Willingness to Pay for Signals of Rare Events

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Abstract

Designing multiple kinds of signals involves trade-offs between false-positive and false-negative costs. We conduct a laboratory experiment to evaluate preferences over these trade-offs in a controlled environment. We find that the choices significantly diverge from the predictions of the model with a risk-neutral decision-maker as well as from some predictions of expected utility frameworks. Relative to a risk neutral decision-maker, willingness-to-pay overreacts to false-negative rates for low priors, but underreacts for high priors. Subjects' preferences demonstrate a reverse bias for false-positive rates. This causes overpaying for signals with positive FP rates when the prior is low, and overpaying for all priors for low-quality signals with positive FP and FN rates. We find that this pattern is not consistent with the EU framework, but most consistent with a decision-making heuristic in which subjects do not differentiate between false-positive and false-negative rates when choosing signals.

JEL Classification: C91, D81, D84, D91
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1 Introduction

The 2010 gas blowout on Deep Horizon oil rig killed 11 workers and caused one of the largest oil spills in history. The death toll was possibly aggravated by the switching off the general safety alarm because the rig "did not want people woke up at 3 a.m. from false alarms" (Brown, 2010). The United States Preventive Services Task Force has to periodically update its cancer screening guidelines as it weighs the costs from failing to detect cancer early against the potential harms from overdiagnosis or overtreatment due to false positive results. These are real-world examples of the trade-off from the two types of errors inherent to all probabilistic warning systems, namely false-positive and false-negative rates.

Most real-world warning systems — e.g., medical diagnostics, security alarms, or extreme weather alerts — transform continuous signals about the likelihood of an adverse state into a yes/no binary signal. This transformation requires choosing a threshold for a positive classification. A lower threshold lowers the probability of failing to trigger in an adverse state (false-negative rate) but increases the probability of incorrect trigger in a safe state (false-positive rate).

In order to understand preferences over these trade-offs, we study the demand for information in the framework with a potential protection action. The subject, first, receives a signal about the probability of an adverse event. Then she decides to protect or not. This environment describes several practically important scenarios including extreme weather alerts, medical testing, and safety alarms.

We find that the value of information only weakly correlates with the willingness-to-pay. First, subjects on average underreact to quality of the signal, resulting in overpaying for low-quality signal and underpaying for high-quaity signals. Second, subjects tend to overreact to false-negative rates when the prior probability is low and overreact to false-positive positive rates when priors are high. We show that this pattern is most consistent with failure to estimate the effect of frequencies of false-positive and false-negative outcomes on the costs of using the signal. (Xu, 2022) similarly finds that individuals do not properly account for priors and often choose tests not affecting optimal decisions even when more useful tests are available.

Our work is one of a few experimental studies measuring demand for information used for decision-making (instrumental information). Previous research studied the demand for signals in the prediction game in which subjects have to choose an optimal state under uncertainty. The field experiment conducted by (Hoffman, 2016) finds that the demand for information increases with initial uncertainty, but decreases with the signal's accuracy. However, the decrease in accuracy is more modest than expected for a Bayesian decision-maker resulting in subjects underpaying for high-quality signals. The laboratory experiment of Ambuehl and Li (2018) finds that subjects tend to underreact to the accuracy of the binary signal about state of the world, but put a premium on completely certain signals. The paper of Xu (2022) also employs a prediction game setup to measure information preferences but varies priors on top of signal characteristics. She finds that many subjects choose non-instrumental over instrumental signals which is most consistent with failures of contingent reasoning about the future value of information.

Our setup differs in two important aspects from (Ambuehl and Li, 2018; Xu, 2022), because we study alerts and not prediction tasks. The subject faces a costly protection decision, resulting in three distinct payoffs: full payoff, full payoff minus protection costs and full payoff minus losses. It means that risk preferences affect the value of information and can change sensitivities to false-positive and false-negative rates. Our findings however are similar to prediction game findings. Consistent with Ambuehl and Li (2018) we also find that subjects overvalue inaccurate signals, but we do not find a premium for certain signals. And similar to Xu (2022) we find that subjects commit reasoning errors making their preferences less correlated with the signal's ability to lower expected costs.

