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Abstract

We compare two genetic testing regulations, Disclosure Duty (DD) and Consent Law (CL), in an environment where individuals choose to take a genetic test or not. DD forces agents to reveal the test results to their insurers, resulting in a discrimination risk. CL allows agents to withhold that information, generating adverse selection. We complement our model with an experiment. We obtain that a larger fraction of agents test under CL than under DD, and that the proportion of individuals preferring CL to DD is non-monotone in the test cost when adverse selection is set endogenously at its steady state level.

JEL-Codes: C910, D820, I180.

Keywords: consent law, disclosure duty, personalized medicine, test take up rate, pooling health insurance contracts.

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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. The trade-off between adverse selection and discrimination risk has received a lot of attention recently, as exemplified by the Econometrica paper by Handel *et al.* (2015) on the health exchanges set up by the Affordable Care Act in the US.

Our objective in this paper 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 development of ever cheaper and more informative genetic tests is behind the development of personalized medicine. These tests allow individuals to obtain very detailed information on their genetic predisposition to several diseases, as well as on potential prevention strategies to decrease the probability of the disease occurring, and on the treatment to be followed if the disease occurs.[1]

Genetic testing affects the trade-off between adverse selection and discrimination risk in two ways. First, these tests may convey very 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 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.

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

[1] See Abrahams and Silver (2010) for a history of personalized medicine. See also Anaya *et al.* (2016).

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 for taking a genetic test.

In this paper, 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 prefer, and whether they would take a genetic test under each regulation. An experimental setting is ideal to understand behavior and preferences with respect to both regulations. 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. This is very unlikely because these regulations have been introduced quite recently in most countries, and have thus varied very little since their inception.

Our theoretical set-up is as follows. 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). Genetic tests are costly to individuals, because of their monetary cost but also because some agents may dislike knowing with precision their genetic background. Agents are then heterogeneous in their testing cost. After deciding to test or not, individuals buy health insurance on a competitive market.

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

[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. The Netherlands and Switzerland are two of the countries applying a Consent Law regime whereas Austria, Belgium, Denmark, France, Israel, Italy, Norway and USA (for health insurance contracts) apply a Strict Prohibition regime.

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

Solving the analytical model allows us to obtain three hypotheses that 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 cost (which, in our theoretical model, stands for both the financial and psychological cost of the genetic test). 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. Referring back to Handel *et al.* (2015), we find like them 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. As for adverse selection, we proceed in two stages. In the first stage, we assume that the level of adverse selection (used by insurers to compute their break-even premia) is exogenously given, and not affected by the test cost. This approach is reasonable in the short run for instance, when insurers take the composition of the pool as given. In a second stage, we use our experimental results to compute the equilibrium (steady state) amount of adverse selection as a function of the test cost, by looking at the proportion of agents who test (and who then claim to be uninformed if they receive bad news) under CL. We obtain that testing (and hence the adverse selection level) is quite insensitive to the test cost when the latter is either low or large, but very sensitive when it is intermediate. We then obtain that preferences for CL (as opposed to DD) are non monotone in the value of the test cost (see Figure 7).[4] Since test costs have been decreasing at a steady and impressive rate, from very high levels, for the last decade,[5] our results then predict that the political support for genetic regulations may become very unstable as the test cost keeps decreasing, especially when it becomes low enough that the testing decisions (and thus adverse selection under CL) become very sensitive to the test cost.

We now turn to the related literature. Barigozzi and Henriet (2011) and Peter *et al.* (2014) also compare DD and CL. 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, with insurers degrading the (coverage rate of the) contract offered to type L to prevent type H from mimicking them. 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 sepa-

[4] In other words, while CL may look more attractive to agents than DD (because it allows them to hide bad news), the resulting equilibrium amount of adverse selection in the pooling contract under CL may actually make this regulation less attractive than DD, in a way which is non monotone with the value of the test cost.

[5] See http://www.genome.gov/sequencingcosts . Accessed on March 3rd, 2017.

rating equilibria, but do not compare the properties of various regulations.[6] Also, to the best of our knowledge, our paper is the only one, with Hoy *et al.* (2003) and Crainich (2017) –who do not compare regulations – to assume that insurers offer a pooling contract under CL. We find this assumption to be much more in line with current practice than the separating contracts à la Rothschild and Stiglitz (1976) used by the rest of the literature. Finally, Schudy and Utikal (2012) 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.

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 design. Section 4 explains our experimental results when the amount of adverse selection under CL is set exogenously, while section 5 revisits these results when adverse selection is endogenous and set at its steady-state level. Section 6 recapitulates our main results.

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

[6] 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.

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.[7] 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.[8]

We denote by p_H the probability that a type H agent who exerts a prevention 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.[9] Agents differ according to K, allowing for different (unmodelled) attitudes towards (genetic)

[7] 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.

[8] Our results would no 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.

[9] 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 J. 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.

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 (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 $I_j = (1-p_j)d$.[10] All agents have the same income y and the same preferences over consumption, which are represented by a classical von Neumann Morgenstein utility function $v(.)$ (with $v'(.) > 0$ and $v''(.) < 0$).

An uninformed policyholder's expected utility is then

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

where the superscript 0 over U_{DD} stands for "no genetic testing".

[10] We also assume that the prevention effort is observable by the insurers, so that this effort is reflected into the premium paid. See Bardey and De Donder (2013) for more details, including a study of the case where the prevention effort is not observable.

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

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

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

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

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

$$U_{DD}^1=\lambda v(y-p_Hd-K-\phi)+(1-\lambda)\,v(y-p_Ld-K),$$

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,

$$\begin{aligned}\Psi_{DD} &= U_{DD}^1-U_{DD}^0 \qquad (1)\\ &= \lambda v(y-p_Hd-K-\phi)+(1-\lambda)\,v(y-p_Ld-K)-v(y-p_Ud-\phi),\end{aligned}$$

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 adopt the approach developed by Crainich (2017) in this context and assume that the insurers offer a pooling contract intended for all those who claim to be uninformed.[11]

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, f measures the intensity of the adverse selection at play, with more adverse selection translating into a lower f. The utility of an agent who does not test is then given by

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

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

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

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

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

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

[11] 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.

K such that $\Psi_{CL} = 0$, and below (resp., above) which agents (resp., do not) take the genetic test under Consent Law.

Assume for the moment that f is exogenous, and not influenced by K (this is the case in the short run if insurers consider the composition of their pool as fixed). Increasing exogenously 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 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^1_{CL} than U^0_{CL}, thus increasing the incentive to test.[12] Applying the implicit function theorem to (2), we obtain the following lemma.

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

We now lift the assumption that f is exogenous. As shown above, f determines the value of K_{CL}, which in turn determines who tests and thus the composition of the clientele of the pooling contract. The following proposition characterizes the equilibrium value of f.

Proposition 1 *There exists an equilibrium (or steady state) value of f, denoted by f^*, with*

$$f^* = \frac{1 - G(K_{CL}(f^*))}{1 - (1-\lambda)G(K_{CL}(f^*))}. \tag{3}$$

The numerator of the right hand side of (3) denotes the proportion of untested agents in the economy, while the denominator denotes the proportion of agents who buy contract U (*i.e.*, everyone except those who are tested L). Existence of a fixed point of this mapping is due to the continuity of the functions $G(.)$ and $K_{CL}(.)$.[13]

In the next section, we compare the two regulations for exogenous values of K and of f. We delay to section 5 the analysis of the case where f is set at its steady state equilibrium value.

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

[13] We assume uniqueness of f^* in the rest of the paper.

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

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

For individuals who 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 separating contract 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 CL degrades the contract offered in case the test is not taken, compared to the DD case (because of adverse selection).

