores 1, a "6" scores 2, and so on). Items can be divided into three categories of ambiguity aversion: aversion to novelty (N), aversion to complexity (C), and insolubility (I). The category is listed as a superscript next to the item number.

$1^{(I)}$. An expert who doesn't come up with a definite answer probably doesn't know too much.

$2^{(N)}$. I would like to take a free genetic test informing me of my probability of developing cancer later in life.

$3^{(I)}$. There is really no such thing as a problem that can't be solved.

$4^{(C)}$. People who fit their lives to a schedule probably miss most of the joy of living.

$5^{(C)}$. A good job is one where what is to be done and how it is to be done are always clear.

$6^{(C)}$. It is more fun to tackle a complicated problem than to solve a simple one.

$7^{(C)}$. In the long run it is possible to get more done by tackling small, simple problems rather than large and complicated ones.

$8^{(C)}$. Often the most interesting and stimulating people are those who don't mind being different and original.

$9^{(N)}$. What we are used to is always preferable to what is unfamiliar.

$10^{(C)}$. People who insist upon a yes or no answer just don't know how complicated things really are.

$11^{(N)}$. A person who leads an even, regular life in which few surprises or unexpected happenings arise really has a lot to be grateful for.

$12^{(I)}$. Many of our most important decisions are based upon insufficient information.

$13^{(N)}$. I like parties where I know most of the people more than ones where all or most of the people are complete strangers.

$14^{(C)}$. Teachers or supervisors who hand out vague assignments give one

a chance to show initiative and originality.

15$^{(C)}$. The sooner we all acquire similar values and ideals the better.

16$^{(C)}$. A good teacher is one who makes you wonder about your way of looking at things.

Appendix C: The bivariate probit regression describing choices in Q1 and Q2

The choices we observe in the experiment can be defined as

$$\boldsymbol{Q1} = \begin{cases} 1 \text{ (test)} & \text{if } V_1 \geq 0 \\ 0 \text{ (no test)} & \text{otherwise} \end{cases}, \quad \boldsymbol{Q2} = \begin{cases} 1 \text{ (test)} & \text{if } V_2 \geq 0 \\ 0 \text{ (no test)} & \text{otherwise} \end{cases}$$

with the underlying latent variables V_1 and V_2 given by

$$\begin{aligned} V_1 &= \boldsymbol{\beta_1'}\, \boldsymbol{X} + \epsilon_1, \\ V_2 &= \boldsymbol{\beta_2'}\, \boldsymbol{X} + \epsilon_2, \end{aligned}$$

where $\boldsymbol{X}$ is the set of covariates reported in Table 2. The error terms from the random utility equations, ϵ_1 and ϵ_2, are assumed to be jointly normally distributed. That is,
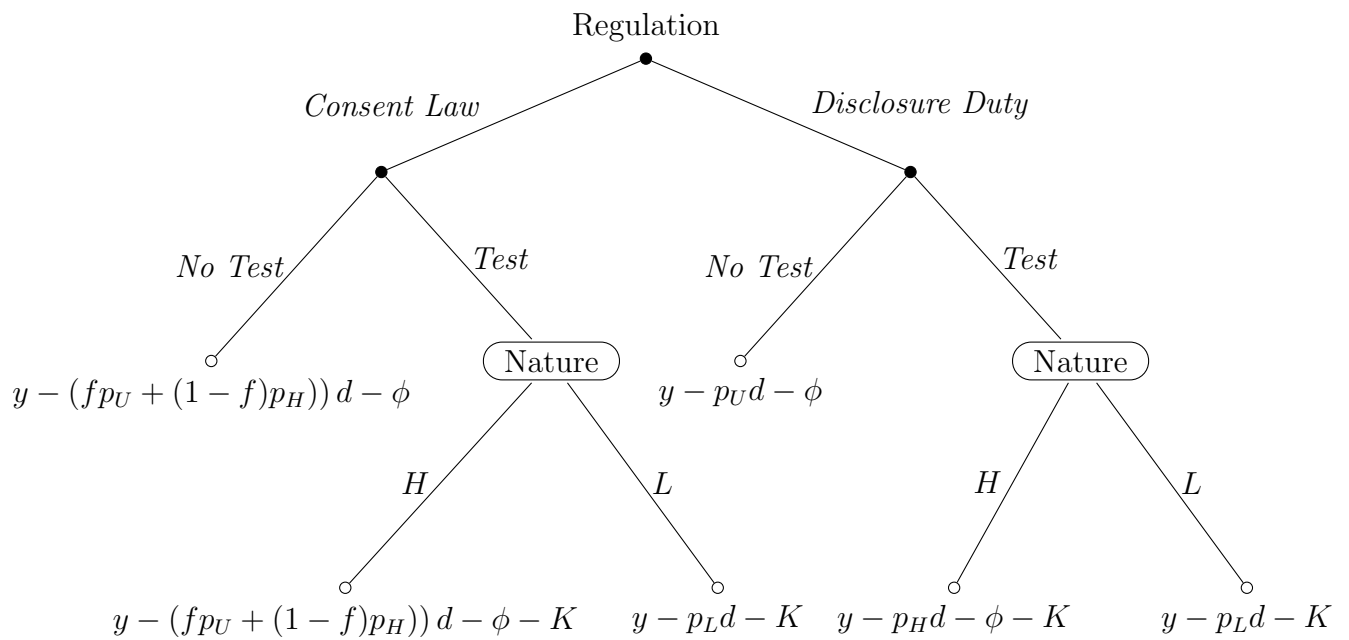
$$\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right].$$

