The Value of Medical Diagnosis: Why People Reject Medical Information

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Abstract

This paper uses a model of reference-dependent preferences proposed by Kőszegi and Rabin (2009) to derive the value of medical information when a decision-maker is loss averse over changes in beliefs. This allows to model the anticipation of potential disappointment upon receiving bad news about one's health status. The information's value in terms of improved subsequent decision-making with regard to a treatment decision is then ammended by the anticipated emotional impact of information. It is shown that this emotional impact changes when information is instrumental, i.e. is affecting the decision about a subsequent action. The questions whether information is desirable from a decision-making or from an emotional point of view can thus not be separated. The model is applied to a patient's choice problem to undergo medical screening. The availability of effective cure and the timing of testing are found to be significant determinants of test uptake. This is in line with empirical research concerning patients' motives to decline testing.

Keywords: Information acquisition, Reference-Dependence, Disappointment Aversion, Medical Diagnosis

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1 Introduction

Medical diagnosis is an important part of health care provision. Tests are conducted to guide medical decision-making, particularly to identify the very need of a medical intervention. The actual use of medical information, or the lack of it, has created a couple of puzzles though. One of them is the unwillingness of some patients to take a medical test. Despite extensive campaigns to raise awareness people are reluctant to take up screening tests for breast or colon cancer. Increasing knowledge in the field of genetics made tests for genetic predispositions for diseases such Huntington's Disease and breast cancer possible. Although most people acknowledge the benefits of such tests uptake rates fall far below expectations. Similarly, low uptake rates for HIV tests remain a concern despite awareness campaigns, the offer of free and anonymous tests, and even the general acknowledgement of the benefits of these tests on the side of both physicians and patients. These observations are not easy to reconcile with the predictions of standard decision theory concerning the value of information. As a result, psychological barriers to testing have drawn increasing attention as possible explanations.[1] Psychological motives are among the most frequently reported reasons to decline testing. Reasons such as "fear of knowing one's status", "fear of a positive test result", "concern about the ability to cope with a positive result", and "emotional reactions" are commonly cited. Some studies suggest that it is in particular the inavailability of effective treatment that drives the fear of being tested positive.[2] The anticipation of the emotional impact of information thus seems to be an important factor determining attitudes toward information. This paper seeks to investigate this particular nuance of attitudes toward information and its interaction with the desirability of information in terms of improved decision-making.

The model we employ was introduced by Kőszegi and Rabin (2009), henceforth KR. It suggests

[1]See e.g. Neumann et al. (2001); Lerman et al. (1995); Geer et al. (2001) on barriers to testing for genetic predispositions for Alzheimer's Disease, Huntington's Disease and various forms of cancer. See Deblonde et al. (2010) for a review of studies on HIV testing in Europe. See Weiser et al. (2001) as an example of a study on HIV testing in Africa (Botswana) and Zapka et al. (1991) as an example of a study on HIV testing in the North America (USA). These examples were selected as they provided reasons given by subjects for obtaining or rejecting an HIV test.

[2]See e.g. Neumann et al. (2001); Zapka et al. (1991)

that people derive (dis)utility from changes in beliefs about future outcomes. We will interpret this utility from a change in belief as the emotional reaction to information. This enables us to model different incentives for information acquisition. On the one side, information is an input to subsequent decision-making, here with regard to a treatment choice. On the other hand, information triggers a potentially unfavorable emotional response. We derive the value of information as a composite of its value in terms of improved decision-making and its value in terms of emotional self-management. We find that these two components are interdependent, thus instrumentality and emotionality of information affect each other. In addition, the value function enables us to make predicitons when to expect test refusal. It turns out that treatment effectivity, in addition to treatment efficiency, plays a major role for the uptake of screening tests. This is because, as suggested by survey responses, the expected emotional response to the information provided by a screening test is particularly severe when there is no effective treatment available. Finally, the timing of testing turns out to be decisive for the desirability of testing as it affects the intensity of the emotional response.

This paper joins the growing literature on reference-dependent preferences. The idea of outcomes being evaluated relative to a reference point has been prominent since Kahneman and Tversky (1979). Kőszegi and Rabin (2006) suggested to endogenizes the reference point as being previously held expectations and later extended the model to stochastic reference points (Kőszegi and Rabin, 2007).[3]. Empirical research lends support to the hypothesis that the reference point is influenced by expectations (Post et al., 2008; Abeler et al., 2011; Crawford and Meng, forthcoming). While there is evidence supporting the idea of the reference point being a function of expectations, theoretical work has focussed on the implications of such preferences (see e.g. Heidhues and Kőszegi (2008, 2010) on pricing strategies, and Herweg et al. (2010) on optimal contracts). Kőszegi and Rabin (2009) further extend the initial model to account for utility being derived from changes in expectations. It is this extension that allows us to model emotions that

[3]In contrast to models in which the reference point is the certainty equivalent of the lottery, such as Bell (1985) and Loomes and Sugden (1986) among others, the reference "point" is characterized by the whole lottery that represents the decision-maker's expectations. An outcome's evaluation can then lead to mixed feelings in the sense that an intermediate outcome compares worse against a better but better against a worse counterfactual. See Kőszegi and Rabin (2007) and Herweg et al. (2010) for more elaborate discussions of this distinction from disappointment theories à la Bell (1985) and Loomes and Sugden (1986).

result from changes in beliefs, in particular from the reception of information. In consequence the model lends itself to the investigation of emotional responses to information and of the attitudes toward information that result from them. KR use the model themselves to investigate information preferences. In contrast to the present paper, however, they concentrate on non-instrumental information, i.e. information that is not affecting subsequent decisions. When they allow information to affect decision-making in a consumption-and-savings model they concentrate on the question how the subsequent action choice is affected, but leave out the question concerning the desirability of information itself. Karlsson et al. (2009) propose a model of selective attention in which an investor can influence the speed of adjustment of his reference point by paying more or less attention to information. They confine analysis to non-instrumental information suggesting that if the information serves as an input to subsequent decision-making it gains an additional option value. We will show in this paper that this suggestion neglects the interdependence between an information's value in terms of instrumentality and emotionality. Close to our paper Panidi (2008) analyses patients' desire to visit the doctor using a reference-dependent preferences framework. Similar to Karlsson et al. (2009) she neglects how the existence of a subsequent choice (here the possibility to treat), to which the information serves as input, changes the emotional impact of the information. Matthey (2008) proposes a different model of utility being derived from changes in beliefs, which she calls "adjustment utility". Apart from the observation that this adjustment utility may induce a distaste for positive but false information, Matthey (2008) focuses on the implications of such preferences for subsequent action choices but neglects their impact on information choices which is the main topic of this paper.[4]

As this paper investigates the emotional impact of changes in belief it is related to the literature on disappointment, pioneered by Bell (1985), and Loomes and Sugden (1986). Bell (1985) investigates how disappointment (elation) occuring when the actual outcome falls below (exceeds) expectations affects decision-making. Applying his insights to the sequential revelation of uncertainty he concludes that bad news should be broken gently while good news are preferred to be received all at once.[5] A similar insight is derived by KR as well. They show that one prefers to

[4]Interestingly though, Matthey (2008) highlights the propensity of such preferences to induce a psychological cost associated to deviations from previously made plans. Although these are not within the focus of this work such penalties from deviations can be observed at different instances in the analytical part of this paper.

[5]While Bell does not explicitly mention that he applies his disappointment model to information and not simply

receive bad news early instead of being surprised by it, while the preference is reversed for good news. While our paper retains the idea of different preferences for good and bad news, it also shows that the instrumentality of information affects the extent to which good (bad) news are good (bad). It is this connection between instrumentality and emotional impact of information this paper seeks to highlight.

A different strand of literature that investigates the role of emotions in people's demand for information uses the concept of *anticipatory utility* (Kőszegi, 2003; Caplin and Eliaz, 2003; Caplin and Leahy, 2004; Kőszegi, 2006; Barigozzi and Levaggi, 2008, 2010). It suggests that individuals derive utility from holding specific beliefs. The psychological motive that affects informational choices is thus the maintenance of a positive - though potentially illusory - belief and not the avoidance of psychological distress (disappointment) resulting from bad news. The difference amounts to a contrast between *anticipatory feelings* and *anticipated feelings* as discussed by Loewenstein et al. (2007).

This paper thus seeks to complement the existing literature by investigating individuals' inclination to take a medical test if the information conveyed by the test both serves as an input to subsequent decision-making and triggers an emotional response. It highlights the interdependence between these two consequences of information choice and makes predictions concerning the determinants of test refusal.

The paper is organized as follows. Section 1 introduces the model. In section 2, we derive the value of information as a function of prior beliefs and the testing technology. At the end of this section, we apply the model to an analytically simple case, the value of perfect information. Section 3 applies the model to the case of a screening test, and derives a condition under which rejection of a screening test is optimal. Section 4 shows comparative statics in order to illustrate how different parameters, such as treatment benefits and costs, severeness of disease, and the timing of the testing affect test refusal and, more generally, the value of information. Section 5 concludes.

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actual outcomes, he does so by assigning psychological utility to information that is received in stages. It must thus be that individuals in his model experience disappointment or elation when receiving information about an outcome that has not yet realized.

2 The Model

A decision-maker faces a problem spanning over three periods $t = 0, 1, 2$. In period 0, he has the possibility to test for a disease. Let $b \in \{i, n\}$ denote the information choice where i denotes the decision to test, n denotes the decision not to test. If he decides in favor of the test he will receive its result in the following period, period 1. Regardless of his information choice he has to make an action choice $a \in \{NT, T\}$ in period 1, where NT denotes "no treatment" and T denotes "treatment". He will make this treatment decision based on his period 1-belief about his health status. If he decided in favor of the test this belief will contain the information conveyed by the test. If he declined to take the test he has to choose an action without further information. In the final period (period 2), health outcomes realize based on his action choice and his health status.

There are two states of nature $\theta \in \{\theta_h, \theta_s\}$, meaning healthy ($\theta_h$) and sick ($\theta_s$). Let $p_0 \in (0, 1)$ be the subjective (prior) probability an individual assigns to being sick when making his information choice in period 0. The individual decides whether to obtain a signal s, a medical test, that conveys one of two possible messages $\{s^-, s^+\}$. It is, henceforth, assumed that the signal $s^-(s^+)$ is conclusive towards state θ_h (θ_s), i.e. s^- denotes a negative, s^+ a positive test result. If the patient chooses to be tested he expects to receive a negative (positive) test result with probability q^- (q^+). Let p_1 denote the (posterior) probability an individual assigns to being sick in period 1, i.e. after potential information reception. This means that $p_1 \in \{p^-, p_0, p^+\}$, where p^- (p^+) is the posterior probability the individual assigns to being sick after having received a negative (positive) test result. Furthermore, let ϵ^- (ϵ^+) denote the false negative (false positive) rate of the test, i.e. the probability of receiving message s^- (s^+) given state θ_s (θ_h). It is assumed that these error rates are objective characteristics of the signal, i.e. they are known statistics, with $\epsilon^- + \epsilon^+ \leq 1$. Thus, the posterior (state) probabilities p^-, p^+ and the probabilities with which the decision-maker expects to receive each test result, denoted by q^-, q^+, can be calculated via Bayes' rule given the characteristics of the signal (ϵ^-, ϵ^+) and the subjective belief p_0 of an individual.

$$p^- = \frac{\epsilon^- p_0}{q^-}, \qquad p^+ = \frac{(1-\epsilon^-)p_0}{q^+}$$

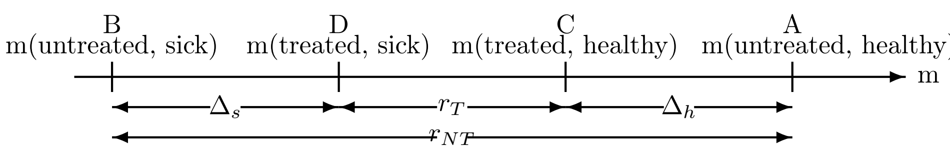
$$q^- = (1-\epsilon^+)(1-p_0) + \epsilon^- p_0, \qquad q^+ = \epsilon^+(1-p_0) + (1-\epsilon^-)p_0$$

Conditional on the state obtaining, the two actions $a = \{NT, T\}$ (no treatment, treatment) lead to different levels of *material utility* $m \in \mathbb{R}$ in period 2, henceforth called payoffs or material outcomes. Let these be

	θ_h	θ_s
NT	A	B
T	C	D

Assume an ordering of payoffs $A > C > D > B$ and define the following differences between payoffs (see Figure 1).

Figure 1: Material Payoffs in a Medical Information Setting



First, the differences across actions given a state are denoted by

$$\Delta_h = m(\text{no treatment, healthy}) - m(\text{treatment, healthy}) = A - C > 0$$

$$\Delta_s = m(\text{treatment, sick}) - m(\text{no treatment, sick}) = D - B > 0.$$

Δ_h denotes the net benefit of not being treated (or the net cost of being treated) to a healthy patient. For simplicity, we will assume that treatment yields no benefit to a healthy individual. This allows Δ_h to be interpreted as the costs of treatment such as potential side effects and/or unpleasantness of the treatment procedure. Δ_s denotes the net benefit of treatment to a sick individual. Both Δ_h and Δ_s are strictly positive, so the optimal action differs across states. Assuming treatment costs to be independent across states, the sum $(\Delta_h + \Delta_s)$ can be interpreted as the (gross) benefit of treatment to a sick.