Due to its applicability for studying preferences over expectations, there is a larger stream of literature on the demand for non-instrumental information. Eliaz and Schotter (2010) find that subjects are willing to pay for signals even when these signals are excessive for making optimal choices. Their design involves subjects choosing between two boxes with one box containing a prize of $20. Most subjects pay just to know the probability of finding $20 in box A even if this box is more likely to contain a prize in all the possible states. This finding is inconsistent with expected utility maximization but indicates instead having preferences for certainty before making choices. Similar to this paper, Masatlioglu et al. (2017) also study preferences over information structures differing in false-positive and false-negative rates but their setup allows for a larger role of expectations. They find that for a positive potential outcome, most subjects prefer facing high false-negative rates rather than high false-positive rates. In other words, they tolerate uncertainty after negative signals better than uncertainty after positive signals. These preferences are salient: subjects require an average payment of 18-35 cents to switch to their least preferred information structure.

There is some mixed evidence that people update beliefs differently when these beliefs are ego-relevant or concern future gains and losses. Eil and Rao (2011) find asymmetry in updating ego-relevant beliefs such as beauty and IQ. Subjects update more after receiving positive signals and do not update enough after negative signals. Additionally, subjects with high posterior ego-relevant beliefs are willing to pay to receive a more precise signals, but require a compensation for learning when their beliefs are low. In contrast, Coutts (2019) does not find any updating asymmetry with respect to either ego-relevant beliefs or beliefs about future payoffs.

Our paper is the first to measure value of information in the experimental setting of diagnostic tests or alarms. Previous work studies the use of alarms in context of medical testing, medical monitoring, safety alarms and extreme weather. Early literature on decision-making of medical professionals finds that doctors suffer from multiple biases when ordering testing, including inaccurate posterior probability estimation due to availability heuristics, hindsight bias and regret (Bornstein and Emler, 2001). Gigerenzer et al. (2007) find that most mammologists tend to overestimate the probability of cancer based on a positive result. Providing practitioners with natural frequencies instead of probabilities tends to reduce this bias.

Patients' willingness-to-pay for medical tests is large and sensitive to test accuracy (Liang et al., 2003; Howard and Salkeld, 2009; Neumann et al., 2012). But test preferences also exhibit several abnormalities. First, users are willing to pay for tests having little or zero diagnostic value (Schwartz et al., 2004; Neumann et al., 2012). For example, Schwartz et al. (2004) find that 73% of Americans in their survey prefer a free full-body CT scan versus one thousand USD cash. However, medical professional do not recommend full-body CT scans for healthy people due to extreme likelihood of false-positive findings. Second, the framing of test accuracy seems to matter a lot. Howard and Salkeld (2009) conduct a discrete-choice experiment to measure willingness-to-pay for the colorectal cancer screening. Their subjects agree to get 23 unnecessary colonoscopies in order to find one additional true cancer, but only 10.4 for reducing the number of cancers missed by one even though these descriptions are equivalent. Surprisingly, the perceived risk of cancer (prior) did not significantly affect the WTP in their study.

Our work also relates to the vast literature on demand for insurance and protection, which also finds some strong behavioral biases. While on average people under-insure with respect to rare natural disasters (Friedl et al., 2014), the demand for insurance goes up immediately after an insurable adverse event happns. One offered explanation (Volkman-Wise, 2015) is that subjects overweight recent evidence leading to under-insurance when there were no negative events in the recent past and to overinsurance after the fact. It is consistent with underweighting prior probabilities relative to more recent signals. At the same time, Laury et al. (2009) find no under-insurance for low-probability events in the laboratory setting.

The bias we are finding is similar to the base-rate and signal neglect phenomenons. Psychology researchers Hammerton (1973) and Kahneman and Tversky (1973) first observed that subjects underweighted prior probabilities (base rates) when calculating posteriors. This phenomenon had received the name of *base-rate neglect*. Multiple studies in economics then confirmed (Grether, 1992; Holt and Smith, 2009) this phenomenon in incentivized laboratory experiments. Most of these studies find that subjects also underweight signals on top of priors. We observe both phenomenons in responses to our belief elicitation task, but the calculation of signals' values differs substantially from the calculation of posterior probabilities. While the calculation of posterior probabilities would require using a Bayes formula, signal's value depends only on products of prior probabilities. However, we observe that subjects underestimate the effect of priors compared to theoretical predictions for an expected-utility decision-maker.