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 2 *Individuals are better off under Consent Law if K is low enough that they take the test under both regulations ($K < K_{DD} < K_{CL}$) and under Disclosure Duty if K is large enough that they do not take the test under either regulation ($K > K_{CL} > K_{DD}$). For intermediate values of K ($K_{CL} > K > K_{DD}$), they take the test only under Consent Law, and the 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

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

which is increasing in K and decreasing in f. ■

Proposition 2 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 $f = 0$ (panel a), $0 < f < 1$ (panel b) and $f = 1$ (panel c). 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.

Insert Figure 2 around here

Solving our model reveals that the comparison of *ex ante* 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.

3 Experimental Design

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: $U^1_{CL} \gtrless U^0_{CL}$, $U^1_{DD} \gtrless U^0_{DD}$ 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^1_{CL} and U^0_{CL})?

If the subject prefers not to test, no further questioning is required for this pair (K, f). If the subject prefers to test ($U^1_{CL} > U^0_{CL}$), 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^1_{CL} and U^0_{DD})?

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

Proposition 3 *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 regulations and between regulations of the subjects for all pairs (K, f) studied.*

Proof. If the answer to Q1 is that $U^0_{CL} > U^1_{CL}$, then using Lemma 2 allows us to infer the full ranking of utility levels of the subject: $U^0_{DD} > U^0_{CL} > U^1_{CL} > U^1_{DD}$.
If the answer to Q1 is that $U^0_{CL} < U^1_{CL}$, then we proceed to Q2. If the answer to Q2 is that $U^0_{DD} > U^1_{CL}$, we know from Q1 and Q2 that $U^0_{DD} > U^1_{CL} > U^0_{CL}$ and from Q2 and Lemma 2 that $U^0_{DD} > U^1_{CL} > U^1_{DD}$. 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^0_{CL} and U^1_{DD}.
If the answer to Q2 is that $U^0_{DD} < U^1_{CL}$, we know from Q2 and Lemma 2 that $U^1_{CL} > U^0_{DD} > U^0_{CL}$ and that $U^1_{CL} > U^1_{DD}$. 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^0_{DD} with U^1_{DD}. Observe that $U^1_{DD} = U^1_{CL}$ when $f = 0$. We then know how the subject ranks

U^1_{DD} and U^1_{CL} either from his answer to Q1 with $f = 0$ (when $U^0_{CL} > U^1_{CL}$ with $f = 0$ so that $U^0_{DD} > U^1_{DD}$) or to Q2 if $U^0_{CL} < U^1_{CL}$ with $f = 0$. ■

The proof of Proposition 3 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 3 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.[14]

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

3.2 Task implementation

We have opted for a neutrally-framed (rather than for a health-framed) experiment for two reasons. First, eliciting the subjects' preferences over lotteries is the most direct way to translate our model into an experiment, as shown by Figure 1. Second, this allows us to control directly for the heterogeneity in K which, in our theoretical model, stands for both the financial cost of the genetic test and for the (monetary equivalent of the) psychological cost or benefit of knowing one's own genetic background.

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.[15] Note that the ordering of the tasks differed between participants. More precisely, for

[14] 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 $U^0_{DD} > U^1_{CL} > U^0_{CL}$ and that $U^0_{DD} > U^1_{DD}$. We do not need the full ranking to be able to assess the preferences for testing within each regulation, and the most-preferred regulation.

[15] 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.

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).

Each task comprised two subtasks, labeled A for Q1 and B for Q2. 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 3 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 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.

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).

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

In all 20 tasks, the payoffs offered were computed from the following parameter values: $y = 36$, $d = 25.2$, $\phi = 3.6$, $p_H = 5/9$, $p_L = 1/9$ 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).

shown in advance all the tasks before any decision was made. We randomized across participants both the task number (1 to 21) and the subtask (A or B, for the first 20 tasks) which would determine their payment.[16] 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).[17]

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 1.47). Sixty percent of them were male. The average earnings for the activity were 23 euros. The activity lasted 45-50 minutes.

3.3 Experimental hypotheses

Our main objective in this paper 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 are informed by our analytical results

[16] 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). Subjects whose letter was printed in the same color were then paid according to the same subtask (A or B), but for a different combination of (K, f).

[17] With this particular feature we manage to block mechanisms such as anticipated regret. It also provides "ecological validity" (Morton and Williams, 2010) to the informational setting of the game.

(Lemmas 1 to 3 and Proposition 2 above).[18]

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.*

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 modifies the impact of adverse selection (as measured by 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 2:

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

[18] 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.

Section 4 tests these three hypotheses using all twenty exogenous pairs $(K,\ f)$ studied in the experiment. Recall from section 2.2.2 that, under CL, f is affected by the testing decisions of agents which are themselves influenced by the value of K. This means that most exogenous pairs (K, f) can be considered as "out of equilibrium" under CL, in the sense that the testing decisions made with (K, f) do not generate a value of f which is identical to the one on which individuals base these testing decision. Recall also that Proposition 1 has established the existence of an equilibrium (or steady state) value of f. In section 5, we then test whether Hypotheses 1 and 3 hold when the value of f is obtained endogenously from the testing decisions of individuals.

4 Individual choices when the adverse selection level is exogenous

We start by studying in the first subsection whether subjects have understood the tasks at hand by focusing on the inconsistencies in their choices across tasks and subtasks, for exogenous values of K and f. We obtain a very low number of inconsistent choices, so that we are confident that the subjects have well understood the protocol.[19] In the second subsection, we study the testing decisions of the subjects, while section 4.3 analyzes their preferences over regulations.

4.1 Inconsistent choices

There are two ways in which we can detect inconsistent choices made by subjects: (i) within tasks, by comparing answers to subtask A (corresponding to question Q1 in section 3.1) and B (question Q2) for given (K, f), and (ii) between tasks, by comparing answers given to subtasks B for given K but varying f. We cover these two types of inconsistencies in sequence.

As explained in section 3.1, for any given $(K,\ f)$ with $f < 1$, agents who prefer the sure payoff in subtask A (so that $U^0_{CL} > U^1_{CL}$) should also prefer the sure payoff in subtask B (so that $U^0_{DD} > U^1_{CL}$) since both subtasks differ only in the sure payoff amount, which is larger in subtask B than in subtask A

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

(with $U^0_{DD} > U^0_{CL}$). We have chosen to ask subjects to answer subtask B even when they prefer the sure payoff in subtask A in order to detect inconsistent choices. We take the unit of observation to be the subject for any given K, so that we have a total of 4 (values of K) times 67 (subjects)=268 observations.[20] Table 1 shows that inconsistencies within tasks only happen 3 times out of 268 observations, corresponding to 1.1% of the possible occurrences.[21] Mann-Whitney tests reveal that differences between sessions, cases where we decreased or increased f in any given answer sheet, and where we decreased or increased K in successive sheets are negligible (p-values are 0.2675, 0.315 and 0.188, respectively).[22]

Table 1: Inconsistencies in individual choices

Type	Frequency	Percentage
Within tasks	3/268	1.1%
Across tasks	9/268	3.4%

We now move to the second type of inconsistencies. Observe that, for any given value of K and focusing on subtask B, moving down the list of tasks in any question sheet in the experiment (see Appendix A) when f increases (respectively, decreases) with the task number improves (respectively, deteriorates) the worst payoff among the two offered in the lottery. At the same time, this move keeps the other payoffs in the task unaffected. Like for the first type of inconsistencies, we take the unit of observation to be the subject for any value of K. As Table 1 shows, we obtain 9 inconsistencies across tasks out of a total of 268 observations, *i.e.* 3.4% of cases. Mann-Whitney tests reveal no statistical differences between sessions (p-value of 0.769) or between protocols with an increasing or decreasing order of K (p-value 0.119). However, inconsistencies across tasks are more likely to appear when f decreases

[20] In other words, one unit of observation corresponds to one experiment sheet (see Appendix A), and so to 5 tasks (one for each of the 5 values of f we consider).

[21] 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.

[22] We also obtain 8 cases out of the 4 (values of K) times 67 (respondents)=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.

from one task to the next within the same sheet (p-value 0.012).