Second, define the differences in utility across states given an action by

$$r_{NT} = m(\text{no treatment, healthy}) - m(\text{no treatment, sick}) = A - B > 0$$

$$r_T = m(\text{treatment, healthy}) - m(\text{treatment, sick}) = C - D > 0.$$

These will be important for determining the psychological evaluation of an outcome. The difference in well-being of an untreated healthy and an untreated sick individual (r_{NT}) can be interpreted as a measure of the severeness of the disease. The difference in well-being of treated healthy and a treated sick individual is denoted by r_T. It is a function of the *effectiveness* of treatment. If $r_T = 0$, the treatment constitutes a perfect cure as a treated sick is as well off as a treated healthy individual. The larger r_T the less effective the treatment.

In classic decision theory the optimal action choice as well as the optimal information choice, and thus the value of information, are a function of Δ_h, Δ_s, and the beliefs p_0 and p_1 of the decision-maker (DM). In contrast, if the DM exhibits reference-dependent preferences (RDP), they depend on r_{NT} and r_T in addition. We will now discuss the preferences of the decision-maker.

2.1 Incentives for Decision-Making

In each period, the forward-looking decision-maker has an objective function encompassing the utility in the current and all future periods.

$$U^t = \sum_{\tau=t}^{2} u_\tau, \qquad t = 0, 1, 2$$

There are two sources of utility. First, material utility is derived from state-contingent consequences of the action taken as was described above. Second, there is gain-loss utility derived from changes in belief regarding material utility. This means that news regarding one's future well-being affect well-being today, or, in the current context, getting a positive or negative test result affects a person's utility in the period these results are obtained. This gain-loss utility will be interpreted as elation or disappointment upon reception of good or bad news.

Changes in the belief about the future health outcome m can occur in all three periods. They can be the result of the reception of new information: in period 1 when a test result is received and in period 2 when the true state of nature is revealed. They can also result from a deviation of actual from planned choice: in period 0 when the information choice is made and in period 1 when the treatment choice is made.

The utility function will be modeled in a way proposed by Kőszegi and Rabin (2009)[6], where the utility derived from changes in beliefs about future outcomes is called *prospective gain-loss utility* (PGLU), and the utility derived from changes in beliefs about current outcomes is called *contemporaneous gain-loss utility* (CGLU). An individual's utility in period t is an additively-separable function of material utility and gain-loss utility obtaining in this period

$$u_0 = \gamma_0 v(F_0, F_{-1})$$
$$u_1 = \gamma_1 v(F_1, F_0)$$
$$u_2 = m + v(F_2, F_1,)$$

where $m \in \mathbb{R}$ is the level of material utility occuring in period 2, $v(\cdot)$ is the level of gain-loss utility resulting from a change in belief about m, $F_t : \mathbb{R} \rightarrow [0, 1]$, $t = 0, 1, 2$ is the belief the patient holds at the end of period t concerning the level of material utility m in period 2, F_{-1} is the belief regarding material utility held immediately prior to information choice in period 0, and $\gamma_0, \gamma_1 \in [0, 1]$ are coefficients weighting the relative impact of prospective gain-loss utility compared to contemporaneous gain-loss utility. Following a suggestion by KR, we assume $0 \leq \gamma_0 \leq \gamma_1 \leq 1$, indicating a decline in the impact of changes in belief on well-being the larger the distance between the time the change in belief occurs and the time the material utility to which the belief refers is realized.

Following KR, the gain-loss utility from a change in belief is a function of how the new belief compares against the old belief. Formally, let $F : \mathbb{R} \rightarrow [0, 1]$ be a cumulative density function over material utility levels and define the function $v : \mathcal{F} \times \mathcal{F} \rightarrow \mathbb{R}$, where $\mathcal{F}$ is the set of all possible cumulative density functions $F(m)$ over material utility m, by

$$v(F_t, F_{t-1}) = \eta \int_{-\infty}^{\infty} \mu \left[F_{t-1}(m) - F_t(m)\right] dm$$

[6]For simplicity we only consider a single-dimensional outcome in period 2, say utility from health status. While health status is clearly a multi-dimensional objective it will be treated as single-dimensional here for the sake of simpler exposition.

where η is a coefficient weighting gain-loss utility in relation to material utility. Analysis is simplified by assuming a two-piece linear representation of μ:

$$\mu(z) = z \text{ if } z \geq 0$$

$$\mu(z) = \lambda z \text{ if } z < 0$$

with $\lambda > 1$ measuring the degree of loss aversion.[7]

2.2 Planning Behavior

Contemplating the decision whether to take the test or not, a forward-looking DM with above preferences will realize that this decision can affect his utility through three channels. First, the information conveyed by the test may affect his decision whether to treat, thereby affecting material and gain-loss utility in the final period. Second, even if the treatment choice remains unaffected, gain-loss utility in the final period will be affected. As this gain-loss utility is derived from the resolution of the remaining uncertainty, the information choice influences this source of utility by changing how much uncertainty there is prevailing until the final period. Third, as the information conveyed by the test changes his belief about his health he experiences gain-loss utility from the reception of information. In other words, he experiences an emotional response upon information reception.

In addition to contemplating the consequences of his behavior, the DM needs to keep in mind two things when laying out his plan how to behave in both instances of choice. First, he cannot

[7] The exact approach of KR is to attribute levels of material utility to each percentile of a belief and then compare the two beliefs percentile by percentile. Adapted to this example, this goes as follows. For any distribution F over $\mathbb{R}$ and any $\pi \in (0,1)$ let $m_F(\pi)$ be the material utility level at percentile π, defined implicitly by

$$F(m_F(\pi)) \geq \pi$$

$$F(m) < \pi \text{ for all } m < m_F(\pi)$$

Define gain-loss utility from a change in belief by

$$\tilde{v}(F_t, F_{t-1}) = \eta \int_0^1 \mu\left[m_{F_t}(\pi) - m_{F_{t-1}}(\pi)\right] d\pi.$$

Under the assumption of two-piece linearity of μ both approaches yield the same gain-loss utility while the approach employed here spares the detour of deriving m_F. A proof is deferred to the Appendix.

rationally plan to make a choice that is not optimal at the time of choice. Second, once he has set up a plan, he will form beliefs about his future health status. Any future deviation from the plan will then result in a change in this belief producing gain-loss utility at the time of the deviation.

KR have proposed the concepts of personal equilibrium and preferred personal equilibrium to accomodate the restrictions just described. Formally, denote by d_t a "plan" for behavior starting in period t, i.e. a state-contingent strategy regarding all possible decisions that might occur in period t and thereafter. Let D_t be the set of feasible plans.

Definition 1. [8] *Define the sets $\{D_t^*\}_{t=0}^T$ in the following backward-recursive way. A plan $d_t \in D_t$ is in D_t^* if, given the expectations generated by d_t, in any contingency, (i) it prescribes a continuation plan in D_{t+1}^* that maximizes the expectation of U^t, and (ii) it prescribes an action in period t that maximizes the expectation of U^t, assuming that future plans are made according to (i). A plan $d_t \in D_t$ is a personal equilibrium (PE) if $d_t \in D_t^*$. A plan $d_1 \in D_1$ is a preferred personal equilibrium (PPE) if $d_1 \in D_1^*$ and it maximizes the expectation of U^1 among plans in D_1^*.*

Adapted to our setting this means that the plan d_1 prescribes a state-contingent treatment decision $a \in \{NT, T\}$ in period 1. This plan being a personal equilibrium requires that for any information set at which the DM finds himself in period 1 it must be optimal to follow the prescription a the plan makes for this information set given the expectations the DM with plan d_1 has at this information set. To give an example: a plan can only prescribe to seek treatment after a positive test result if, given the belief jointly determined by the information of the positive test result and the plan of the DM to treat in this instance, the DM finds it optimal to choose treatment. One step earlier, a plan d_0 comprises a planned information choice and a vector of planned treatment choices, $d_0 = (b, \vec{a})$. The vector of planned treatment choice $\vec{a}$ comprises the planned treatment choice a for each possible information set in period 1. To give two examples: a plan d_0 may prescribe to test, and seek treatment upon a positive and abstain from treatment upon a negative test result; or it may prescribe not to test and abstain from treatment. Again, for $d = 0$ to be a personal equilibrium it must be optimal to follow this plan given its anticipation. Note that more than one plan can constitute a personal equilibrium. In this case we will assume that the DM chooses his preferred personal equilibrium, that is the plan that maximizes the expected

[8] This definition is identical to the one given in Kőszegi and Rabin (2009).

utility from its implementation.

With these restrictions in mind, we will now consider the three channels through which the information choice may affect utility. First, we will investigate which treatment choices a can be part of personal equilibria. This is important as an information's propensity to influence decisions constitute an important part of its value.

2.3 The Decision whether to Treat

In period 1, the DM decides whether to seek treatment. He bases his decision on the expected consequences, both material and psychological. First, each action will result in different material utility in the final period. Second, unless the DM is certain about his health status in period 1, the remaining uncertainty will be resolved in period 2. Thus there will be a change in belief accompanied by gain-loss utility in the final period. The extent of this gain-loss utility is a function of the action chosen. Finally, if the DM decides to deviate from the planned choice there will be an immediate change in belief accompanied by gain-loss utility in period 1. Suppose e.g. the DM has made the plan not to seek treat. The expected utility of the two options "no treatment" and treatment" are then given by:

$$
\begin{aligned}
\mathbb{E}_1 U^1(NT|NT) =& \mathbb{E}_1\left[u_2(NT)\right] && \\
=& (1-p_1)A + p_1 B && \text{expected material utility in period 2} \\
& - p_1(1-p_1)\eta(\lambda-1)r_{NT} && \text{expected gain-loss utility in period 2} \\
\mathbb{E}_1 U^1(T|NT) =& \mathbb{E}_1\left[u_2(T)\right] + \gamma_1 v\left(F_1|a=T, F_1|a=NT\right)\right) && \\
=& (1-p_1)C + p_1 D && \text{expected material utility in period 2} \\
& - p_1(1-p_1)\eta(\lambda-1)r_T && \text{expected gain-loss utility in period 2} \\
& + \gamma_1\eta\left[-\lambda(1-p_1)\Delta_h + p_1\Delta_s\right] && \text{immediate gain-loss utility due to deviation}
\end{aligned}
$$

Given the plan not to treat it is optimal not to treat if and only if $\mathbb{E}_1 U^1(NT|NT) \geq \mathbb{E}_1 U^1(T|NT)$. Let p^*_{NT} be the probability p_1 for which the DM is indifferent between the two options "treatment and "no treatment" given he previously had the plan not to treat. Similarly, let p^*_T be the probability p_1 for which the DM is indifferent between the two options given he previously had the plan to seek treatment. As part of the proof of the following lemma we will show that these probabilities are well-defined. Finally, define

$$V_T = \mathbb{E}_1 U^1(T|T) - \mathbb{E}_1 U^1(NT|NT) = -V_{NT}. \quad (1)$$

We will see that the values $V_T(V_{NT})$ are an important part of the value of information. Denote by p^* the probability p_1 at which $V_T = V_{NT} = 0$: $p^* = \{p_1 : \mathbb{E}_1 U^1(NT|NT) = \mathbb{E}_1 U^1(T|T)\}$. The three probabilities (p^*, p_T^*, p_{NT}^*) are all bounded away from zero and one, and have a clear order.

Lemma 1. $0 < p_T^* < p^* < p_{NT}^* < 1$

Proof. See Appendix. □

The inequality shows that the probability of being sick below which it is optimal not to treat given the expectation not to treat, p_{NT}^*, is strictly larger then the probability of being sick above which it is optimal to treat given the expectation to treat, p_T^*. Hence, given a belief $p_1 > p_{NT}^*$ it is optimal to choose T irrespective of the planned action. Equivalently, it is optimal to choose NT irrespective of the planned action if $p_1 < p_T^*$. This implies that the DM cannot rationally plan to take action T (NT) at information sets in which he entertains a belief p_1 that falls below p_T^* (exceeds p_{NT}^*). For information sets where $p_T^* < p_1 < p_{NT}^*$, he can plan to take the action he prefers at the planning stage as, once the plan is set up, he can expect himself to follow through on it.

From lemma 1 it follows that if the DM selects to test and his posterior probabilities are "extreme enough" his treatment choice must differ across information sets.

Corollary 1. *(1) If $p^+ > p_x^*$ and $p^- < p_y^*$, a plan $d_0 \in D_0^*$ prescribing to test (i), must prescribe*

$$NT \text{ if } s = s^-$$

$$T \text{ if } s = s^+,$$

i.e. an individual planning to test must plan to follow the signal.
(2) For all prior beliefs $p_0 \in (0,1)$ there exist error rates $\epsilon^- > 0, \epsilon^+ > 0$ such that an individual planning to test must plan to follow the signal for all tests with smaller error rates.