When determining willingness-to-pay, our subjects has to reason through contingencies. Aina et al. (2023) recently find that contingent reasoning increases bias in belief elicitation. Eliciting responses after presenting a signal results in smaller belief biases. It implies that decisions to acquire information, such as decisions made in our experiment, might suffer from persistent inherent biases, because they always involve thinking through contingencies.

2 Model

Environment. Let $\omega \in \{0,1\}$ denote the state of world, where 1 corresponds to an adverse event that happens with probability π and induces a loss, L. An agent can take protective action $a \in \{0,1\}$ to avoid losing L under the adverse state. The loss is only realized when $\omega(1-a) = 1$.

The agent's preferences are described by a utility function which depends on income Y, protective action a, and the protective outcome $\omega(1-a)$. Taking the protective action costs $c > 0$. Utility is separable in wealth, protection cost $c > 0$ and the potential loss $L > c$ in the adverse state if not protected:

$$U = U(Y, a, \omega(1-a)) = u(Y - ac - \omega(1-a)L)$$

The agent considers a purchase of a testing instrument (hereafter, a tester) that produces a binary signal $s \in \{0,1\}$ about the state of the world. Let $P_{ij} \equiv P(s = i|\omega = j)$ be the probability that signal s takes the value i conditional on the state of the world being j. After receiving the signal, the agent updates her belief on the likelihood of the adverse event to $\mu(s)$. We assume that she is Bayesian and her posterior belief equals to:

$$\mu(s) = \frac{\pi P_{s1}}{\pi P_{s1} + (1-\pi)P_{s0}}$$

where a larger $\mu(s)$ implies a higher posterior probability of the adverse event.

Preferences. Without a tester, the agent protects if and only if it increases her expected utility:

$$EU_0 = \max[u(Y-c), \pi u(Y-L) + (1-\pi)u(Y)]$$

The tester can increase expected utility if its signal informs her posterior. Under these assumptions, her expected utility with a signal is:

$$EU_s = \pi P_{11} u(Y-c) + \pi P_{01} u(Y-L) + (1-\pi)P_{10} u(Y-c) + (1-\pi)P_{00} u(Y)$$

Denote as b the agent's willingness to pay for the tester, to wit, she is indifferent between purchasing it at price b and not having its signal. Its value is equal to the maximum between zero and the solution to the following equation:

$$\begin{aligned} P(s=1)u(Y-b-c) + \pi P_{01} u(Y-b-L) + (1-\pi)P_{00} u(Y-b) = \\ = \max[u(Y-c), \pi u(Y-L) + (1-\pi)u(Y)] \end{aligned} \tag{1}$$

where $P(s = 1) \equiv \pi P_{11} + (1-\pi)P_{10}$. The left-hand side expression of this equation is a strictly decreasing function of b. Additionally, for $b \to \infty$ the left-hand side is smaller than the right-hand side. It implies that equation (1) has at most one positive solution.

Obviously, $b > 0$ for a perfectly accurate tester because the payoff distribution with the signal first-order stochastically dominates the distribution without the signal. However, determining the value of an imperfect tester non-trivial, as it requires more restrictions on preferences to allow weighing $u(Y - L)$ against $u(Y - c)$.

Risk-neutral agent. If the agent is risk-neutral, the expression above collapses to:

$$b + P(s = 1)c + \pi P_{01}L = \min[c, \pi L]$$

The tester's value is just:

$$b = \max[0, \min[c, \pi L] - P(s = 1)c - \pi P_{01}L]$$

We can express the WTP for the tester, b, as a function of priors, false-positive (FP), and false-negative rates (FN) denoted correspondingly as P_{10} and P_{01}. This is the equation we use in our empirical work:

$$b = \max[0, \min[c, \pi L] - \pi(1 - P_{01})c - (1 - \pi)P_{10}c - \pi P_{01}L] \tag{2}$$

When $b > 0$, its with respect to FP (P_{10}) and FN (P_{01}) rates is given by:

$$\frac{db}{dP_{10}} = -(1 - \pi)c \tag{3}$$

$$\frac{db}{dP_{01}} = -\pi(L - c) \tag{4}$$

The tester's value is decreasing in both FP and FN rates. The effect is proportional to the non-adverse (adverse) state probability for the false-positive (false-negative) rate.