In the light of Table 1, we feel confident that subjects have well understood the experiment protocol, and we move to the 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 $K_{CL} > 0$, whatever the value of f. 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). 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

We present in Appendix B the result of a logit regression where we study the determinants of the probability of testing under CL. We are especially interested in the impact of adverse selection f and of its interaction with subjects' risk aversion. Recall that we elicit subjects' risk aversion by asking them to choose among six lotteries that are increasing in both expected value

and variance. We then do not have a continuum measure of risk aversion. We have chosen to contrast the test choices of the extreme groups in terms of risk aversion. On the left panel of Table B1, we keep as sample the individuals who have chosen either the two most risky lotteries (43% of the respondents), or the two least risky lotteries (27% of respondents). On the right panel, we concentrate on the subjects who have chosen either the most risky lottery (16% of the subjects) or the least risky one (18% of the subjects). In both cases, we use a dummy variable taking the value one for the most risk averse agents, and zero for the least risk averse ones.

We see that the coefficient for adverse selection f is negative and significant in both columns, confirming that the test take-up rate increases with the adverse selection intensity (Hypothesis 2 (a)). Also, the coefficient for the interaction of adverse selection f and risk aversion is positive and significant in both columns. The interaction term has the opposite sign to the coefficient for f, meaning that the negative effect of adverse selection is less pronounced for subjects with a more concave utility. The latter result is supportive, although not definitive evidence, of Hypothesis 2 (b).[23]

4.3 Preferences over regulations

We now move to the preferences over regulations. The left panel of Figure 4 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 no 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 recall that y is the endowment of the subject when the experiment starts, the proportion

[23] We do not check whether Hypothesis 2 (b) holds for large values of K only, as this would drastically reduce the estimation sample. Confidence intervals would be very imprecise, a problem particularly acute in our setting because for large values of K we have very little variation in the testing decisions.

of subjects preferring CL increases when the intensity of adverse selection decreases (*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 2 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 for 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 4 around here

We complement this analysis by estimating, using a bivariate probit regression, the binary testing decisions in subtask A (corresponding to the answer to Q1) and subtask B/Q2. Using a bivariate probit regression allows us to model the two binary choices as dependent from each other. Choosing to test under Q1 (*i.e.*, the lottery) corresponds to choosing to test under CL, while choosing to test under Q2 corresponds to preferring CL to DD (as explained in Proposition 3). We describe in Appendix C how we proceed, and we report the results from this regression in Table 2. More precisely, the reported coefficients correspond to changes in the random utility model on which the bivariate probit model described in Appendix C is based. Our objective is to try and predict agents' choices based on the values of f and K for different specifications. The sparsest specification is model (4) to which we add the ordering of f and K in the individual questionnaires to obtain model (1), and individual characteristics such as gender, risk aversion and ambiguity aversion to obtain models (2) and then (3).

Table 2 provides additional evidence supporting Hypotheses 1, 2 (a) and 3. The negative coefficients of K in both the Q1 and Q2 choices in model (4) indicate that the higher the test cost, the less likely it is that the subjects test

under CL (in accordance with Hypothesis 1 (b)), and the more likely they are to prefer DD over CL, validating Hypothesis 3. We also observe that the probability of testing within CL decreases with f (confirming Hypothesis 2 (a)), and that the probability of preferring CL over DD increases with f. The coefficients are highly significant, and they are robust to the introduction of individual characteristics (risk aversion, aversion to ambiguity and gender), of the ordering of f and K in the experiment's sheets, and of individual fixed effects (see models 1-3 in Table 2).

The right panel of Figure 4 displays the predicted preferences for CL over DD, corresponding to the marginal effects of the probit regression whose results are reported in model (1) of Table 2.[24] The comparison of the two panels of Figure 4 shows that our probit regression makes a good job at fitting the experimental data.

Models (1) to (3) in Table 2 also allow us to check the presence of order effects. We obtain, on the one hand, that both within- and between-regulations choices are not affected by whether tasks are presented in increasing or decreasing order of f. On the other hand, presenting tasks by decreasing value of K increases both the likelihood that a subject chooses to test within CL (test in Q1) and that he prefers CL over DD (test in Q2). The order effects associated to the cost of the test are particularly striking since, in our particular setting, K is modified only every five tasks (*i.e.*, when moving to the next questions sheet in the experiment, see Appendix A). One potential explanation for these order effects is that the reference point in a given task is embedded in past decisions, and that the reference point depends on the early value of K. A decreasing cost of the test implies a relatively high value of K in the initial tasks for Q1 and Q2. Hence, the most likely reference point was not testing.[25] This may be policy relevant since the cost of genetic testing has been decreasing by several orders of magnitude over the last decade.

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

[24] We concentrate on model (1), since it is an improvement over model (4) (since coefficients corresponding to f^2, K^2, and decreasing K are significative), while models (2) and (3) do not improve upon model (1), since the added coefficients are non significative (with one exception for Model 3).

[25] Future research can formalize this intuition through a model of reference-dependent preferences (Tversky and Kahneman, 1991; Kőszegi and Rabin, 2006).

Table 2: Coefficients from the bivariate probit estimation. For each model the reported coefficients correspond to changes in the utility of testing in Q1 and Q2, respectively. The ρ coefficient corresponds to the covariance of the error terms of both testing decisions, as captured in **Q1** and **Q2**.

	(1)		(2)		(3)		(4)	
VARIABLES	Q1: Test	Q2: Test	Q1: Test	Q2: Test	Q1: Test	Q2: Test	Q1: Test	Q2: Test
f	-2.862***	2.215***	-1.559***	2.466***	-1.578***	2.467***	-2.008***	3.433***
	(0.453)	(0.593)	(0.181)	(0.260)	(0.175)	(0.257)	(0.166)	(0.249)
K	-19.55***	-34.10***	-19.84***	-20.29***	-14.84	-5.889	-25.40***	-27.49***
	(6.523)	(5.997)	(1.926)	(2.055)	(10.69)	(8.731)	(1.227)	(1.714)
f squared	1.317***	0.411						
	(0.366)	(0.487)						
K squared	-1.982	55.16**						
	(19.09)	(22.04)						
Decreasing K	0.422**	0.559***	0.399**	0.523***	0.407**	0.521***		
	(0.180)	(0.157)	(0.192)	(0.171)	(0.183)	(0.172)		
Decreasing f	-0.111	0.0198	-0.0904	-0.00757	-0.0929	-0.000796		
	(0.164)	(0.167)	(0.174)	(0.170)	(0.172)	(0.170)		
Risk aversion			-0.0126	-0.0260	0.229	0.0178		
			(0.0430)	(0.0534)	(0.199)	(0.122)		
Ambiguity Aversion Score			-0.00465	0.00161	-0.00528	0.0257		
			(0.0120)	(0.0113)	(0.0349)	(0.0177)		
Male			0.0337	0.192	0.0345	0.197		
			(0.164)	(0.181)	(0.158)	(0.183)		
$K\times$ Lottery					-1.669	-0.282		
					(1.295)	(1.173)		
$K\times$ Ambiguity Aversion Score					-0.00110	-0.252*		
					(0.192)	(0.135)		
Constant	3.936***	0.420	4.026***	-0.385	3.355*	-1.827	5.187***	1.102**
	(0.508)	(0.327)	(0.641)	(0.750)	(1.850)	(1.122)	(0.480)	(0.435)
ρ	0.784***		0.758***		0.758***		0.931***	
	(0.078)		(0.079)		(0.077)		(0.052)	
Observations	1,340		1,260		1,260		1,340	
Session fixed effects	Yes		Yes		Yes		No	
Player fixed effects	No		No		No		Yes	

Standard errors clustered at the subject's level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The risk aversion variable refers to the choice among six lotteries with increasing expected value and variance. The ambiguity aversion score was computed using the Budner's scale (1962).

light on the subjects' preferences. In Figure 5, we report the probability of testing with 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 (1) 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 5 around here

Figure 5 allows us to perform an additional exercise to determine the sensitivity of decisions to f holding K constant. Take a row and analyze its color gradient. The maximum sensitivity of the decision to f is different in each panel. When choosing between regulations (right panel), the adverse selection becomes more important for low to intermediate levels of the test cost (such as when $K = y/18$, with a change in probability of 86 percentage points when f goes from 0 to 1). Within CL (left panel), subjects are more sensitive to adverse selection for intermediate levels of the test cost (such as when $K = y/6$, with a change in probability of 78 percentage points when f goes from 0 to 1).