The corollary says that if the DM chooses to test and the posteriors are such that $p^+ > p_x^*$ and $p^- < p_y^*$ the DM will choose to seek treatment upon a positive test result and abstain from treatment upon a negative test result. Part (2) says that for any prior p_0 there exists a test that, if taken, influences treatment choice. Any test that is more accurate than this test will also influence treatment choice.

We can also make the following prediction concerning any plan that prescribes not to test.

Lemma 2. *A plan $d_0 \in D_0^*$ prescribing not to test (n), must prescribe*

$$NT \text{ if } p_0 < p^*$$
$$T \text{ if } p_0 > p^*$$

as continuation plan d_1.

The reason is simple. Suppose it is part of a personal equilibrium to choose "no test". If this is true the DM expects to make the treatment choice based on the prior p_0. Then by part (ii) of the definition of personal equilibrium he chooses the continuation plan, here the action choice, that gives him highest ex ante utility among all plans he will eventually follow. Thus, he will plan to seek treatment if and only if $\mathbb{E}_0 U^1(T|T) - \mathbb{E}_0 U^1(NT|NT) V_T = \mathbb{E}_1 U^1(T|T) - \mathbb{E}_1 U^1(NT|NT) = V_T > 0$ which is equivalent to $p_0 > p^*$. Lemma 2 characterizes personal equilibria that involve test refusal when there is an option to test. It is easy to see that the result extends to the setting where there is no such choice. Lemma 2 thus pins down what the DM would do if he could not test, assuming that in this case the DM would choose his preferred personal equilibrium. Hence we will speak of action T (NT) being the DM *default action* if $p_0 > (<) p^*$.

The considerations we have made so far focussed on what treatment choices we can expect for a given belief p_1. They will become important when determining how a given test influences this choice. It is this potential influence that is a major part (in classic decision theory the only part) of an information's value. We will now turn to another consequence of choosing to test: the impact on the emotional response to learning the truth in the final period, or, more technically, the impact on contemporaneous gain-loss utility.

2.4 Psychological Utility upon Learning the Truth

Even if the test has no influence on the treatment choice, it will have an influence on utility in the final period. Unless the DM is certain about the state of health at the time he makes his treatment choice the remaining uncertainty will be resolved in the final period. This will result in a change in belief and thus trigger an emotional response. The information choice affects this final emotional response indirectly as it already resolves part of the uncertainty earlier. To give an example: if the test is perfect and turns out, say, positive the DM already knows with certainty that he is sick in period 1. Thus he cannot be disappointed anymore in the final period by learning about his bad health. More technically, as the information conveyed by the test changes the reference belief, the gain-loss utility from the evaluation of the final outcome against this reference lottery must also change. Given some treatment choice, this change in contemporaneous gain-loss utility (CGLU) due to choosing to test (i) instead of not testing (n) is

$$\mathbb{E}_0\left[v\left(F_2, F_1|i\right)\right] - \mathbb{E}_0\left[v\left(F_2, F_1|n\right)\right] = \begin{cases} q^+q^-\eta(\lambda-1)(p^+-p^-)^2 r_{NT} & \text{if NT chosen} \\ q^+q^-\eta(\lambda-1)(p^+-p^-)^2 r_{T} & \text{if T chosen} \end{cases} \tag{2}$$

The derivation is not difficult, but tedious. The results indicate that the DM gains from learning about his health status earlier apart from potential gains by making better decisions. This is because the information shifts the reference belief F_1 closer to the final belief F_2, at least in expectation. This diminishes both gains and loss, but, as the DM cares more about the latter under loss aversion, the net effect is positive.

So far we have investigated two ways in which the DM gains (in expectation) from taking the test. We will now turn to the downside of testing: the expected emotional impact of information. This will turn out to be the major psychological cost of testing in this model.

2.5 Psychological Utility upon Reception of the Test Result

When patients test for a serious disease the reception of the test result usually triggers an emotional response. One advantage of the model of reference-dependent preferences proposed by KR is to offer a possibility to model this emotional response as the (dis-)utility derived from the change in belief triggered by the reception of the test result. The focus of this section is thus to derive the expected emotional impact of information, in formal terms $\mathbb{E}_0\left[v(F_1, F_0)\right]$.

The following observation will help the analysis. Under Bayesian updating the prior belief F_0 equals the expected posterior belief: $F_0 = q^- F_1^- + q^+ F_1^+ = \mathbb{E}_0\left[F_1\right]$ where F_1^- is the posterior belief after a negative, F_1^+ the posterior belief after a positive test result. With this in mind, the binary signal structure allows us to make a useful simplification.[9]

$$\mathbb{E}_0\left[v(F_1, F_0)\right] = q^- \cdot \underbrace{q^+ v(F_1^-, F_1^+)}_{v(F_1^-, F_0)} + q^+ \cdot \underbrace{q^- v(F_1^+, F_1^-)}_{v(F_1^+, F_0)}. \tag{3}$$

The emotional impact of a negative result is thus a function of how the (factual) belief after these news compares against the (counterfactual) belief the DM would have had, had he received a positive test result. Similarly, the emotional impact of a positive test result depends on how the factual belief compares against the counterfactual. This observation is helpful as it allows us to confine attention to how the two posterior distributions F_1^- and F_1^+ compare against each other.

Note that the distributions F_1^-, F_1^+ are not only a function of the posterior beliefs p^-, p^+ but also of the treatment choice the DM plans to make in each contingency. The emotional response to information thus not only depends on the informational content of the signal but also on what one plans to do with this information. Let us distinguish two cases. First, call information *instrumental* if it affects the treatment choice, i.e., in this context, that the DM seeks treatment afer a positive test result and abstains from treatment after a negative test result. Second, call information *non-instrumental* if it does not affect treatment choice. In that case the DM sticks to the action he would have chosen without any further infomation, the *default action* no matter how the test turns out.

2.5.1 Prospective Gain-Loss Utility upon Receiving Non-instrumental Information

The second case turns out to be the simpler of the two. If the information does not result in a change of action, both F_1^+ and F_1^- have the same support, the two material payoffs associated with the default action. The information received then only tells the DM how much probability weight to put on the high and the low outcome associated with the default action.

[9] It is important to note that this simplification is only valid due to the binary signal structure.

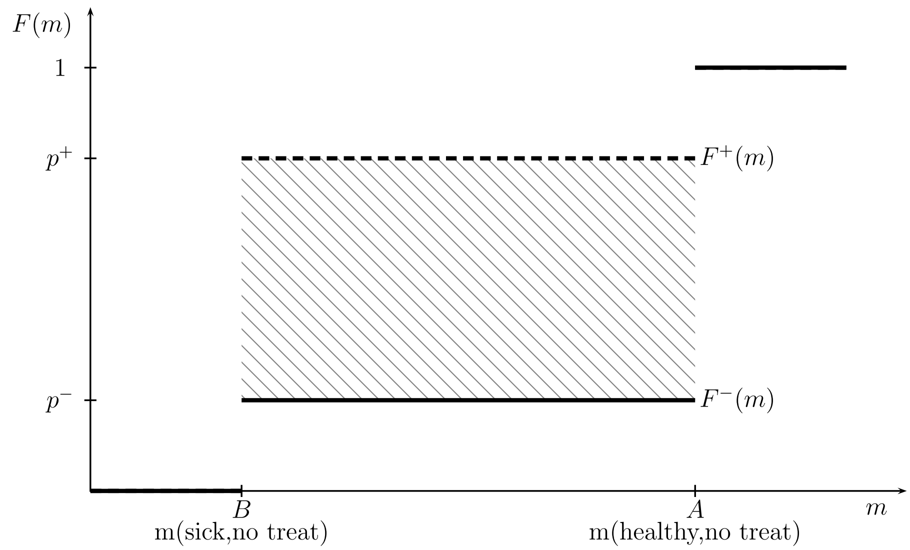


Figure 2: Gain Loss Utility when Information is Noninstrumental (default action NT)

Suppose e.g. the default action was NT (don't treat). The gain-loss utility derived in period 1 (see Figure 2) is

$$v(F_1, F_0) = \begin{cases} \eta\left[(p_0 - p^-)r_{NT}\right] = q^+\eta(p^+ - p^-)r_{NT} & \text{if } s = s^- \\ \eta\left[-\lambda(p^+ - p_0)r_{NT}\right] = -q^-\eta\lambda(p^+ - p^-)r_{NT} & \text{if } s = s^+ \end{cases}$$

When information is non-instrumental, the emotions arising upon reception of the test result are a function of (a) the probability with which the alternative message was expected, (b) the distance between the posterior probabilities the two signals induce, and (c) the distance between the higher and the lower payoff associated with the default action. Note that the emotional response is unambiguously positive upon a negative test result and unambigously negative upon a positive test result.

Taking expectations over u_1 at $t = 0$ the expected utility in period 1 depending on one's default action is

$$\begin{aligned} \mathbb{E}_0 u_1 &= \gamma_1\left[q^- v\left(F_1^-, F_0\right) + q^+ v\left(F_1^+, F_0\right)\right] \\ &= \begin{cases} -q^+q^-\gamma_1\eta(\lambda-1)(p^+ - p^-)r_{NT} & \text{if } NT \text{ is default action} \\ -q^+q^-\gamma_1\eta(\lambda-1)(p^+ - p^-)r_{T} & \text{if } T \text{ is default action} \end{cases} \end{aligned}$$

2.5.2 Prospective Gain-Loss Utility upon Reception of Instrumental Information

The case is different when the information is instrumental, i.e. when the DM seeks treatment after a negative and abstains from treatment after a positive test result. In this case, the distributions F_1^- and F_1^+ do not only differ in the probability they assign to being sick but also in the outcome associated with each state. (see Figure 3).

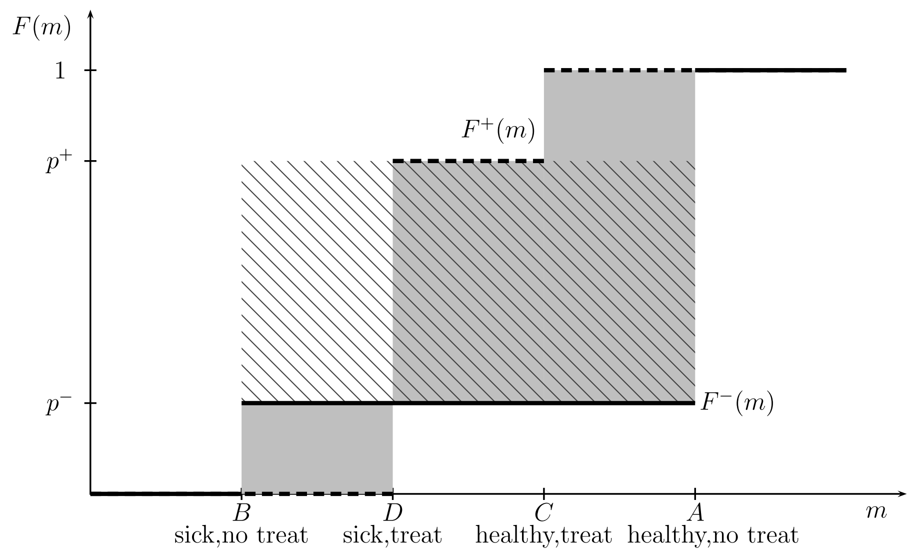


Figure 3: Gain Loss Utility when Information is Instrumental

The gain-loss utility (PGLU) induced by the reception of a message is then

$$u_1 = \begin{cases} q^+\gamma_1\eta\left[-\lambda p^-\Delta_s + (p^+ - p^-)r_T + (1-p^-)\Delta_h\right] & \text{if } s = s^- \\ q^-\gamma_1\eta\left[p^-\Delta_s - \lambda(p^+ - p^-)r_T - \lambda(1-p^-)\Delta_h\right] & \text{if } s = s^+ \end{cases}$$

The interpretation of this formula is easier if one remembers that this constitutes a percentile-wise comparison. A negative test result fares worse than a positive test result in the lower percentiles. This is because s^- induces no treatment and s^+ induces treatment, and the worst-case under a negative test (untreated and sick) fares worse than the worst-case under a positive test (treated and sick). On the other hand, a negative test result fares better in the higher percentiles. The best-case under a negative test result (untreated and healthy) is better than the best-case under a positive test result (treated although healthy). In the "middle range" a negative test result fares better as well because (a) it puts more probability weight on the preferred state of the world (healthy) and (b) it results in a higher payoff in the preferred state of the world. Note the difference between the emotional impact of non-instrumental and instrumental information. While a negative result under non-instrumentality is unambigously good it is accompanied by mixed feelings under instrumentality, unless the test is perfect. The same is true for the emotions generated by a positive result. While the effect is unambigously bad under non-instrumentality it is accompanied by mixed feelings under instrumentality. This difference in the emotional impact of information will become important when determining the value of information.