Risk Aversion Effects. In an expected utility framework, risk aversion can both increase and decrease an agent's valuation of the tester. More specifically, risk aversion decreases her WTP when protection costs are low:

Proposition 1. *If protection costs are low $c < \pi L$, then a strictly risk-averse decision-maker pays less than a risk-neutral one.*

Proof. See the Appendix. □

Things are more ambiguous when risks are low or protection costs are high. For example, risk aversion increases the value of a perfect tester as long as a risk-averse decision-maker still chooses to not protect without a signal. This follows from the standard argument that demand for insurance increases with risk aversion, and the fact that the protection problem with a perfect tester is isomorphic to the insurance problem with deductible c.

Next, we study the effect of a tester's false-positive and false-negative rates on the WTP, b. Assuming a differentiable utility function $u(.)$, we use implicit differentiation to derive sensitivities of b to false-positive and false-negative rates:

$$\frac{db}{dP_{10}} = -\frac{(1-\pi)(u(Y-b)-u(Y-c-b))}{D(\pi, P_{01}, P_{10}, b)}$$
$$\frac{db}{dP_{01}} = -\frac{\pi(u(Y-c-b)-u(Y-L-b))}{D(\pi, P_{01}, P_{10}, b)}$$

with the denominator equal to the expected marginal utility:

$$D(\pi, P_{01}, P_{10}, b) \equiv P(S=1)u'(Y-c-b) + \pi P_{01}u'(Y-L-b)+$$

$$+(1-\pi)P_{00}u'(Y-b) = E[MU] > 0$$

The tester's value decreases with FP and FN rates $\frac{db}{dP_{10}}, \frac{db}{dP_{01}} < 0$. We can also say a bit more about the sensitivity to FN rates:

Proposition 2. *Risk-averse and imprudent decision-maker has higher sensitivity to FN rates as compared to a risk-neutral one.*

Proof. See the Appendix. □

However, risk aversion can both increase and decrease subject's sensitivity to FP rates depending on the utility function's curvature and the signal's characteristics. Intuitively, an expected marginal utility of a strongly risk-averse subject with a bad tester can be lower than the average slope of the utility function between $(Y-c-b)$ and $(Y-b)$ which reduces sensitivity to FP rates. It can also be higher if either the tester is good or the curvature is small. We can only say that it is very likely that for low protection costs and small priors π (leading to no automatic blind protection) the ratio of sensitivities to FP rates over FN rates should be lower for risk-averse subjects.

Proposition 3. *For low protection costs c and small risks π, risk aversion lowers relative sensitivity to FP rates.*

Proof. See the Appendix. □

The model offers two testable hypotheses on the WTP that can be brought to the experiment. *First,* as a natural starting point, we can test whether subjects' WTPs are equal to the values predicted for risk-neutral expected-utility maximizers. *Second,* the model of a risk-neutral agent suggests that subjects' WTP should have equal sensitivity to costs from false-positive and false-negative signals. Moreover, we show above that the relative weight of false-negative costs can be either below or above one depending only on risk preferences.

3 Experimental Design

We conduct the experiment in the Behavioral Business Research Lab (BBRL) at the University of Arkansas between October and November 2021. A total of 105 subjects participated in an individual decision task implemented using Qualtrics. On average, including a \$5 show-up fee, subjects earned \$26 for a session lasting around 45 minutes.

Subjects were endowed with \$25 (on top of the show-up fee) that they could potentially lose in the experiment, an outcome which was determined by a series of decisions in four sets of tasks played in the following order: (i) Blind Protection; (ii) Informed Protection; (iii) Belief Elicitation; and (iv) Willingness to Pay Elicitation. Subjects took a quiz of understanding prior to each task; the correct answer and an explanation were provided if a subject answers a question incorrectly.[1] Each task consisted of 6 rounds, resulting in 24 total rounds. At the end of the experiment, one of these 24 rounds is is randomly selected as the payment round. The instructions can be found in the appendix.

Blind Protection (BP). Subjects must decide whether to protect against an adverse event: a random draw of a black ball. Subjects know the prior probability that a black ball is drawn. Protection costs \$5. A subject who draws a black ball will lose nothing if they chose to protect and \$20 if they did not. The prior probability of drawing a black ball across the 6 rounds is denoted as $p \in \{0.05, 0.10, ..., 0.3\}$. The order was common for all the subjects and started at the lowest probability. Subjects did not receive feedback on the realization of the decision.