As explained in section 4.3., the testing decisions in Q1 and Q2 are expected to be positively correlated (*i.e.*, $\rho > 0$) given the contingent character of our analysis.

Since we have repeated observations for each participant the standard errors of the model are clustered at the individual level. The estimated coefficients for all the covariates, as well as the marginal effects for f and K, are shown in Table 2. An inspection of the two panels in Figure 5 shows that the observed and predicted behavior are qualitatively similar.

Figures

Figure 1: Payoff structure of the model.

Regulation

Consent Law   *Disclosure Duty*

No Test   *Test*   *No Test*   *Test*

$y - (fp_U + (1-f)p_H))\, d - \phi$ Nature $y - p_U d - \phi$ Nature

H L H L

$y - (fp_U + (1-f)p_H))\, d - \phi - K$ $y - p_L d - K$ $y - p_H d - \phi - K$ $y - p_L d - K$

Terminal nodes are represented by hollow circles, while nodes with solid circles are used when a choice has to be made by society (first stage) or individuals (second stage).

Figure 2: Utility differences between Disclosure Duty and Consent Law, measured at the optimal testing decision of agents in each regulation.
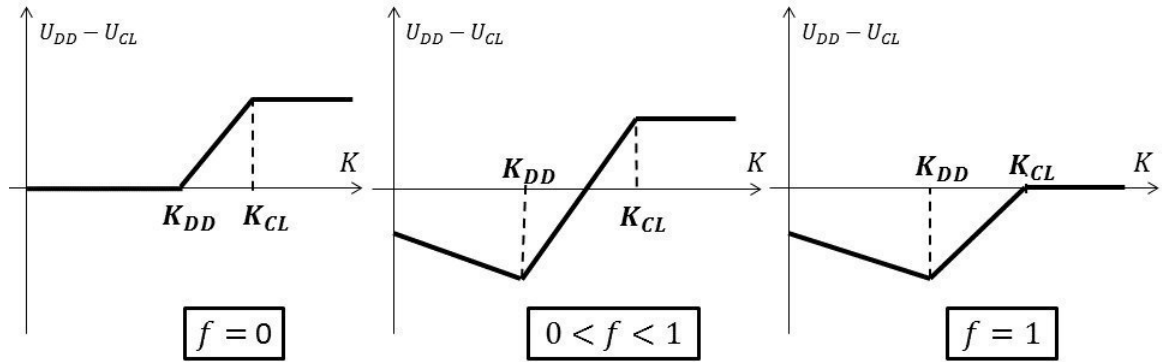