Taking expectations of u_1 at $t = 0$ the expected utility in period 1 is

$$\gamma_1 \mathbb{E}_0 v\left(F_1, F_0\right) = -\, q^- q^+ \gamma_1 \eta (\lambda - 1) \left[(1-p^-)\Delta_h + p^- \Delta_s + (p^+ - p^-) r_T\right] \tag{4}$$

$$= -\, q^- q^+ \gamma_1 \eta (\lambda - 1) \left[(1-p^+)(\Delta_h + \Delta_s) + (1-2p^-)\Delta_s + (p^+ - p^-) r_{NT}\right] \tag{5}$$

Finally, let us define the difference between the expected emotional response to instrumental and and the expected emotional response to non-instrumental information, and call it *emotional differential.*

$$ED(NT) = -\, q^- q^+ \gamma_i \eta (\lambda - 1) \left[(1-p^+)(\Delta_h + \Delta_s) + (1-2p^-)\Delta_s\right] \tag{6}$$

$$ED(T) = -\, q^- q^+ \gamma_i \eta (\lambda - 1) \left[(1-p^-)\Delta_h + p^- \Delta_s\right] \tag{7}$$

This difference depends of course on the default action of the DM. Suppose it to be NT (no treatment). The belief over outcomes F_1^- a negative result induces is the same for both non-instrumental and instrumental information. The difference lies in the belief F_1^+ a positive result induces. Under instrumentality the belief F_1^+ fares better at the lowest and middle percentiles compared to the belief F_1^+ under non-instrumentality. This is because it induces the choice of a better action (treatment) in the bad state of the world (sickness). The belief F_1^+ under instrumentality, however, fares worse at the highest percentiles than under non-instrumentality. In case of a false positive, i.e. in case of being healthy, it induces a lower utility by inducing a treatment despite full health. On average, the bad news for someone with NT as default become better. As the emotional impact (the prospective gain-loss utility) of a test result is a function of how the belief it induces compares to the counterfactual belief the emotional impact of the negative result is changed as well. As the bad news get, on average, better, the good news get, on average, worse because they are not as good as before compared to the bad news. The net effect on the expected emotional impact is given by the emotional differential.[10] The emotional differential will turn out to be one component of the value of information. The existence of this emotional differential suggests that instrumental information "feels different" than noninstrumental information controlling for the informational content.

Observation 1. *The emotional response to information depends not only on the content of information but also on whether the information is instrumental.*

We have now investigated the three channels through which the information decision affects utility. In the following section we will connect the pieces to derive the overall value of information. This will enable us to see when it is optimal to reject testing.

3 The Value of Information

The value of information (in utility terms) is computed by subtracting the expected utility of refusing to test from the expecting utility of taking the test. To calculate the expected utility of each information choice we need to know what treatment choice follows. Lemma 2 helps us to answer this question for someone opting out of testing. He will seek treatment if the prior p_0 is above p^* and he will not do so if the prior is below that threshold. The question concerning the treatment choice following the decision to test is essentially the question of whether the information is instrumental. As for some beliefs p_1 both treatment choices can be (credibly) made part of a plan, this question is far from trivial. We will proceed as follows. First, we will derive the value of a test assuming that it is non-instrumental. Second, we will derive the value of a test assuming it is instrumental. Finally, we will apply the concept of preferred personal equilibrium to deduce

[10] Similar considerations apply to someone with T (treatment) as default action. Now, it is the belief F_1^+ that is the same between instrumentality and non-instrumentality. The belief F_1^- is different. Under instrumentality, it compares worse at the lowest percentiles than under non-instrumentality. This is because in the case of a false negative, i.e. in case of sickness despite a negative test, it results in no treatment despite sickness. It, however, fares better at the middle and highest percentiles as it induces a better action choice (NT instead of T) in the case of being healthy. On average, the good news get better under instrumentality. As the emotional impact stems from a relative comparison, the bad news thus fare worse. The expected net effect for someone with T as default is given by the emotional differential.

which of the values is the appropriate one for a DM with a given prior p_0 facing the option of taking a test with given characteristics (ϵ^+, ϵ^-). In order to illustrate the concept, the section concludes with an application to an analytically simple case: the value of a perfect test.

3.1 The Value of Non-instrumental Information

A test is non-instrumental if the default action is taken no matter how the test turns out. Formally, the value of non-instrumental information (VoNI), the difference in expected utility between the two alternatives of information choice $\{i, n\}$, is given by

$$\begin{aligned} VoNI =& \mathbb{E}_0 U^0(i) - \mathbb{E}_0 U^0(n) \\ =& \underbrace{\gamma_1 \mathbb{E}_0 \left[v\left(F_1, F_0\right)\right]}_{\text{PGLU}} + \underbrace{\mathbb{E}_0 \left[v\left(F_2, F_1|i\right)\right] - \mathbb{E}_0 \left[v\left(F_2, F_1|n\right)\right]}_{\text{Change in CGLU}} \\ =& \begin{cases} q^- q^+ \eta(\lambda - 1) \left[(p^+ - p^-)^2 - \gamma_1 (p^+ - p^-)\right] r_{NT} & \text{if } NT \text{ is default} \\ q^- q^+ \eta(\lambda - 1) \left[(p^+ - p^-)^2 - \gamma_1 (p^+ - p^-)\right] r_{T} & \text{if } T \text{ is default} \end{cases} \end{aligned}$$

Note that the value of non-instrumental information does not depend on what information choice was planned if the test is non-instrumental, i.e. $\mathbb{E}_0 U^0(i|i) = \mathbb{E}_0 U^0(i|n)$ and $\mathbb{E}_0 U^0(n|i) = \mathbb{E}_0 U^0(n|n)$. This is because a deviation from an anticipated information choice does not result in a change in the belief F_0 regarding future material payoffs.

As noninstrumental information is not affecting treatment choice and thus material utility, its sole value lies in its potential to affect contemporaneous gain-loss utility, i.e. its potential to mitigate disappointment in the final period. This, however, comes at the cost of earlier disappointment when receiving the test result which is felt the more intense the larger the weight on prospective gain-loss utility γ_1. The benefits of the information, meaning its potential for reference point management so-to-say, increase in the distance between the potential posterior probabilities $(p^+ - p^-)$. The larger this difference the more probable the reference point is shifted closer to the actual outcome. Lending the terminology of Eliaz and Schotter (2010) the test's value increases in the confidence it induces in the individual.[11] In line with empirical results provided by Eliaz

[11] Instead of assuming a preference for confidence, i.e. making the difference between the posteriors an argument of the utility function, as is done in Eliaz and Schotter (2010) the RDP model endogenizes this "confidence effect" of information as a desire to manage one's reference point.

and Schotter (2010) and Eliaz and Schotter (2007), the value of non-instrumental information (a) increases in the distance between the posteriors ($p^+ - p^-$) and (b) increases in the time distance between test results and outcome resolution if γ_1 is negatively correlated with this time distance as was assumed in the beginning.

One can make the following prediction concerning the desirability of noninstrumental information.

Proposition 1. *(Kőszegi and Rabin 2009). The value of non-instrumental information is positive if and only if*

$$\gamma_1 < p^+ - p^-$$

This result generalizes an example provided by Kőszegi and Rabin (2009) in which there is no action choice.[12] If an information has no impact on subsequent decision-making it will be sought if it is precise enough, but avoided if it is too imprecise. KR conclude that agents may seek to cluster information in order to receive one informative signal as opposed to a large number of less informative signals (avoidance of piecemeal information). However, as will be pointed out in the next step, the more informative a signal, the more likely it is to affect behavior if optimal actions differ across states. But, instead of simply adding an instrumental value of information, the potential to affect behavior also influences an information's emotional impact. To see this, it is necessary to derive the value of an instrumental signal.

3.2 Value of Instrumental Information

Remember that a test is instrumental if a positive result leads to treatment and a negative result leads to no treatment. To determine the value of such a test one needs to compare the expected utility of each information choice. Similar to the value of non-instrumental information there will a term relating to the change in CGLU in the final period and a term capturing the emotional impact of information. In addition to these two terms, the value of instrumental information includes

[12] KR assume a prior $p_0 = 1/2$ and posteriors $q, 1-q$, $q > 1/2$. An interesting implication that is missed by this assumption is that, holding the quality of the signal fixed (i.e. its error rates), non-instrumental information looses value the more extreme the prior.

another two terms. First, if the actual information choice differs from the planned information choice, there will be a change in belief at $t = 0$ resulting in prospective gain-loss utility (PGLU). Second, due to its impact on treatment choice the information choice affects material utility in the final period.

Take e.g. a DM who planned to take the test. The value of instrumental information (VoII) given by the difference in expected utility between the two possible information choices is

$$\begin{aligned} VoII(i) &= \mathbb{E}_0 U^0(i|i) - \mathbb{E}_0 U^0(n|i) \\ =& \mathbb{E}_0\left[u_2|i\right] - \mathbb{E}_0\left[u_2|n\right] + \mathbb{E}_0\left[u_1|i\right] - \mathbb{E}_0\left[u_1|n\right] + u_0(i|i) - u_0(n|i) \\ =& \underbrace{\mathbb{E}_0\left[m_2|i\right] - \mathbb{E}_0\left[m_2|n\right]}_{\text{difference in expected material in t=2}} + \underbrace{\mathbb{E}_0\left[v\left(F_2, F_1|i\right)\right] - \mathbb{E}_0\left[v\left(F_2, F_1|n\right)\right]}_{\text{difference in expected CGLU in t=2}} \\ &+ \underbrace{\gamma_1 \mathbb{E}_0\left[v\left(F_1, F_0|i\right)\right] - 0}_{\text{difference in expected PGLU in t=1}} + \underbrace{0 - \gamma_0 v\left(F_0(n), F_{-1}(i)\right)}_{\text{difference in PGLU in t=0}} \end{aligned} \tag{8}$$

Similarly, given the plan of choosing not to test (n), the difference in expected utility between the two possible choices is

$$\begin{aligned} \mathbb{E}_0 U^0(i|n) - \mathbb{E}_0 U^0(n|n) =& \mathbb{E}_0\left[m_2|i\right] - \mathbb{E}_0\left[m_2|n\right] \\ &+ \mathbb{E}_0\left[v\left(F_2, F_1|i\right)\right] - \mathbb{E}_0\left[v\left(F_2, F_1|n\right)\right] \\ &+ \gamma_1 \mathbb{E}_0\left[v\left(F_1, F_0\right)\right] + \gamma_0 v\left(F_0(i), F_{-1}(n)\right) \end{aligned} \tag{9}$$

Denote by W the value of instrumental information neglecting the term capturing the gain-loss utility in period 0 due to a deviation from the planned information choice.

$$W \equiv \mathbb{E}_0 U^0(i|i) - \mathbb{E}_0 U^0(n|n) \tag{10}$$

While $VoII$ captures the value of information at the moment of choice, W can be interpreted as the value of instrumental information at the planning stage. The latter will be important to determine the DM's preferences over plans. The former will be important to determine whether a plan prescribing instrumental testing is a self-enforcing, i.e. whether such a plan is a personal equilibrium.

Plugging in the respective formulas, one can show that the value of information W can be simplified to

$$W(NT^d) = q^+ V_T(p^+) + \text{VoNI}(NT^d) + ED(NT^d) \tag{11}$$

$$W(T^d) = q^- V_{NT}(p^-) + \text{VoNI}(T^d) + ED^(T^d) \tag{12}$$

where $T^d(NT^d)$ denotes $T(NT)$ being the default action. The exact derivation is given in the appendix. The equations show what determines the value of instrumental information. The second term gives the value of this test if it were noninstrumental. With reference to the discussion of the value of non-instrumental information I will refer to it as the information's *value for confidence.* This term is ammended by the term $q^- V_{NT}$ (or $q^+ V_T$ respectively). It captures the test's impact on utility by changing the treatment decision away from the default action for one of the test results. I will refer to it as the information's *instrumental value* as it is reminiscent of the classic economic idea of information being solely an input to decision-making. Finally, the last term is the emotional differential capturing the difference in emotional impact stemming from the information being instrumental. The triple structure we find contrasts with the suggestion of Karlsson et al. (2009) that the value of instrumental information can be found by simply adding the instrumental value to the value of the information if it were noninstrumental. This procedure neglects the emotional differential between instrumental and noninstrumental information.

While above considerations focus on the part of the value of instrumental information that is independent of the planned information choice the value *at the moment of choice* includes a term capturing the (dis-)utility arising from deviating from the planned information choice. The value of information at the moment of choice is thus affected by which information choice (i, n) was planned by the DM.

$$VoII(NT^d, n) = W(NT^d) + \gamma_0 \eta q^+ \left[p^+ \Delta_s - \lambda(1 - p^+)\Delta_h\right] \tag{13}$$

$$VoII(NT^d, i) = W(NT^d) + \gamma_0 \eta q^+ \left[\lambda p^+ \Delta_s - (1 - p^+)\Delta_h\right] \tag{14}$$

$$VoII(T^d, n) = W(T^d) + \gamma_0 \eta q^- \left[(1 - p^-)\Delta_h - \lambda p^- \Delta_s\right] \tag{15}$$

$$VoII(T^d, i) = W(T^d) + \gamma_0 \eta q^- \left[\lambda(1 - p^-)\Delta_h - p^- \Delta_s\right] \tag{16}$$

Equipped with these equations and the concept of preferred personal equilibrium we can now determine which of the equations actually applies to a given test.