Informed Protection (IP). Similar to the BP task, subjects must make a protection decision given the prior probability of drawing a black ball. Subjects receive a prior and a signal produced by a tester with varying degrees of inaccuracy. Following Coutts (2019), we use a group of hinting gremlins to convey tester accuracy: a gremlin, randomly drawn from a group, gives out the signal. The gremlin is one of three types: (i) honest; (ii) "black-swamp" who always says that the ball is black; and (iii) "white-swamp" who always says that the ball is white. Figure 1 illustrates how the different gremlin types were presented to the subjects. The composition of the group of gremlins determines tester accuracy: a higher share of black(white)-swamp gremlins produces a signal with higher FP (FN) rate. Subjects know the group composition, but do not know which gremlin provides the hint. We vary the proportion of prior probability of drawing a black ball and the composition of gremlins across rounds.

[1]Incorrect answers in quiz for the Informed Protection section results in subjects facing additional questions. In our opinion, clear understanding of the Informed Protection task is essential for subsequent tasks, hence the added requirement. These questions consist of XXX; complete details are in the appendix.

Figure 1: Signals Presentation

Belief Elicitation (BE). As in the IP task, subjects know the prior probability of drawing a black ball and the composition of the group of gremlin providing hints. Instead of making a protection decision, however, subjects are asked to estimate the probability that: (i) the ball is black when the gremlin says that it is white; (ii) the ball is black when the gremlin says that it is black.

To elicit incentive-compatible responses, we follow the stochastic version of the Becker-DeGroot-Marshak mechanism developed by Grether (1992) and Holt and Smith (2009) but stated equivalently in terms of losses rather than gains. Subjects submit their beliefs about the probability of the adverse event $\mu \in [0, 1]$. If μ is above some uniform random number $r \in [0, 1]$, they lose \$20 only if this event happens (i.e., a black ball is drawn). If $r > \mu$, then they draw an independent lottery that will lose \$20 with probability r and 0 otherwise.[2] Motivated by Danz et al. (2020), who find that providing a detailed explanation of payoffs can lower trustful reporting, we instead explain that reporting true belief μ maximizes their payoffs, and give an example of payoff calculation under different reporting strategies.

Willingness to Pay Elicitation (WTPE). The WTPE task measures a subject's willingness to pay (WTP) for a signal. As before, subjects know the prior probability of drawing a black ball and the composition of the group of gremlin providing hints. Unlike the IP task, subjects do not automatically receive a hint, instead they provide their WTP for a hint by choosing a value $\in \$0, \$5$ in \$0.50 increments. The elicitation is incentive compatible: if a WTPE round is selected as the payment round, a random price of a hint will be drawn. If that price exceeded the subject's WTP, they will play a BP round, otherwise the subject pays their WTP and plays an IP round.

After the WTPE task, subjects answered a few demographic questions.[3] The payment task and the payment round were then randomly chosen to calculate the subject's payoff.

[2]The benefit of this mechanism versus other probability elicitation mechanisms (e.g., quadratic scoring) is that reporting truthfully is a dominant strategy regardless of risk preferences (Karni, 2009). The only requirements a subject must satisfy are probabilistic sophistication and dominance: they rank lotteries based on their probabilities only and prefer higher probabilities of higher payoffs.

[3]These were the questions on subjects' gender, age, and experience of taking statistics classes.

For tasks other than BP, subjects go through two different priors and three types of signals. The order is such that subjects go consecutively over all three signals starting from the honest one for each prior. The order of priors and signals stays constant for each subjects across tasks, but can vary between subjects. Table 1 summarizes our treatments.

Table 1: List of Treatments

	Gremlins composition				
Prop. of black balls (p)	Honest	Black-eyed	White-eyed	FP rate	FN rate
0.1, 0.2, 0.3, 0.5	2	0	0	0	0
0.1, 0.2, 0.3, 0.5	3	1	0	0.33	0
0.1, 0.2, 0.3, 0.5	3	0	1	0	0.33
0.1, 0.2, 0.3, 0.5	3	1	1	0.33	0.33
0.1, 0.2, 0.3, 0.5	5	1	0	0.2	0
0.1, 0.2, 0.3, 0.5	5	0	1	0	0.2
0.1, 0.2, 0.3, 0.5	5	1	1	0.2	0.2

4 Subject Decisions By Task

Decisions in the Blind Protection (BP), Informed Protection (IP), and Belief Elicitation (BE) tasks measure determinants of WTP in our model. Protection choices in the BP task reveals subjects' risk preferences with known probabilities. Choices in the IP task demonstrate how subjects use signals given their characteristics. Finally, the BE task provides insight into subjects' beliefs for given signals. We briefly discuss patterns of subject decisions below. They suggest that subjects generally understand these tasks reasonably well.