5 Individual choices when the adverse selection level is endogenously determined

The previous section has presented results for exogenous values of pairs (K, f). This can be interpreted as a short run analysis, where insurers consider the composition of their pooling contract under CL as fixed at the level f, and not affected by the test cost K. Most of these pairs correspond to "out of equilibrium" allocations, in the following sense. Individuals base their decision to test or not under CL on the values of K and f, since the latter determines the premium charged for the pooling contract. At the same time, the proportion of tested agents determines the composition of the pool –*i.e.*, the value of f. Proposition 1 has shown that there exists an equilibrium, or steady state, value of f, denoted by f^*, solving this fixed point problem. In

other words, when subjects are proposed the pair (K, f^*), the proportion of agents who decide to test under CL (when the premium charged for the pooling contract is based on f^*) results endogenously in the fraction f^* of uninformed (*i.e.*, untested) agents among those who buy the pooling contract. This steady state value of f is given by equation (3).

Note that Proposition 1 assumes that there exists a distribution of values of K, while we perform the experiment by fixing the same monetary value of K for all subjects, with subjects differing in their unobserved non-monetary psychological cost of knowing their type. So, with a slight abuse of notation, we denote from now on the steady state value of f as $f^*(K)$, since f^* depends on the value we have attributed to K in the questionnaires.

We compute the function $f^*(K)$ by using the marginal effects of the bivariate probit regression (left columns of Model 1 in Table 2). We vary the values of K from 1.25 to 25 percent of the endowment y, with increments of 0.25% for $K \in [0.125y, 0.15y]$ and of 1.25% outside this range. For each value of K considered, we compute the value of f^* with a tolerance of 0.5%. More precisely, we start from an exogenous value of f, which together with the value of K gives us, thanks to the biprobit regression, the proportion of subjects who test under CL. This proportion is then used to compute the proportion of untested agents in the pooling contract under CL. We then iterate again this procedure, starting with the computed value of f, and we stop when two subsequent values of f differ by at most 0.5%.

We report in Figure 6 the value of $f^*(K)$. We first observe that $f^*(K)$ is increasing in K. This is intuitive, for the following reason. An increase in K discourages testing under CL, leading to more truly uninformed individuals. This in turn means that a larger fraction of the agents buying the pooling contract under CL are not informed about their type, so that there is less adverse selection in the pool and a larger value of f at the steady state.

Insert Figure 6 around here

Figure 6 shows that the sensitivity of f^* to K varies a lot with K. More precisely, f^* is not very sensitive to K when K is either quite low (less than 10% of income) or high (more than 15% of income). This is due to the fact that the testing decision under CL is not very sensitive to the value of the test cost when the latter is either low (since most people do test anyway) or high (since most people do not test). For intermediate values of K (between

10% and 15% of endowment y), the testing decision is very sensitive to the test cost, resulting in large variations of the steady state value of f.

In terms of testable predictions one can draw from this analysis, observe that the genetic testing costs are indeed still large for the moment (and that the take-up rate of genetic tests is very low), but are predicted to decrease significantly within the next years (see footnote 5). This means that the pooling contracts observed in the health insurance market currently exhibit little adverse selection, but that this may change very quickly as K decreases below a threshold.

Figure 7 reports both the predicted fraction of population choosing to test under CL, and the predicted fraction preferring CL to DD, as a function of K, when f is set at its steady state value depicted in Figure 6. Looking first at the preferences for testing under CL, we obtain that Hypothesis 1 (a) and (b) still hold when measured at the steady state value of f. As for Hypothesis 1 (a), we have already seen in section 4.2 that take-up rates are higher under CL than under DD for any value of K and any value of f, so that this remains true when measured at $(K, f^*(K))$ for any K. As for Hypothesis 1 (b), Figure 7 shows that the test take-up rate under CL remains decreasing in K when f is measured at its steady-state $f^*(K)$.

Insert Figure 7 around here

We then move to the preferences between regulations as a function of the test cost K when f is computed at its steady state level. Recall from Proposition 2 and Figure 2 that choosing to test under CL is a necessary (but not sufficient) condition to prefer CL to DD. The predicted fraction of agents preferring CL to DD is then lower than the predicted fraction of agents choosing to test under CL, in Figure 7.[26] When K is either low or high, varying the test cost K does not affect much the testing decisions under CL. Decreasing K (the empirically relevant case) then increases more the utility under CL than under DD (because more agents pay the testing cost under the former regulation than under the latter), so that more people prefer CL

[26] When $f > 0$, all agents who test under both CL and DD strictly prefer CL. When K is low enough that everyone tests under CL, so that $f = 0$, all agents who test under both CL and DD are actually indifferent between the two regulations (see left panel of Figure 2). This explains why the fraction predicted to (strictly) prefer CL to DD in Figure 7 starts at the lowest value of K consistent with $f^*(K) > 0$.

to DD. This is what we observe on Figure 7 when K is either lower than 10% of endowment (but large enough that $f^* > 0$, see footnote 26), or larger than 15%. For intermediate values of K, the testing decision under CL is very sensitive to K, and a lower value of K translates into a much smaller value of f^*, which is detrimental to agents buying the pooling contract under CL, since more adverse selection increases the premium charged for the pooling contract. When this effect is very important, as for the intermediate values of K, the CL regulation becomes less attractive when K decreases, and we observe from Figure 7 that the proportion of people preferring CL to DD actually decreases when K decreases.

So, we obtain that the proportion of subjects preferring CL to DD is non monotone with test cost K when f adjusts to its steady-state level: mimicking the current situation and decreasing the value of the test cost K from a large starting point, this proportion first increases (since f^* is kept nearly constant), then decreases (as f^* becomes very sensitive to K) and finally increases again (as f^* remains roughly constant). When K is low enough that everyone tests under CL (i.e., $f^*(K) = 0$), then no one strictly prefers CL to DD. As can be seen from Figure 7, a strict minority of subjects is predicted to prefer CL to DD, whatever the value of K, when f is set at its steady-state.

6 Conclusion

Our main results from the experiment run as follows. First, 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. Note that these results hold for any exogenous amount of adverse selection under CL, as well as when the adverse selection level is measured at its steady state. 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 separating 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), we obtain contrasted results whether we consider the amount of adverse selection under CL as exogenous (for instance, in the short term) or endogenous. When the adverse selection level is exogenously set, the support for CL over DD increases when the genetic test cost decreases (as is currently the case). 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 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.

This reasoning holds for any exogenous adverse selection level, for instance in the short term when insurers cannot adapt their contracts to the proportion of agents falsely claiming to be uninformed. Results become more intricate when the adverse selection level is set at its steady state level (*i.e.*, when it is obtained from the testing decisions under CL). When the test cost is either low or high, the decision whether to test under CL or not is quite insensitive to variations in the value of this test cost, so that the adverse selection level barely changes, and the analysis reported above still holds: a smaller test cost increases the support for CL. As for intermediate values of the test cost, many more people do test under CL when the cost decreases, which increases the amount of adverse selection and thus the premium in the pooling contract offered under CL, and results in a sharp decrease in the fraction of agents preferring CL to DD.

Personalized medicine is currently in its infancy, with genetic test costs still large currently but falling at an impressive rate. As these costs decrease in the future, our analysis predicts that we could observe a sudden increase in the amount of adverse selection (and in the premia charged) under CL, with a concurrent decrease in the political support for CL. At the same time, discrimination risk seems to be very salient, with few agents testing under DD even for low values of the genetic test costs.