3.3 The Value of a Test

Lemma 1, 2, and corollary 1 become very helpful when determining the value of a test with error rates (ϵ^-, ϵ^+) to a DM with prior p_0. First, the two posterior probabilities (p^-, p^+) can be calculated via Bayes' rule. Second, the default action of the DM can be deduced using Lemma 2.

There are two rather simple cases arising when the posteriors are extreme. First, if both posteriors are above p^*_{NT} (below p^*_T) the information must be noninstrumental as no plan prescribing the test to be instrumental would be followed through (lemma 1). Second, if $p^+ > p^*_{NT}$ and $p^- < p^*_T$ the information must be instrumental as no plan prescribing the test to be noninstrumental would be followed through (corollary 1). In all other cases, the difference between W and $VoNI$ will determine whether the DM perceives the test as instrumental or not. We can thus distinguish four cases and their respective conditions for test refusal.

1. If $p^- > p^*_{NT}$, the only credible continuation plan, given information is chosen, is to treat. The value of the test is $VoNI(T^d)$ and ignorance is the PPE if and only if $VoNI(T) < 0$.

2. If $p^+ < p^*_T$, the only credible continuation plan, given information is chosen, is not to treat. The value of the test is $VoNI(NT^d)$ and ignorance is the PPE if and only if $VoNI(NT) < 0$.

3. If $p^+ > p^*_{NT}$ and $p^- < p^*_T$, the only credible continuation plan, given information is chosen, is to follow the signal, i.e. to treat if tested positive and not to treat if tested negative. The value of the test is given by $VoII$. Ignorance is the PPE if and only if $VoII(n) < 0$ and $W < 0$.

4. If $p^+ < p^*_x$ or $p^- > p^*_y$, there is more then one credible continuation plan $d_1 \in D^*_1$ given information is chosen. The DM will prefer the test to be instrumental if $W > VoNI$. If the DM prefers the test to be instrumental, the value of the test is given by $VoII$ and ignorance is the PPE if and only if $VoII(n) < 0$ and $W < 0$. If the DM prefers the test to be non-instrumental, the value of the test is given by $VoNI$ and ignorance is the PPE if and only if $VoNI < 0$.

It is interesting to consider an analytically simple case: the value of a perfect test, i.e. $\epsilon^- = \epsilon^+ = 0$. KR show that someone with $\gamma_1 < 1$ would always prefer a perfect, but non-instrumental signal to remaining uninformed, and someone with $\gamma_1 = 1$ would be indifferent between receiving perfect information and remaining ignorant (compare Proposition 1). In addition, classic decision theory predicts a strictly positive value whenever information is instrumental. Intuition might thus lead one to expect that the value of information is strictly positive and ignorance never to be part of the preferred personal equilibrium if the test delivers perfect, instrumental information. It can be shown that there are cases in which this intuition is wrong.

3.4 The Value of Perfect Information

A test with error rates $\epsilon^- = \epsilon^+ = 0$ delivers perfect information about the state of health. The intent of this section is to derive the value of such perfect information (VoPI). It can be shown that someone who is sufficiently confident to be healthy ($p_0 < p^*$) never rejects a perfect test while this might not necessarily true for someone who entertains considerable doubts with regard to his health ($p_0 < p^*$).

Proposition 2. *Preferences for perfect information. An individual with prior $p_0 < p^*$ will never reject perfect, instrumental information. On the other hand, for a person with $p_0 > p^*$, and $\gamma_1 > \frac{C-D}{A-D} = \frac{r_T}{r_T+\Delta_h}$ there exists a degree of loss aversion $\lambda^* < \infty$ above which this person prefers to ignore perfect, instrumental information.*

Proof. See Appendix. □

Now, why can it be optimal to reject perfect information for someone with T as default action while this cannot happen for someone with NT as default action? Both the *instrumental value* as well as the *value for confidence* of perfect information are positive if $\gamma_1 < 1$ regardless of the prior. The difference lies in the *emotional differential.* While it is strictly positive for someone with NT as default it is strictly negative for someone with T as default action. As perfect information is instrumental it affects behavior. Due to this potential its emotional impact is different from its impact if this potential were absent. For someone with NT as default, good news get worse but bad news get better. For someone with T as a default, bad news get worse but good news get better. Due to loss aversion, the DM cares primarily about the emotional impact of bad news. Thus, making good news better while making bad news worse by an equal amount results in a more detrimental emotional impact in expectation while making good news worse and bad news better by an equal amount results in a more favorable emotional impact in expection. If the patent with default T cares sufficiently about the emotional impact of information (γ_1 is large enough) and the degree of loss aversion λ is large enough this rise in expected emotional disutility due to instrumentality outweighs the benefits of improved decision-making and higher confidence. It is then optimal to reject perfect information. This could not happen to someone with default NT because instrumentality implies improved decision-making as well as a more favorable emotional impact, i.e. a positive emotional differential.

It is still questionable whether people actually exhibit a degree of loss aversion that is high enough to make rejection of perfect information an optimal choice. There is a large literature providing estimates of loss aversion. The results most commonly support estimates of λ of around 3. A degree of loss aversion of 3 would be below λ^* assuming reasonable parameter values. Proposition 2, however, illustrates the point that (a) the degree of loss aversion can have a positive or negative impact on the value of information depending on the prior belief p_0 and the extent to which the DM cares about the emotional impact of information γ_1, and (b) the value of information does not necessarily increase when information becomes instrumental.

4 Screening and the Test as Gate-Keeper

The section on the value of perfect information underlined that the instrumentality of information has two major effects on its value. First, there is a positive effect through improved decision-making. Second, there is an effect through a change in the emotional impact of information. While the example of perfect information illustrates the general working of the model it might not be appropriate for the cases of test refusal presented in the introduction as there exists no perfect test. In addition, when looking at screening tests for HIV, colon, or breast cancer, patients should not expect to be treated without being tested positive. This is because (a) their prior probability of being sick is very close to zero, and (b) their action choice set without a positive test result is restricted to “no treatment”. The first reason underlines that the tests we are concerned about are screening tests, i.e. the test of patients that do not show symptoms of the disease. The second reason highlights that for diseases such as HIV or cancer positive tests work as a gate-keeper to treatment. It is thus important to investigate under what circumstances the model can explain the refusal of an imperfect test by someone who is rather certain to be healthy and with "no treatment" as default action.

Asymptomous screening is a type of medical test that is repeatedly a matter of discussion. On the one hand, as it concerns testing patients that do not exhibit any a priori evidence of a disease it amounts to testing a population that has a very low prior probability of being sick. On the other hand, there are diseases for which the benefits of identification of the disease are huge either because it facilitates containment of the disease (e.g. HIV) or it allows early treatment that comes with huge benefits compared to remaining untreated (e.g. breast cancer). It is often found that for diseases for which physicians recommend screening and patients generally acknowledge its benefits actual uptake rates fall below approval rates of patients.

This section seeks to replicate this setting in the following way. First, the patient's prior belief p_0 is close to zero. This and the fact that treatment is only possible after a positive test result make NT (no treatment) the patient's default action. Second, we want to replicate a setting in which a physician recommends a screening test but the patient refuses. As a consequence the physician must face incentives different from the patient. We will assume that the physician uses an expected utility model of decision-making while having a standard von Neumann-Morgenstern utility function given by m. This can be imagined as a situation in which the physician's incentives are such that he seeks to maximize the patient's expected health status $\mathbb{E}(m)$. Most importantly, he does not take into account the prospective or contemporaneous gain-loss utility arising from different decisions and health outcomes. This could be because he faces an incentive scheme (e.g. through the reimbursement/payment schemes of the medical system) that is purely focussed on physical health outcomes. It could also be the result of the physician seeing himself primarily as a provider of physical health services leaving psychological services and considerations to specialized colleagues. The recommendation of the test will thus only be based on its potential to improve expected physical health outcomes $\mathbb{E}(m)$ ignoring its psychological impact through gain-loss utility.[13]

[13]There are, of course, numerous other sources of incentive misalignment between patient and physician. In order to single out the effect of emotional responses to information we assume gain-loss utility to be the sole source of

Recall that the value of perfect information is strictly positive for someone with default NT. Thus ignorance can, if at all, only occur for tests with imperfect precision. However, to simplify calculations, we will assume a false-negative rate $\epsilon^- = 0$ which implies $p^- = 0$. This assumption should not be a significant one in the screening setting as the prior p_0 is already assumed to be close to zero and $p^- < p_0$. Furthermore, if at all, it will bias the results against ignorance as it increases the precision of the signal. Under these assumptions we can find the following condition for the rejection fo a screening test.

Proposition 3. *Rejection of Screening. Assume an individual with RDP preferences and a physician using an expected utility-based decision model. Assume further that $p_0 < p^*$ such that without the test both agree on "no treatment" being the optimal action. Finally, assume that there is no false-negative error $\epsilon^- = 0$. The physician will recommend a test whenever the false-positive rate is such that $p^+ \geq \frac{\Delta_h}{\Delta_h + \Delta_s}$. Given a prior belief p_0, there exists a range of tests, i.e. there exists a range of false-positive rates ϵ^+ for which the physician recommends the test while the patient refuses to take the test if*

$$\Delta_s < q^- r_{NT} \left(\gamma_1 - \frac{\Delta_h}{\Delta_h + \Delta_s} \right).$$

Proof. See Appendix. □

Note that the prior p_0 plays an important role in the condition for the rejection of screening through its effect on q^-. The closer the prior is to zero (the more seldom the disease, the less the perceived risk) the lower the false-positive rate the physician requires to recommend a test. Still, even if the error rate is sufficiently low for the physician to recommend, it might not be low enough for the patient to agree to testing.

Condition 3 is interesting when comparing it to the reasons patients give for refusing a medical test. First, the lower the perceived risk the more likely is information refusal. The RHS is decreasing in p_0, the subjective probability of being sick, through its impact on q^- making ignorance more likely the lower p_0. Second, although recognizing the benefits of treatment, people reject information if treatment does not constitute a "cure". As was explained in the model setup, the

incentive divergence in this setting.

fraction $\Delta_h/(\Delta_h + \Delta_s)$ can be interpreted as the cost-to-benefit ratio of treatment. If benefits of treatment are large relative to costs, γ_1 will exceed this ratio making the RHS of the condition positive. In addition, $r_{NT} = r_T + \Delta_h + \Delta_s$, where r_T can be interpreted as a measure of effectiveness of treatment. If $r_T = 0$ treatment constitutes a perfect cure. Now, suppose r_T is large relative to $\Delta_h + \Delta_s$, i.e. there is a beneficial treatment which does not cure the disease ("care" instead of "cure"). This is the setting where it is most likely that the RHS exceeds the LHS, i.e. condition 3 for ignorance holds. Summing up, the setting in which the model predicts ignorance of screening tests to occur despite recommendation by a physician are those in which a patient may test for a disease that (a) is severe, (b) for which there exists an efficient treatment but (c) this treatment is rather ineffective compared to a perfect cure. This seems to match the situation with the medical screening tests presented in the introduction: the diagnosis of a predisposition for Alzheimer's, Huntington's disease, or cancer, or the diagnosis of HIV. There is a treatment available that is highly beneficial, but there is no perfect cure. Thus the model's prediction is in line with the stated reason of "there is no cure" for information rejection.

5 Comparative Statics

We are now interested in how certain parameters of the model affect the value of information and the incentives for test refusal. We will look both on the impact of a variation in the parameters on non-instrumental and instrumental information. For simplicity, we will look at the value of instrumental information W at the planning stage thus abstracting from the utility from deviation at $t = 0$. In addition, for instrumental information we will confine ourselves to the value of perfect information. Concerning the question which parameters to vary, it helps to have a second look at the model setup where the interpretation of the different parameters was discussed.

First, we will look at a variation in the health outcomes m. More precisely, we will ask what happens if the benefits of treatment, the costs of treatment, and the severeness of the disease change. Second, we will investigate what happens when the parameters γ_0 and γ_1, which capture the impact of prospective gain-loss utility, are varied as these are assumed to be connected to the timing of testing. All proofs are in the appendix.

5.1 Effectiveness of Treatment

An increase in the effectiveness of treatment should (a) increase Δ_s, the net benefit of treatment, and (b) decrease r_T, which is the smaller the more effective the treatment. It is possible to capture this effect by differentiating with respect to r_T while assuming $\partial \Delta_s / \partial r_T = -1$.

Proposition 4. *Treatment Effectiveness. If the test is noninstrumental, a change in treatment effectiveness has no impact on test uptake. If the test is istrumental, an increased treatment effectiveness increases the incentives for test refusal among those who would treat without further information but reduces incentives for test refusal among those who would (or could) not treat without being tested positive.*

The impact of a variation in r_T (holding r_{NT} and Δ_h constant) is rather straightforward if information is non-instrumental. Treatment effectiveness has, of course, no impact on the value of information if the default is "not treatment", and the action taken after information reception is "no treatment" as well. If the default action is "treatment", an increase in r_T increases the value of non-instrumental information if $\gamma_1 < p^+ - p^-$. This is the same condition that determines whether a patient prefers non-instrumental information to remaining uninformed. Thus, a change in the benefits of treatment has no impact on the incentives for information rejection. The benefits of treatment may determine *how much* someone is willing to pay for confidence in the treatment decision, but, they will not change *whether* someone is willing to pay for confidence.