Figure 3: Observed test take-up rate within Consent Law (CL) and Disclosure Duty (DD).
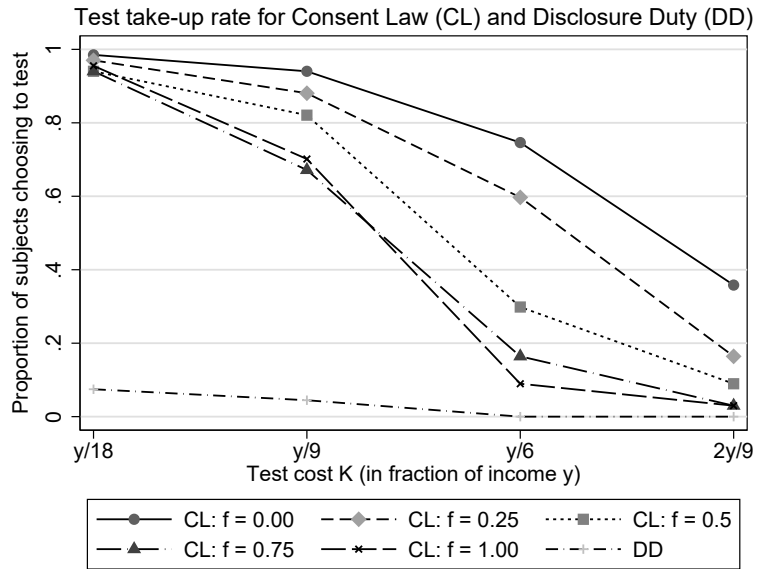
Figure 4: Marginal effects for testing under CL between risk aversion categories for the largest test cost ($K = 2y/9$)
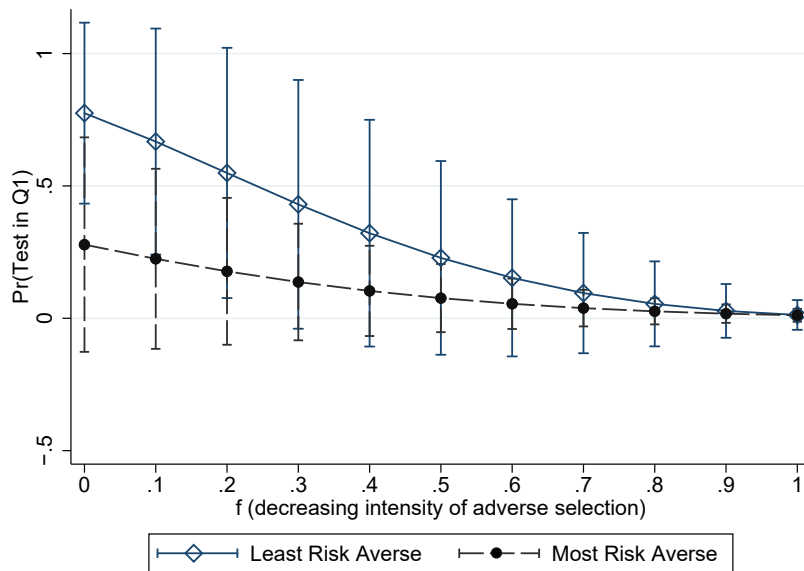

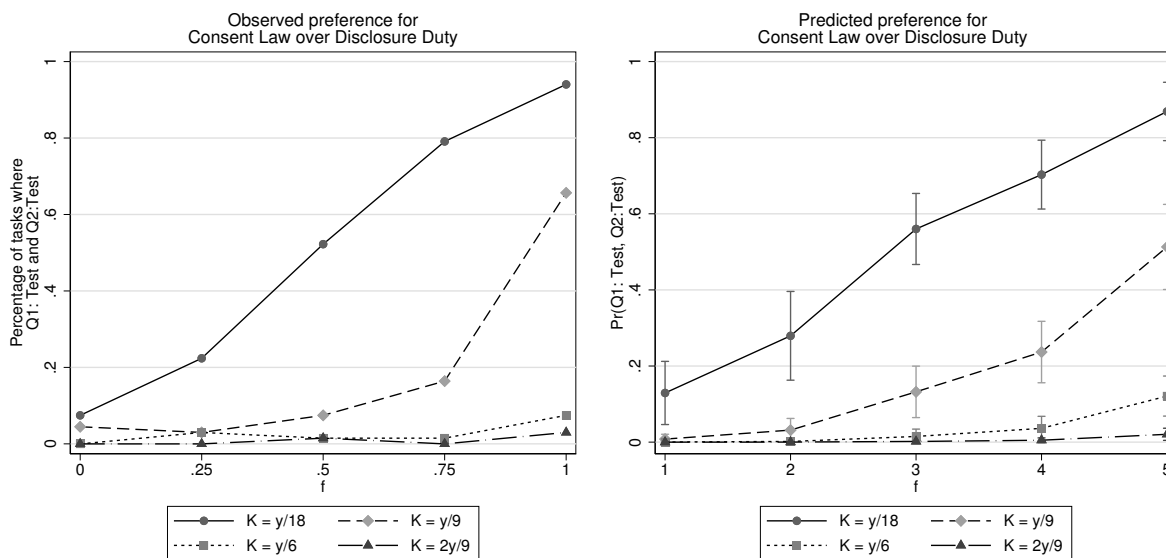Figure 5: Observed and predicted preferences between regulations.

Figure 6: Predicted probabilities between and within genetic testing regulations.