To conclude, observe that we obtain a minority support for CL, whatever the value of the test cost K, and that an equilibrium with DD and very little testing seems pretty bleak from a normative perspective, as the advent of personalized medicine would not be translated into better informed prevention decisions, since very few people would actually perform the necessary

genetic tests.

References

[1] Abrahams, E. and M. Silver. 2010. The History of Personalized Medicine. In E. Gordon and S. Koslow (Eds.), Integrative Neuroscience and Personalized Medicine (3-16). New York, NY: Oxford University Press.

[2] Allard, M., JP Cresta and JC Rochet. 1997. "Pooling and separating equilibria in insurance markets with adverse selection and distribution costs." *The Geneva Papers on Risk and Insurance Theory*, 22(2), 103-120.

[3] Anaya, J. M., Duarte-Rey, C., Sarmiento-Monroy, J. C., Bardey, D., Castiblanco, J., & Rojas-Villarraga, A. 2016. "Personalized medicine. Closing the gap between knowledge and clinical practice." *Autoimmunity Reviews*, 15(8), 833-842.

[4] Bardey D. and Ph. De Donder, "Genetic Testing with Primary Prevention and Moral Hazard", *Journal of Health Economics*, 2013, 32 (5), 768-779 & 1007-1012.

[5] Barigozzi F. and D. Henriet, 2011, "Genetic information: comparing alternative regulatory approaches when prevention matters", *Journal of Public Economic Theory*, 13(1), p. 23-46.

[6] Barigozzi F. and R. Levaggi, 2010. "Emotional decision-makers and anomalous attitudes towards information," *Journal of Risk and Uncertainty*, vol. 40(3), pages 255-280

[7] Budner S., 1962, "Intolerance for ambiguity as a personal variable", *Journal of Personality*, vol. 30: 29-50.

[8] Caplin A, and J. Leahy 2001. "Psychological Expected Utility Theory and Anticipatory Feelings", *Quarterly Journal of Economics*, 55-80.

[9] Cox, J. C., Sadiraj, V., and Schmidt, U., 2015. "Paradoxes and mechanisms for choice under risk." *Experimental Economics*, 18(2), p. 215-250.

[10] Crainich, D. 2017. "Self-Insurance With Genetic Testing Tools", *Journal of Risk and Insurance*, 84(1), 73-94.

[11] Eckel C. and P. Grossman, 2008, "Forecasting risk attitudes: an experimental study using actual and forecast gamble choices", *Journal of Economic Behavior and Organization*, vol. 68: 1-17.

[12] Epstein, L., 1999. "A Definition of Uncertainty Aversion". *The Review of Economic Studies,* 66 (3): 579.

[13] Handel B., I Hendel and M. Whinston, 2015. "Equilibria in Health Exchanges: Adverse Selection versus Reclassification Risk", *Econometrica*, 83(4), p.1261-1313.

[14] Hirshleifer J., 1971, "The Private and Social Value of Information and the Reward to Incentive Activity", *The American Economic Review*, 61, p. 561-74.

[15] Hoel M. and Iversen T, Nilssen T. and Vislie J., 2006, "Genetic testing in competitive insurance markets with repulsion from chance: A welfare analysis", *Journal of Health Economics*, 25, p. 847-860.

[16] Hoy M. and Orsi F, Eisinger F. and Moatti JP, 2003. "The Impact of Genetic Testing on Healthcare Insurance," *The Geneva Papers on Risk and Insurance - Issues and Practice*, 28(2), p. 203-221.

[17] Hoy M. R. Peter and A. Richter, 2014. "Take-up for genetic tests and ambiguity," *Journal of Risk and Uncertainty*, 48 (2), p. 111-133

[18] Kőszegi, B. and Rabin M., 2006. "A model of reference-dependent preferences.", *The Quarterly Journal of Economics*, 121 (4), p. 1133-1165.

[19] Morton, R. B. and Williams, K. C., 2010. "Experimental political science and the study of causality: From nature to the lab". *Cambridge University Press.*

[20] Newhouse J. 1996. "Reimbursing health plans and health providers: efficiency in production versus selection." Journal of economic literature 34(3) : 1236-1263.

[21] Otlowski, M., S. Taylor, and Y. Bombard. 2012. "Genetic Discrimination: International Perspectives" *Annual Review of Genomics and Human Genetics* 13: 433–454.

[22] Peter, R., Richter A. and P. Thilste. 2014. Endogenous Information, Adverse Selection, and Prevention: Implications for Genetic Testing Policy, Working Paper.

[23] Posey, L. and Yavas, A. 2007. "Screening equilibria in experimental markets"? Geneva Risk Insur Rev, 32: 147-167.

[24] Rothschild, M., and Stiglitz, J. E., 1976. "Equilibrium in competitive insurance markets: An essay on the economics of imperfect information." *The Quarterly Journal of Economics*, 90 (4): 629-649.

[25] Schudy S. and V. Utikal, 2012. "Does imperfect data privacy stop people from collecting personal health data?", Research Paper Series Thurgau Institute of Economics and Department of Economics at the University of Konstanz, 76.

[26] Tversky, A. and Kahneman D., 1991, "Loss aversion in riskless choice: A reference-dependent model.", *The Quarterly Journal of Economics*, 106 (5), p. 1039-1061.

[27] Wilson, C., 1977, "A model of insurance markets with incomplete information", *Journal of Economic Theory*, 16(2), p. 167-207.

Appendix A: Experimental Protocol

IFIK

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:

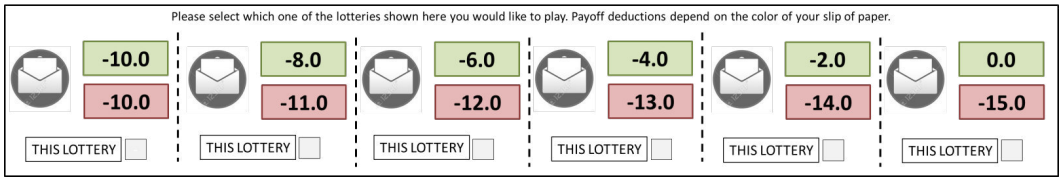
Please indicate, **for both subtasks A and B**, whether you prefer to OPEN the envelope (by putting an "X" next to OPEN) or NOT TO OPEN the envelope (by putting an "X" next to NOT TO OPEN).

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:



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.