The impact on the value of perfect information depends on the default action as well. An increase in the benefits of treatment may influence the three components of the value of information described in the derivation of the value of information. The first term, the instrumental value, is not affected if treatment is the default action, but influenced positively if no treatment is the default action. This is straightforward as the instrumental value is the increase in expected period 2 utility that results from switching to the alternative action. This value is only affected positively by an increase in the benefits of treatment if the alternative action is "treatment". The second term, the value for confidence, is affected in the same way as the value for non-instrumental information as it is the value of perfect information if it were non-instrumental. Thus, this value will remain constant if the default action is no treatment and will increase if the default action is treatment.

Finally, there may be an impact on the emotional differential. The emotional differential is only affected by an increase in the benefits of treatment if the default action is NT. Remember that the emotional differential for default NT captures that the emotional impact of instrumental information is, in expectation, better than the impact of non-instrumental information because bad news get better. Bad news get better by the degree to which treatment leads to a better outcome if one is sick. Thus, increasing the benefits of treatment, makes bad news better. Although it also makes good news, comparatively, worse, the patient cares more about the emotional impact of bad news due to loss aversion. The net effect is, in expectation, positive. A change in the benefits of treatment has no impact on the emotional differential for default T because this is determined by the degree to which good news become better. The extent to which good news become better is, however, not a function of the benefits of treatment if information is perfect. Summing over all effects, an increase in the effectiveness of treatment increases the value of perfect information if the patient has a default action NT but decreases the value of perfect information if the patient has the default action T. In accordance with this finding, recall that a large r_T compared to $\Delta_1 + \Delta_2$, i.e. the inavailability of a cure, is a major prerequisite for the rejection of screening tests by those with default NT. Thus, a larger treatment effectiveness should lower the refusal rates for screening tests.

It is important to highlight the difference of this result to the result obtained in a standard decision theoretic framework when assuming von Neumann-Morgenstern utility functions. In the latter framework the value of information is positive, thus information desirable, whenever the probability of sickness after a positive test p^+ is larger than $\Delta_h/(\Delta_h + \Delta_s)$. The question whether to obtain a test is, hence, a function of the accuracy of the test through p^+ on the one hand, and the efficiency of the treatment through the cost-benefit ratio $\Delta_h/(\Delta_h + \Delta_s)$ on the other hand. A test can thus be desirable in a standard decision-theoretic framework if treatment is highly efficient, though not necessarily highly effective. In contrast to this, a patient with reference-dependent preferences will be affected by treatment effectiveness, in addition to treatment efficiency, in his information decision due to psychological considerations.

5.2 Costs of Treatment

The desire to be tested may also be a function of the expected costs of treatment. A variation in these costs can be investigated while holding r_T and r_{NT} fixed. A rise in the costs of treatment should increase Δ_h, but decrease Δ_s, the net benefit of treatment to a sick, when treatment costs are identical across states as is assumed. In the derivation we will thus assume $\partial\Delta_s/\Delta_h = -1$.

Proposition 5. *Treatment Costs. The value of nonistrumental information is independent of treatment costs. In contrast, if information is instrumental, an increase in treatment cost has a negative effect on test uptake for those who have "no treatment" as a default action. The effect on those with "treatment" as default action depends on the degree of loss aversion.*

It is easy to see that a variation in treatment cost has no impact on the value of non-instrumental information $VoNI$ regardless of the default action as both r_T and r_{NT} remain unchanged. When looking at the value of instrumental information one can, again, look at the effects on the three main components of the value of information, abstracting from the impact on prospective gain-loss utility in period 0. The instrumental value decreases for someone with no treatment as default and increases for someone with treatment as default. This is because in the first case, the alternative action (treatment) gets worse if treatment costs increase and in the second case, the alternative action (no treatment) gets better because higher treatment costs are avoided. As treatment costs do not affect the value of non-instrumental information they do not affect the value for confidence of instrumental information. Finally, the emotional differential is negatively affected by an increase in treatment costs. As treatment costs increase good news get better, however, bad news get, comparatively, worse. Due to loss aversion, the second effect dominates which leads to a worse emotional impact in expection. While the overall effect is clearly negative for someone with default NT it is ambiguous for someone with default T. If the latter puts sufficient weight on the gain-loss utility and/or loss aversion is large enough the second effect will dominate.

These insights are important for determining the impact of the variation on refusal rates. For someone with NT as default, an increase in treatment costs lowers the incentives to test and increases the incentives for test refusal. For someone with T as default, refusal rates will increase as a result of a rise in treatment costs if the individual is sufficiently loss averse (compare Proposition 2). One can, again, compare this result to the predictions of a standard decision-theoretic framework. As a rise in treatment costs decreases the efficiency of treatment, it leads to lower incentives for testing for someone with NT as default and higher incentives for someone with T as default. If patients have reference-dependent preferences the incentives in favor of testing for someone with NT as default should decrease stronger in treatment costs and the incentives for testing for someone with T as default should increase less in treatment costs compared to the predictions of standard decision theory.

5.3 Severity of the Disease

Finally, we are concerned whether the severity of the disease itself (r_{NT}) has an impact on the value of information. It is easy to show that this effect is rather simple.

Proposition 6. *Severity of Disease. Holding the characteristics of available treatment, i.e. benefit-to-cost ratio $(\Delta_s + \Delta_h)/\Delta_h$, and relative effectiveness (r_T/r_{NT}), constant, a variation in the severity of disease has no impact on uptake rates.*

The reader should keep in mind that proposition 6 does not imply that the value of information is independent of the severity of the disease. However, it highlights that uptake rates are a function of treatment characteristics only.

5.4 Timing of Testing

Kőszegi and Rabin (2009) suggest that the impact of gain-loss utility depends negatively on the distance between the point in time gain-loss utility is realized through a change in belief and the point in time the material utility is realized this belief is about. Denote by $\tau_1(\tau_0)$ the time distance between information reception in period 1 (information choice in period 0) and the resolution of health outcomes in period 2.KR thus suggest that $\partial\gamma_1/\partial\tau_1 < 0$ and $\partial\gamma_0/\partial\tau_0 < 0$. Taking up these assumptions we can address questions concerning the timing of testing.

First, consider a variation in the **speed of testing**. Fixing the time of information choice τ_0, an increase in the speed of testing implies an increase in τ_1. In addition, one can investigate the desirability of **earlier tests**. To vary the time of the test, without varying its speed, both τ_0 and τ_1 need to be varied simulatneously by an equal amount, say τ. While the effect of a variation in the speed of testing is straightforward, the effect of earlier tests is ambiguous in general.

Proposition 7. *Timing of Tests.*

(i) The value of information, be it instrumental or not, is increasing in the speed of testing. Faster tests induce higher uptake rates.

(ii) If information is non-instrumental, earlier tests have higher value. Information rejection is less likely the earlier the test is conducted. If information is instrumental, earlier tests have a higher value if

$$q^-(\lambda-1)\left[(1-p^-)\Delta_h+(p^+-p^-)r_T+p^-\Delta_s\right]\left[-\frac{\partial\gamma_1}{\partial\tau_1}\right]>\left[\lambda p^+\Delta_s-(1-p^+)\Delta_h\right]\left[-\frac{\partial\gamma_0}{\partial\tau_0}\right]$$

when "no treatment" is the default action, and

$$q^+(\lambda-1)\left[(1-p^-)\Delta_h+(p^+-p^-)r_T+p^-\Delta_s\right]\left[-\frac{\partial\gamma_1}{\partial\tau_1}\right]>\left[\lambda(1-p^-)\Delta_h-p^-\Delta_s\right]\left[-\frac{\partial\gamma_0}{\partial\tau_0}\right]$$

when "treatment" is the default action.

The impact of an increase in the speed of testing is straightforward. As γ_1 is the weight on the emotional impact of information, which is, in expectation, always negative, the value of information always increases in the speed of testing. The lower the weight on prospective gain-loss utility in period 1, the higher the value of information. Thus, the faster the patient receives his test results, the more desirable is a test. The importance of the parameter γ_1, and thus the speed of testing, is underlined by the fact that it plays a role in every condition for information rejection (see Propositions 2 and 3). Each of these conditions says that γ_1 needs to be sufficiently large to make ignorance the PPE. The model, thus, identifies the speed of testing as a crucial factor in mitigating the emotional distress associated with information reception, and as a key variable in influencing test uptake.

The effect of the time of testing is similar to the effect of testing speed if information is noninstrumental, as for noninstrumental infomation there is no gain-loss utility in period 0. As $\frac{\partial\gamma_1}{\partial\tau_1}<0$, the value of a non-instrumental test increases the earlier the test is conducted. As was already discussed in the section on the value of non-instrumental information this effect is in line with empirical findings by Eliaz and Schotter (2007).

Concerning the value of instrumental information, a change in the time of the test leads to an equally-sized change in τ_0 and τ_1 denoted by $d\ \tau$. There are two effects. The first one is familiar from the change in the speed of testing. It has a positive sign. The second term has a negative sign if the test's error rates are low enough, i.e. p^+ is large enough and p^- small enough. Assuming sufficient accuracy it is not straightforward to see which effect dominates. One can, however, make the following predictions. Suppose $\partial\gamma_0/\partial\tau_0 = \partial\gamma_1/\partial\tau_1$. If r_T is relatively large compared to $\Delta_1 + \Delta_2$ the first effect will dominate. Thus, again, for diseases for which there is no perfect cure available, the second effect is likely to dominate. Second, suppose γ_0 (γ_1) is a convex function of τ_0 (τ_1), i.e. the impact of gain-loss utility declines non-linearly in the time distance. Thus $\partial\gamma_0/\partial\tau_0 > \partial\gamma_1/\partial\tau_1$ which implies that the first effect is given a higher weight. Under these conditions, inavailability of a perfect cure and/or a higher responsiveness of the impact of gain-loss utility in period 1 compared to period 0 to changes in timing, earlier tests will be regarded with higher value by the patient. As earlier tests decrease γ_1 this should result in higher uptake rates of tests.

These considerations are in line with observations concerning increased uptake rates for faster HIV tests[14]. Patients seem to prefer faster tests even if the increase in speed comes at the cost of reduced accuracy. While this observation can also be explained by travel/time costs associated with collecting the test result when a second appointment is necessary, Proposition 7 suggests an additional psychological motive for the observed preference for faster tests.

6 Conclusion

The paper investigates how anticipated emotional responses to information may affect information preferences. It seeks to highlight the connection between instrumentality and emotional impact of information and how they jointly determine the value of information. It is shown that instrumentality influences the emotional impact of information and this influence depends on an

[14]See e.g. Kassler et al. (1997) and Greenwald et al. (2006)

individual's prior. The impact of loss aversion on testing decisions might thus be quite different across people. Furthermore, it is possible to isolate different determinants of refusal rates. A large value of the parameter γ_1, measuring the impact of prospective gain-loss utility, can be identified as a major determinant of test refusal. If the emotional effects of information play a large role one may look into ways how to dampen these effects. One possibility would be to address timing issues, in particular the speed of testing. It is also worth noting that uptake rates vary with treatment characteristics. Here, the availability of cure plays an important role. This is a result in contrast to the value of information in classic decision theory which does not depend on the size of potential benefits, i.e. on the gap between actual benefits and perfect cure. In this light it is worth remembering that it is "absence of a cure" that is stated as a rational for test refusal, and not that available treatments provide little benefit.

With an ongoing debate on whether to transfer responsibility for medical decisions towards patients ("shared responsibility") it needs to be underlined that physicians' and patients' decisions can be quite different. If physicians use decision models based on expected utility theory thus not fully incorporating patients' preferences they will disagree with patients even if they are able to perfectly elicit the desirability of different health outcomes. The model presented here offers the patient's intent to balance material (or here: physical) and psychological concerns as a possible explanatory.

Finally, while this paper concentrates on the issue of evaluating medical information, conclusions can be transferred to the evaluation of information in similar settings, i.e. to decision problems that exhibit a clear state preference on the side of the individual. It is worth investigating information preferences that result from reference-dependent preferences. With mounting evidence that a person's reference point is a function of his expectations, it is, at least partly, a result of prior information. Hence, when an individual's preferences are influenced by prior information acquisition and these preferences determine future information acquisition, complementarities in information choice and information preferences arise. It would be worth investigating the results of these interactions in settings different from the one investigated here.