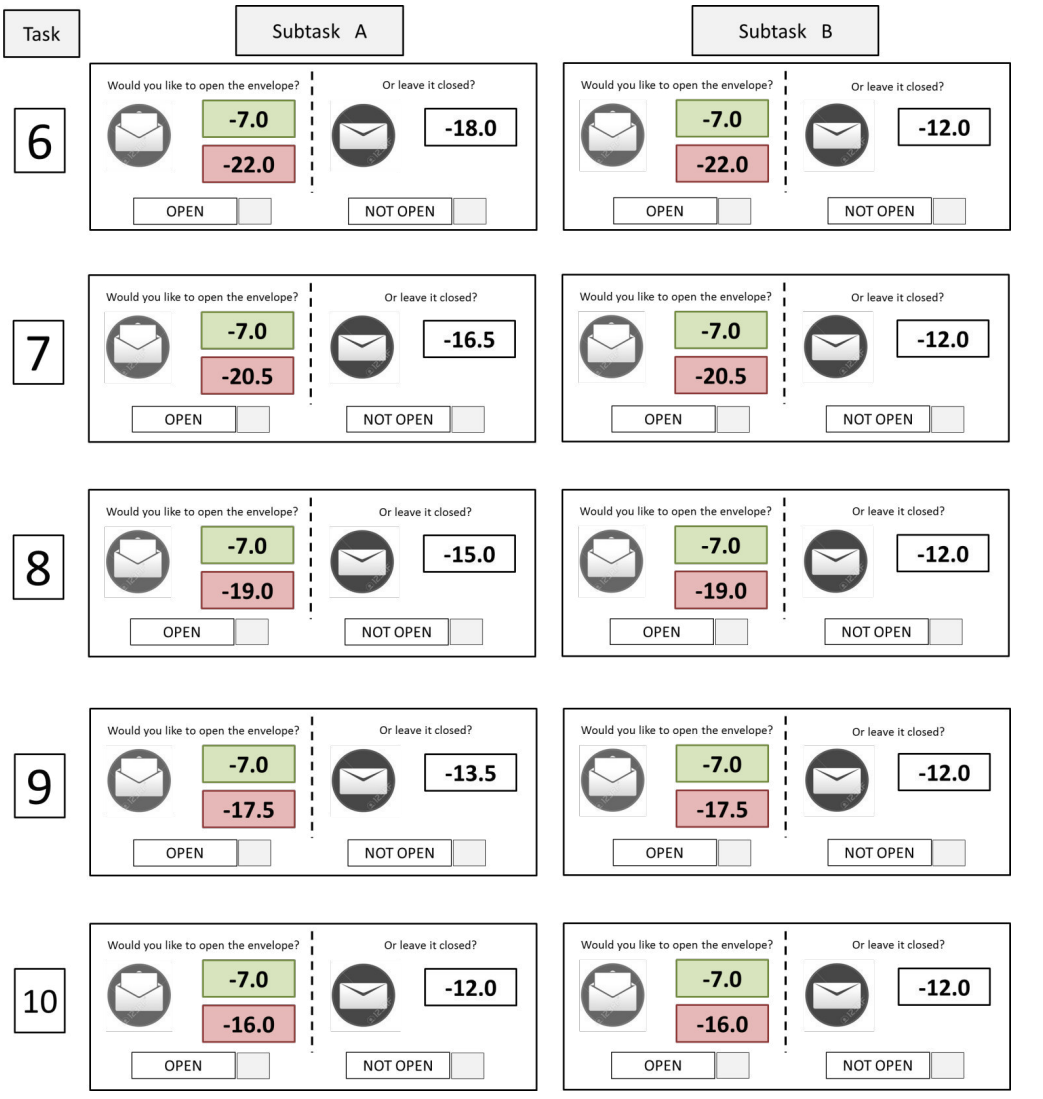
Thank you for your participation!

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

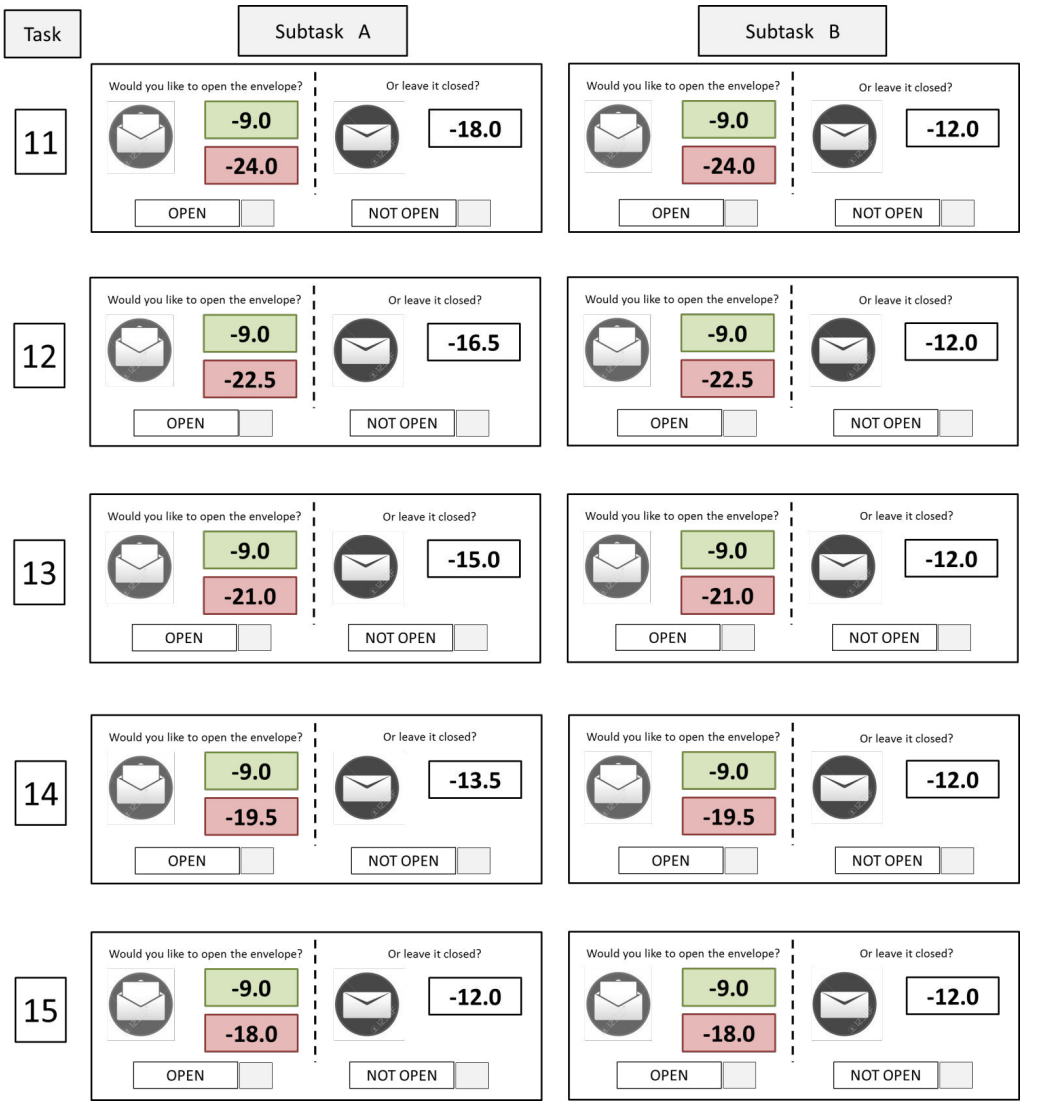
IFIK


Task
Subtask A
Subtask B
1
Would you like to open the envelope?
-5.0
-20.0
OPEN
Or leave it closed?
-18.0
NOT OPEN
Would you like to open the envelope?
-5.0
-20.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
2
Would you like to open the envelope?
-5.0
-18.5
OPEN
Or leave it closed?
-16.5
NOT OPEN
Would you like to open the envelope?
-5.0
-18.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
3
Would you like to open the envelope?
-5.0
-17.0
OPEN
Or leave it closed?
-15.0
NOT OPEN
Would you like to open the envelope?
-5.0
-17.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
4
Would you like to open the envelope?
-5.0
-15.5
OPEN
Or leave it closed?
-13.5
NOT OPEN
Would you like to open the envelope?
-5.0
-15.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
5
Would you like to open the envelope?
-5.0
-14.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
Would you like to open the envelope?
-5.0
-14.0
OPEN
Or leave it closed?
-12.0
NOT OPEN

IFIK


Task
Subtask A
Subtask B
6
Would you like to open the envelope?
-7.0
-22.0
OPEN
Or leave it closed?
-18.0
NOT OPEN
Would you like to open the envelope?
-7.0
-22.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
7
Would you like to open the envelope?
-7.0
-20.5
OPEN
Or leave it closed?
-16.5
NOT OPEN
Would you like to open the envelope?
-7.0
-20.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
8
Would you like to open the envelope?
-7.0
-19.0
OPEN
Or leave it closed?
-15.0
NOT OPEN
Would you like to open the envelope?
-7.0
-19.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
9
Would you like to open the envelope?
-7.0
-17.5
OPEN
Or leave it closed?
-13.5
NOT OPEN
Would you like to open the envelope?
-7.0
-17.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
10
Would you like to open the envelope?
-7.0
-16.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
Would you like to open the envelope?
-7.0
-16.0
OPEN
Or leave it closed?
-12.0
NOT OPEN

IFIK


Task
Subtask A
Subtask B
11
Would you like to open the envelope?
-9.0
-24.0
OPEN
Or leave it closed?
-18.0
NOT OPEN
Would you like to open the envelope?
-9.0
-24.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
12
Would you like to open the envelope?
-9.0
-22.5
OPEN
Or leave it closed?
-16.5
NOT OPEN
Would you like to open the envelope?
-9.0
-22.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
13
Would you like to open the envelope?
-9.0
-21.0
OPEN
Or leave it closed?
-15.0
NOT OPEN
Would you like to open the envelope?
-9.0
-21.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
14
Would you like to open the envelope?
-9.0
-19.5
OPEN
Or leave it closed?
-13.5
NOT OPEN
Would you like to open the envelope?
-9.0
-19.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
15
Would you like to open the envelope?
-9.0
-18.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
Would you like to open the envelope?
-9.0
-18.0
OPEN
Or leave it closed?
-12.0
NOT OPEN

IFIK


Task
Subtask A
Subtask B
16
Would you like to open the envelope?
-11.0
-26.0
OPEN
Or leave it closed?
-18.0
NOT OPEN
Would you like to open the envelope?
-11.0
-26.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
17
Would you like to open the envelope?
-11.0
-24.5
OPEN
Or leave it closed?
-16.5
NOT OPEN
Would you like to open the envelope?
-11.0
-24.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
18
Would you like to open the envelope?
-11.0
-23.0
OPEN
Or leave it closed?
-15.0
NOT OPEN
Would you like to open the envelope?
-11.0
-23.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
19
Would you like to open the envelope?
-11.0
-21.5
OPEN
Or leave it closed?
-13.5
NOT OPEN
Would you like to open the envelope?
-11.0
-21.5
OPEN
Or leave it closed?
-12.0
NOT OPEN
20
Would you like to open the envelope?
-11.0
-20.0
OPEN
Or leave it closed?
-12.0
NOT OPEN
Would you like to open the envelope?
-11.0
-20.0
OPEN
Or leave it closed?
-12.0
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
THIS LOTTERY
-18.0
-26.5
THIS LOTTERY
-12.5
-29.0
THIS LOTTERY
-7.0
-32.0
THIS LOTTERY
-1.5
-34.5
THIS LOTTERY
0.0
-36.0
THIS LOTTERY

Appendix B: The logit regression describing test take-up rates under CL

Table B.1: Coefficients from the logit estimation of the test take-up under CL

Dependent variable:	(1)	(2)
Probability of testing in Q1	Risk averse Top 43%	Risk averse Top 16%
f	-8.095***	-8.466***
	(1.484)	(1.847)
Risk averse	-1.805	-4.946**
	(2.551)	(2.369)
f × Risk averse	4.687**	5.714**
	(1.844)	(2.290)
K	-25.22	-40.35
	(23.27)	(24.71)
K × Risk averse	-18.06	10.59
	(30.14)	(31.14)
Constant	8.096***	8.685***
	(2.092)	(2.072)
Observations	1,000	460
Session Fixed Effects × Top averse tertile	Yes	Yes

Controls included: quadratic polynomial for f and K, their interactions with Risk Averse. Decreasing f and K and their interactions with Risk Averse.

Clustered standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

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

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

where $\boldsymbol{X}$ is the set of covariates reported in Table 1. The error terms from the random utility equations, ϵ_1 and ϵ_2, are assumed to be jointly normally distributed. That is,

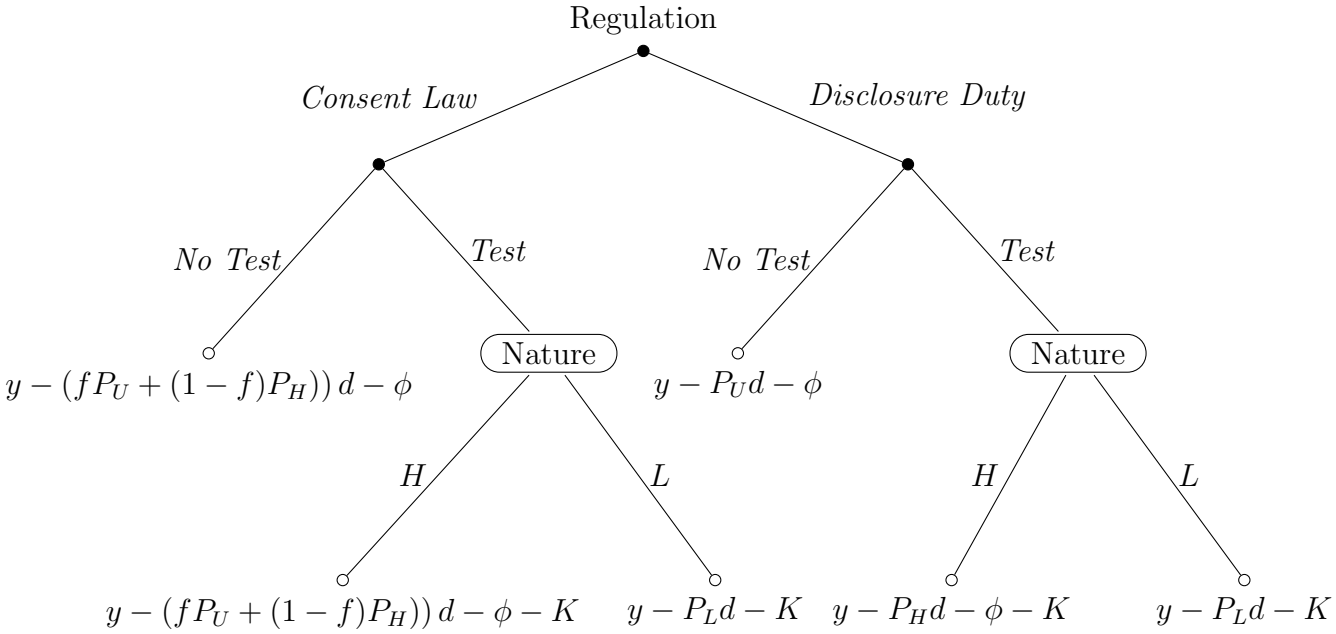
$$\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right].$$

Intuitively, the testing decisions in Q1 and Q2 are expected to be positively correlated (*i.e.*, $\rho > 0$) given the contingent character of our analysis. We show in section 3.1 that choosing not to test in Q1 implies that is rational not to test in Q2 either (because the sure payoff associated to not testing is higher in Q1 than in Q2, while both questions offer the same lottery). Alternatively, this also means that, for subjects testing in Q2 it is rational that they 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).

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 are shown in Table 2. An inspection of the two panels in Figure 4 shows that the observed and predicted behavior are qualitatively similar. However, the predicted preferences depict a smaller gradient for f when $K = y/18$ and $K = y/9$.

Figures

Figure 1: Payoff structure of the model.



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.