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Appendix

Equivalence of two Approaches to calculate Gain-Loss Utility

Proof. KR derive a percentile-wise comparison of material outcomes for some belief $F(m)$ over outcomes. Formally, they define the material outcome at percentile π:
For any distribution F over $\mathbb{R}$ and any $\pi \in (0,1)$ let $m_F(\pi)$ be the material utility level at percentile π, defined implicitly by

$$(i) F(m_F(\pi)) \geq \pi$$
$$(ii) F(m) < \pi \text{ for all } m < m_F(\pi)$$

This definition yields a unique function $m_F(\pi) : (0,1) \to \mathbb{R}$ with

$$m_F = \begin{cases} m_1 & \forall \pi \in (0, F(m_1)] \\ m_2 & \forall \pi \in (F(m_1), F(m_2)] \\ ... & \\ m_k & \forall \pi \in (F(m_{k-1}), 1) \end{cases} \tag{17}$$

where $(m_1, ..., m_k)$ constitutes the support of $F(m)$ with $m_1 < m_2 < ... < m_k$.

Proof. First, $m_F = m_1 \quad \forall \pi \in (0, F(m_1)]$. Suppose not. In this case, there exists a $\pi \in (0, F(m_1)]$ for which either $m_F(\pi) < m_1$ or $m_F(\pi) > m_1$. If $m_F(\pi) < m_1$ there is a contradiction to (i), since $F(m_F(\pi)) = 0 < \pi \quad \forall \pi \in (0, F(m_1)]$. If $m_F(\pi) > m_1$ there is a contradiction to (ii), since there exists a level of m, namely m_1, for which $F(m) \geq \pi \quad \forall \pi \in (0, F(m_1)]$.
Simlarly, for all $m_i, \quad i = 2..k-1, m_F = m_i \quad \forall \pi \in (F(m_{i-1}, F(m_i)]$. Suppose not. Then there exists a $\pi \in (F(m_{i-1}, F(m_i)]$ such that either $m_F(\pi) < m_i$ or $m_F(\pi) > m_i$. If $m_F(\pi) < m_i$ there is a contradiction to (i) as $F(m_F(\pi)) < \pi$. If $m_F(\pi) > m_i$ there is a contradiction to (ii), since there exists an $m < m_F(\pi)$, namely m_i such that $F(m) \geq \pi$.
Finally, $m_F(\pi) = m_k \quad \forall \pi \in (F(m_{k-1}), 1)$. Suppose not. Then there exists a $\pi \in (F(m_{k-1}, 1)$ such that either $m_F(\pi) < m_k$ or $m_F(\pi) > m_k$. The first case contradicts (i) since $F(m_F(\pi)) < \pi$. The second case contradicts (ii) since there exists an $m < m_F(\pi)$, namely m_k such that $F(m) \geq \pi$. □

Looking at Figure 4, one can see that the unique function $m_F(\pi)$ "matches" the steps of the step function $F(m)$. KR want to define gain-loss utility in the following way: at each percentile

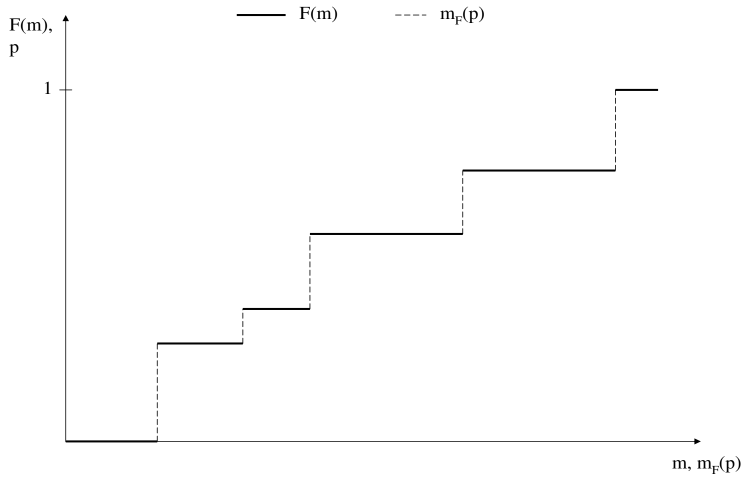

Figure 4: Derivation of $m_F(\pi)$ from $F(m)$

the material outcome of the new belief is compared to the material outcome of the old belief. If the former is higher than the latter the individual experiences a gain at this percentile, otherwise it experiences a loss at this percentile. Formally, define psychological utility from a change in belief by

$$\tilde{v}(F_t, F_{t-1}) = \eta \int_0^1 \mu \left[m_{F_t}(\pi) - m_{F_{t-1}}(\pi) \right] d\pi$$

with:

$$\mu(z) = z \text{ if } z \geq 0$$

$$\mu(z) = \lambda z \text{ if } z < 0$$

Looking at Figure 5, one can see that, if the gain-loss function is two-piece linear as is assumed, the same result can be obtained by comparing the old and new belief directly without deriving functions $m_F(\pi)$. One can calculate gain-loss utility instead by assigning a gain to any level of material outcome to which the new belief, say G, assigns lower density than the old belief (F), i.e. when $G(m) < F(m)$. A loss is assigned to any level of material outcome to which the new belief (G) assigns higher density than the old belief (F), i.e. when $G(m) > F(m)$. Thus, one can

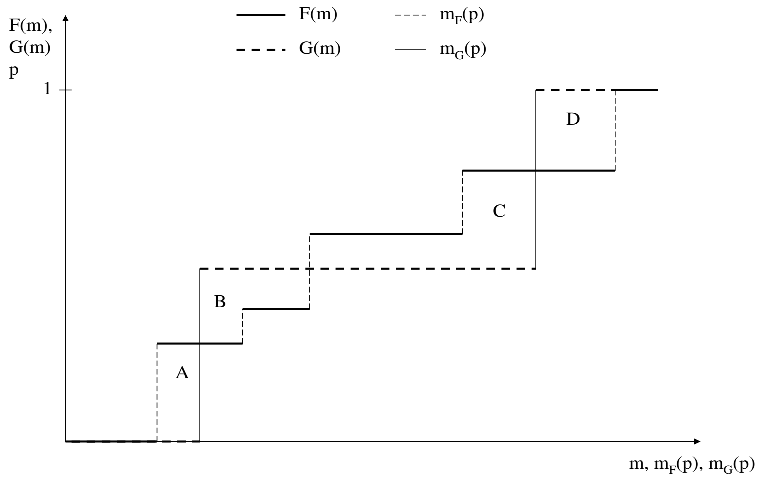

Figure 5: Comparing F and G versus comparing m_F and m_G.

calculate the gain-loss utility directly by comparing the beliefs at each level of material outcome.

$$v(F_t, F_{t-1}) = \eta \int_{-\infty}^{\infty} \mu \left[F_{t-1}(m) - F_t(m)\right] dm.$$

Both approaches yield the same result as they both calculate gains for the areas A and C and losses for the areas B and D. The second approach, however, spares the detour over deriving the functions $m_F(\pi)$, $m_G(\pi)$ first. Note, however, that this simplification is only valid when assuming the two-piece linear representation of gain-loss utility. □

Proof of Lemma 1

Proof. To prove Lemma 1, one needs to show that (i) there exist beliefs p_1 for which $\mathbb{E}_1 U^1(NT|NT) - \mathbb{E}_1 U^1(T|NT)$, $V_{NT} = \mathbb{E}_1 U^1(NT|NT) - \mathbb{E}_1 U^1(T|T)$, and $\mathbb{E}_1 U^1(T|T) - \mathbb{E}_1 U^1(NT|T)$ equal zero respectively, (ii) these beliefs are unique, and (iii) have the order described by Lemma 1. Define

$$\Gamma_{NT} \equiv \mathbb{E}_1 U^1(NT|NT) - \mathbb{E}_1 U^1(T|NT) \tag{18}$$

$$\Gamma_T \equiv \mathbb{E}_1 U^1(T|T) - \mathbb{E}_1 U^1(NT|T) \tag{19}$$

Furthermore, recall the definition $V_{NT} \equiv \mathbb{E}_1 U^1(NT \mid NT) - \mathbb{E}_1 U^1(T \mid T)$.

(i) Existence

The proof is simple. Note that $\Gamma_{NT} > 0$, $V_{NT} > 0$ and $\Gamma_T < 0$ for $p_1 = 0$ while $\Gamma_{NT} < 0$, $V_{NT} < 0$, and $\Gamma_T > 0$ for $p_1 = 1$. By continuity of Γ_{NT}, V_{NT} and Γ_T, the functions have at least one root on the interval $(0, 1)$. Denote by p^*_{NT}, p^*, p^*_T a root of $\Gamma_{NT}, V_{NT}, \Gamma_T$ respectively.

(ii) Uniqueness

It can be shown that the first derivatives of Γ_{NT} and V_{NT} with respect to p_1 are strictly negative at their respective root while the first derivative of Γ_T with respect to p_1 is strictly positive at its root. This, coupled with continuity, implies the uniqueness of the roots.

(ii,a) Γ_{NT} *is strictly decreasing in* p_1 *at* $\Gamma_{NT} = 0$.

At $p_1 = p^*_{NT}$, $\Gamma_{NT} = \mathbb{E}_1 U^1(NT|NT) - \mathbb{E}_1 U^1(T|NT) = 0$. This implies

$$(1 - p^*_{NT})\Delta_h - p^*_{NT}\Delta_s - p^*_{NT}(1 - p^*_{NT})\eta(\lambda - 1)(\Delta_h + \Delta_s) + \gamma_1\eta\left[\lambda(1 - p^*_{NT})\Delta_h - p^*_{NT}\Delta_2\right] = 0$$

$$\Rightarrow \chi_1 \equiv (\Delta_h + \Delta_s) - p^*_{NT}\eta(\lambda - 1)(\Delta_h + \Delta_s) + \gamma_1\eta(\lambda\Delta_h + \Delta_s) = \frac{1}{1 - p^*_{NT}}\Delta_2(1 + \gamma_1\eta) > 0$$

Differentiating Γ_{NT} w.r.t. p_1 yields

$$\frac{\partial \Gamma_{NT}}{\partial p_1} = (\Delta_h + \Delta_s) - (1 - 2p_1)\eta(\lambda - 1)(\Delta_h + \Delta_s) + \gamma_1\eta(\lambda\Delta_h + \Delta_s)$$

At $p_1 = p^*_{NT}$ this differential is negative as

$$\begin{aligned}\frac{\partial \Gamma_{NT}(p^*_{NT})}{\partial p_1} &= -(\Delta_h + \Delta_s) - (1 - 2p^*_{NT})\eta(\lambda - 1)(\Delta_h + \Delta_s) - \gamma_1\eta(\lambda\Delta_h + \Delta_s) \\ &= -\chi_1 - (1 - p^*_{NT})\eta(\lambda - 1)(\Delta_h + \Delta_s) < 0\end{aligned}$$

(ii,b) V_{NT} *is decreasing in* p_1 *at* p^*.

At p^*, $V_{NT} = 0$. This implies

$$V_{NT} = -\Delta_s + (1 - p^*)\left[(\Delta_h + \Delta_s) - p^*\eta(\lambda - 1)(\Delta_h + \Delta_s)\right]$$

$$\Rightarrow \chi_2 \equiv (\Delta_h + \Delta_s) - p^*\eta(\lambda - 1)(\Delta_h + \Delta_s) = \frac{\Delta_s}{1 - p^*} > 0$$

Differentiating V_{NT} w.r.t. p_1 yields

$$\frac{\partial V_{NT}}{\partial p_1} = -(\Delta_h + \Delta_s) - (1 - 2p_1)\eta(\lambda - 1)(\Delta_h + \Delta_s)$$

At $p_1 = p^*$ this differential is negative as

$$\begin{aligned}\frac{\partial V_{NT}(p^*)}{\partial p_1} &= -(\Delta_h + \Delta_s) - (1-2p^*)\eta(\lambda-1)(\Delta_h+\Delta_s) \\ &= -\chi_2 - (1-p^*)\eta(\lambda-1)(\Delta_h+\Delta_s) < 0\end{aligned}$$

(ii,c) Γ_T *is increasing in* p_1 *at* p_T^*.

At p_T^*, $\Gamma_T = 0$. This implies

$$\begin{aligned}\Gamma_T = p_T^*\Delta_s - (1-p_T^*)\Delta_h + p_T^*(1-p_T^*)\eta(\lambda-1)(\Delta_h+\Delta_s) + \gamma_1\eta\left[-(1-p_T^*)\Delta_h + \lambda p_T^*\Delta_2\right] = 0 \\ \Rightarrow \chi_3 \equiv (\Delta_h+\Delta_s) - p_T^*\eta(\lambda-1)(\Delta_h+\Delta_s) + \gamma_1\eta(\Delta_h + \lambda\Delta_s) = \frac{1}{1-p_T^*}\Delta_s(1+\gamma_1\eta\lambda) > 0\end{aligned}$$

Differentiating Γ_T w.r.t. p_1 yields

$$\frac{\partial \Gamma_T}{\partial p_1} = (\Delta_h+\Delta_s) + (1-2p_1)\eta(\lambda-1)(\Delta_h+\Delta_s) + \gamma_1\eta(\Delta_h+\lambda\Delta_s)$$

At $p_1 = p_T^*$ this differential is positive as

$$\begin{aligned}\frac{\partial \Gamma_T(p_T^*)}{\partial p_1} =& (\Delta_1+\Delta_2) + (1-2p_T^*)\eta(\lambda-1)(\Delta_h+\Delta_s) + \gamma_1\eta(\lambda\Delta_h+\Delta_s) \\ =& \chi_3 + (1-p_T^*)\eta(\lambda-1)(\Delta_h+\Delta_s) > 0\end{aligned}$$

(iii) Order: $0 < p_T^* < p^* < p_{NT}^* < 1$.