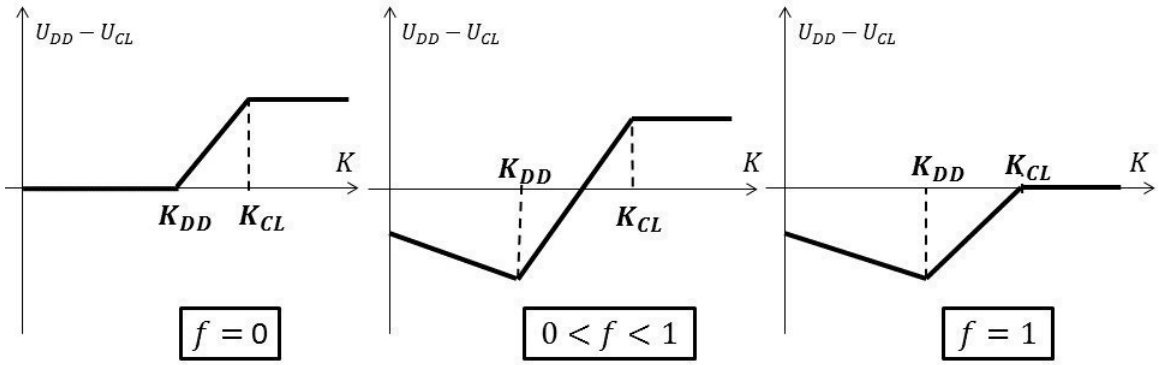


Figure 3: Observed test take-up rate within Consent Law (CL) and Disclosure Duty (DD).

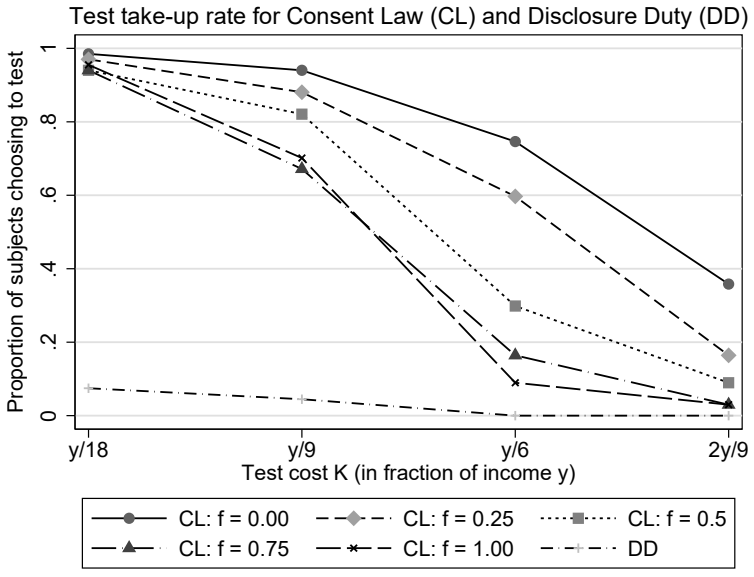


Figure 4: Observed and predicted preferences between regulations.

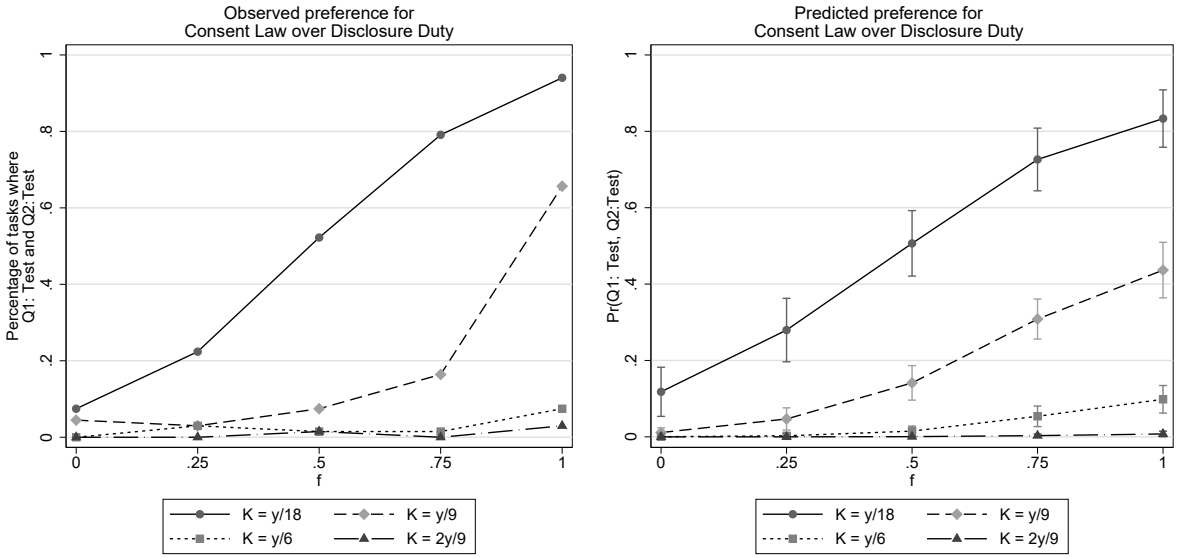


Figure 5: Predicted probabilities between and within genetic testing regulations.

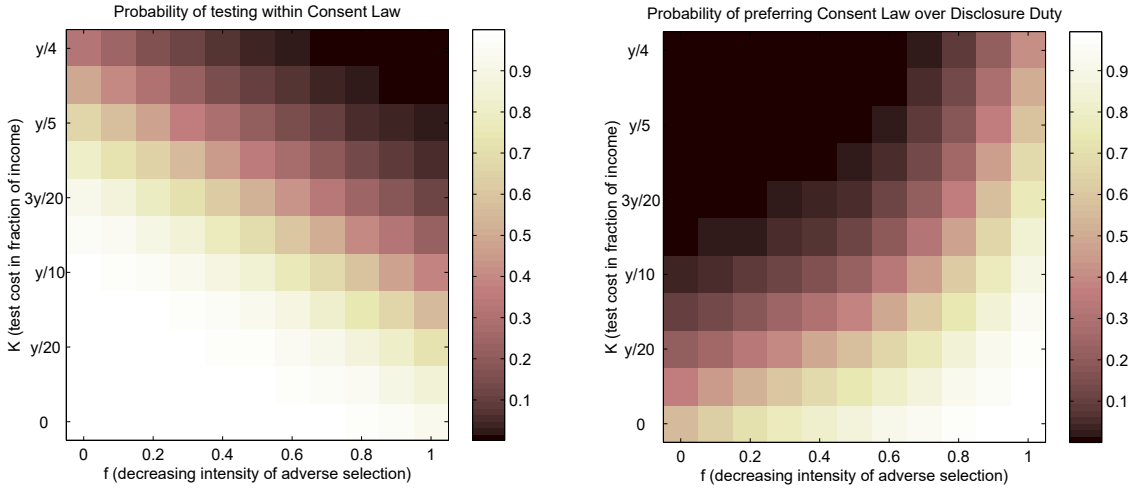


Figure 6: Steady state value of f as a function of test cost.

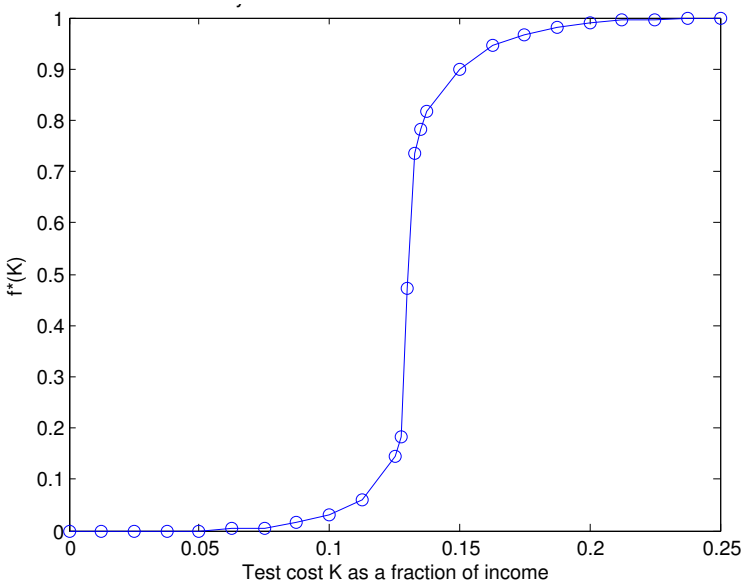


Figure 7: Fraction of people predicted to test under CL, and to prefer CL to DD, when f is set at its steady state level.