To complete the proof of the Lemma, it needs to be shown that the roots have the stated order. Note that $\Gamma_{NT} > 0$ and $\Gamma_T < 0$ for $p_1 = 0$ and $\Gamma_{NT} < 0$ and $\Gamma_T > 0$ for $p_1 = 1$. This implies that the roots are bounded away from zero and one. Furthermore, it can be shown that both $\Gamma_{NT} > 0$ and $\Gamma_T > 0$ at $p_1 = p^*$. These observations, in addition to the existence of unique roots and continuity of the functions, imply that $p_T^* < p^*$ and $p_{NT}^* > p^*$.

(iii,a) $\Gamma_{NT}(p^*) > 0$.

$$\begin{aligned}\Gamma_{NT}(p^*) =& V_{NT}(p^*) - \gamma_1\eta\left[-\lambda(1-p^*)\Delta_h + p^*\Delta_s\right] \\ & 0 + \gamma_1\eta\left[\lambda(1-p^*)\Delta_h - p^*\Delta_s\right]\end{aligned}$$

Note that $r_{NT} - r_T = \Delta_1 + \Delta_2 > 0$. This means that at p^*, $V_{NT} = 0$ implies

$$\begin{aligned}V_{NT} = (1-p^*)\Delta_h - p^*\Delta_s - p^*(1-p^*)\eta(\lambda-1)(\Delta_h+\Delta_s) = 0 \\ \Leftrightarrow (1-p^*)\Delta_h - p^*\Delta_s > 0 \\ \Rightarrow \lambda(1-p^*)\Delta_1 - p^*\Delta_2) > 0\end{aligned}$$

Thus Γ_{NT} is positive at p^*.

(iii,b) $\Gamma_T(p^*) > 0$

At $p_1 = p^*$, $\Gamma_T(p^*) = \gamma_1\eta\left[-(1-p^*)\Delta_h + \lambda p^*\Delta_s\right]$. For this to hold it is necessary that $(1-p^*)\Delta_h < \lambda p^*\Delta_s$. Note that, by definition of p^*, $(1-p^*)\Delta_h = p^*\Delta_s + p^*(1-p^*)\eta(\lambda-1)(\Delta_1+\Delta_2)$. Using this equation and solving for λ gives

$$\begin{aligned}(1-p^*)\Delta_h &< \lambda p^*\Delta_s \\ \Leftrightarrow p^*\Delta_s + p^*(1-p^*)\eta(\lambda-1)(\Delta_h+\Delta_s) &< \lambda p^*\Delta_s \\ \Leftrightarrow p^*\Delta_s - p^*(1-p^*)\eta(\Delta_h+\Delta_s) &< \lambda\left[p^*\Delta_s - p^*(1-p^*)\eta(\Delta_h+\Delta_s)\right] \\ \Leftrightarrow 1 &< \lambda\end{aligned}$$

which is true by assumption. □

Proof of Proposition 2

Proof. First, by corollary 1, perfect information must be instrumental. Second, by Lemma 2, the default action is NT if $p_0 < p^*$ and T if $p_0 > p^*$. For ignorance to be a PPE, (a) the value of perfect information must be negative given that the plan is not to test: $VoII(\cdot, n) < 0$, and (b) the plan prescribing not to test must be preferred to the plan to test: $W < 0$.

If $p_0 < p^*$, the default action is not to treat (NT). The value of perfect information is then

$$VoPI(NT^d, n) = p_0\Delta_s\left[1 + (1-p_0)\gamma_1\eta(\lambda-1) + \gamma_0\eta\right] + p_0(1-p_0)\eta(\lambda-1)(1-\gamma_1)r_{NT}$$

which is strictly positive. Thus ignorance cannot be a PPE for someone with default NT as condition (a) is never satisfied.

Now suppose $p_0 > p^*$, the default action is to treat (T). It is easy to see that for perfect information $W < VoII(\cdot, n)$, thus condition (a) implies condition (b). In other words, if rejection of perfect information is a PE then it must be the PPE. The value of perfect information for someone with default T is given by

$$VoPI(T^d, n) = (1-p_0)\Delta_h(1-\gamma_0\eta) + p_0(1-p_0)\eta(\lambda-1)\left[r_T - \gamma_1(r_T+\Delta_h)\right].$$

This value is negative if and only if $\gamma_1 > \frac{r_T}{r_T+\Delta_h}$ and the degree of loss aversion exceeds a critical value λ^* given by

$$\lambda^* \equiv \frac{\Delta_h(1+\gamma_0\eta)}{\eta p_0\left[\gamma_1(r_T+\Delta_h)-r_T\right]}+1. \tag{20}$$

□

Proof of Proposition 3

Proof. We will look at the value of a particular test: a test with $\epsilon^- = 0$ as assumed and $\epsilon^+ = \frac{p_0}{1-p_0}\frac{\Delta_s}{\Delta_h}$. Such a test produces the posterior $p^+ = \Delta_h/(\Delta_h+\Delta_s)$. It is of particular interest as it is the worst test in terms of ϵ^+ (among those with $\epsilon^- = 0$) that is still instrumental from the point of view of the physician. Any test with a smaller false positive rate would be recommended by the physician as it yields a strictly positive value of information from his point of view. We will derive a condition under which this particular test is rejected by a patient with reference-dependent preferences. If the value of information for the patient turns out to be negative for such a test, by continuity of $VoII$ it will still be negative for a test with slightly smaller ϵ^+ to which the physician attributes a strictly positive value. Then there exists a range of tests in terms of ϵ^+ to which the physician assigns positive value but the patient assigns negative value.

To derive whether the patient agrees to being tested or refuses to being tested we first need to find out whether the patient would regard the test as instrumental or noninstrumental. The patient will regard the test as instrumental if

$$W(NT^d) - VoNI(NT^d) \geq 0$$

It can easily be verified that this is the case with $p^- = 0$ and $p^+ = \frac{\Delta_h}{\Delta_h+\Delta_s}$. In order for ignorance to be a PPE, it suffices to check whether $W(NT^d) < 0$ as for above posteriors $VoII(NT^d, n) < W(NT^d)$. This means that if $W(NT^d) < 0$ ignorance is both a personal equilibrium and, in addition, the preferred personal equilibrium.

With $p^- = 0$ and $p^+ = \frac{\Delta_h}{\Delta_h+\Delta_s}$, $W(NT^d)$ equals

$$q^+p^+(1-p^+)\eta(\lambda-1)(\Delta_h+\Delta_s) + VoNI(NT^d)$$

Thus if $VoNI(NT^d)$ is sufficiently negative ignorance is optimal. This is the case if

$$\Delta_s < q^- r_{NT} \left(\gamma_1 - \frac{\Delta_h}{\Delta_h + \Delta_s} \right). \tag{21}$$

If condition 21 is satisfied a patient with default NT refuses a test that results in posterior probabilities of being sick of 0 or $\Delta_h/(\Delta_h + \Delta_s)$. Together with the fact that this patient would not refuse a perfect test yields the result that there exists a threshold $p^+ > \Delta_h/(\Delta_h + \Delta_s)$ above which the patient agrees to being tested and below which the patient refuses to being tested. Thus for any prior $p_0 \in \left(0, \frac{\Delta_h}{\Delta_h+\Delta_s}\right)$ for which above condition is satsified, there exists an interval of false-positive rates ϵ^+ for which the physician recommends the test but the patient refuses. □

Proof of Proposition 4

Proof.

$$\frac{\partial VoNI(NT^d)}{\partial r_T} = 0 \tag{22}$$

$$\frac{\partial VoNI(T^d)}{\partial r_T} = q^- q^+ \eta(\lambda - 1)(p^+ - p^-) \left[(p^+ - p^-) - \gamma_1\right] \tag{23}$$

$$\left(\frac{\partial W(NT^d)}{\partial r_T} \right)_{\epsilon^+ = \epsilon^- = 0} = - p_0(1 + (1 - p_0)\gamma_1) < 0 \tag{24}$$

$$\left(\frac{\partial W(T^d)}{\partial r_T} \right)_{\epsilon^+ = \epsilon^- = 0} = p_0(1 - p_0)\eta(\lambda - 1)(1 - \gamma_1) > 0 \tag{25}$$

□

Proof of Proposition 5

Proof.

$$\frac{\partial VoNI(NT^d)}{\partial r_T} = 0 \tag{26}$$

$$\frac{\partial VoNI(T^d)}{\partial r_T} = 0 \tag{27}$$

$$\left(\frac{\partial W(NT^d)}{\partial \Delta_h} \right)_{\epsilon^+ = \epsilon^- = 0} = - p_0 - p_0(1 - p_0)\eta(\lambda - 1)\gamma_1 \tag{28}$$

$$\left(\frac{\partial W(T^d)}{\partial \Delta_h} \right)_{\epsilon^+ = \epsilon^- = 0} = (1 - p_0) - p_0(1 - p_0)\eta(\lambda - 1)\gamma_1 \tag{29}$$

□

Proof of Proposition 6

Proof. To distinguish the effects of an increase in disease severity from changes in the characteristics of treatment we will assume

$$\begin{aligned} \Delta_s &= \alpha r_{NT} \\ r_T &= \beta r_{NT} \\ \Delta_h &= (1-\alpha-\beta) r_{NT}. \end{aligned}$$

These assumptions insure that (a) the benefit-cost ratio of treatment, and (b) the relative effectiveness of treatment remain constant. Using these assumptions it is easy to see that the value of information, be it non-instrumental, instrumental, perfect, or imperfect, is simply a linear function of r_{NT} of the form $\psi \cdot r_{NT}$ where ψ denotes some constant. The change in the value of information will thus be equal to ψ. More importantly, it means that the change in value is positive (negative) if and only if the value itself is positive (negative). □

Proof of Proposition 7

Proof. (i) Speed of testing: variation in τ_1.

$$\frac{d\, VoNI(NT^d)}{d\, \tau_1} = -q^- q^+ (p^+ - p^-) \eta (\lambda - 1) r_{NT} \frac{\partial \gamma_1}{\partial \tau_1} > 0 \tag{30}$$

$$\frac{d\, VoNI(T^d)}{d\, \tau_1} = -q^- q^+ (p^+ - p^-) \eta (\lambda - 1) r_T \frac{\partial \gamma_1}{\partial \tau_1} > 0 \tag{31}$$

$$\frac{d\, VoII(NT^d, i)}{d\, \tau_1} = \frac{d\, VoII(NT^d, n)}{d\, \tau_1} = -q^- q^+ \eta (\lambda - 1) \left[(1-p^-)\Delta_h + (p^+ - p^-) r_T + p^- \Delta_s \right] \frac{\partial \gamma_1}{\partial \tau_1} > 0 \tag{32}$$

$$\frac{d\, VoII(T^d, i)}{d\, \tau_1} = \frac{d\, VoII(T^d, n)}{d\, \tau_1} = -q^- q^+ \eta (\lambda - 1) \left[(1-p^-)\Delta_h + (p^+ - p^-) r_T + p^- \Delta_s \right] \frac{\partial \gamma_1}{\partial \tau_1} > 0 \tag{33}$$

(ii) Time of testing, variation of τ_1, τ_0 by equal amount τ.

$$\frac{d\,VoNI(NT^d)}{d\,\tau} = -q^-q^+(p^+ - p^-)\eta(\lambda - 1)r_{NT}\frac{\partial\gamma_1}{\partial\tau_1} > 0 \tag{34}$$

$$\frac{d\,VoNI(T^d)}{d\,\tau} = -q^-q^+(p^+ - p^-)\eta(\lambda - 1)r_T\frac{\partial\gamma_1}{\partial\tau_1} > 0 \tag{35}$$

$$\begin{aligned}\frac{d\,VoII(NT^d, i)}{d\,\tau} &= -q^-q^+\eta(\lambda - 1)\left[(1 - p^-)\Delta_h + (p^+ - p^-)r_T + p^-\Delta_s\right]\frac{\partial\gamma_1}{\partial\tau_1} \\ &+ \eta q^+\left[\lambda p^+\Delta_s - (1 - p^+)\Delta_h\right]\frac{\partial\gamma_0}{\partial\tau_0}\end{aligned} \tag{36}$$

$$\begin{aligned}\frac{d\,VoII(T^d, i)}{d\,\tau} &= -q^-q^+\eta(\lambda - 1)\left[(1 - p^-)\Delta_h + (p^+ - p^-)r_T + p^-\Delta_s\right]\frac{\partial\gamma_1}{\partial\tau_1} \\ &+ \eta q^-\left[\lambda(1 - p^-)\Delta_h - p^-\Delta_s\right]\frac{\partial\gamma_0}{\partial\tau_0}\end{aligned} \tag{37}$$

□