4.1 Blind Protection

Figure 2 plots the likelihood of choosing to protect against the posterior probability of a drawing a black ball for the BP task, where the posterior is equivalent to the prior, and in the IP task. On aggregate in the BP task, subjects' likelihood of protecting increases in the probability of a negative outcome: only 13% subjects protect when the probability of a black ball is 10% in contrast to 70% protecting when the probability is 30%.

At the individual level, BP responses indicate significant heterogeneity in risk preferences. For approximately 70% of subjects (72/105), protection action increases monotonically in probability. The remaining 30% make at least one switch from protecting to not protecting and back, which is inconsistent with EU maximization. Among these switchers, however, 83% (24/39) skip only a single increment of the presented probability scale, suggesting an inattention error.[4]

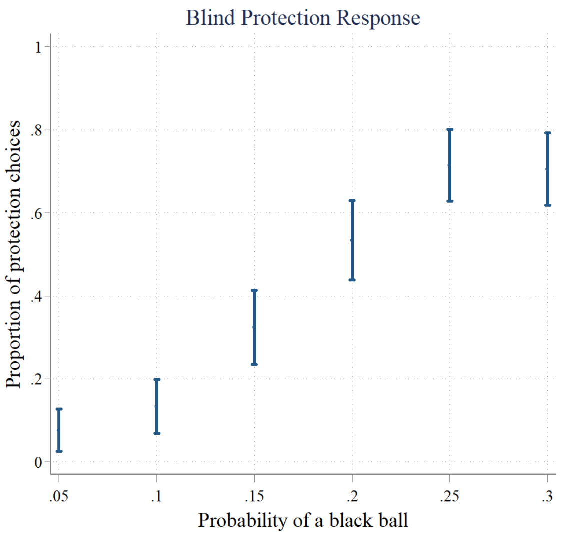
[4]For comparison, Holt and Laury (2002) for a similar instrument find that 28 of 212 subjects (13%) switched back to a low-risk option with an increasing likelihood of high payoffs in a risky option at least once when decisions were presented in increasing order, which they are not here.

Risk-neutral agents who maximize their expected utility should start protecting when the prior exceeds 0.25, i.e., at the ratio of the protection cost to the potential loss = \$5/\$20). Many of our subjects start protecting at lower priors, indicating strict risk aversion.[5] A smaller group of subjects makes choices consistent with risk loving by protecting at a probability of 0.3 or never protecting.

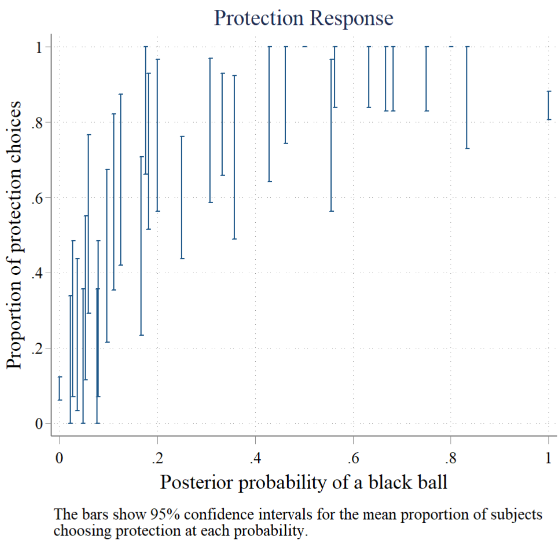
4.2 Informed Protection

Recall that, in the IP task, subjects receive a signal about the color of the ball in addition to the prior. Figure 2 shows that protection actions are increasing in the posteriors, though roughly 28% of subjects break monotonicity in their protection responses with respect to posterior probabilities — approximately the percentage of non-monotonic responses in the BP task.[6] At the individual level, we also find that the total number of times subjects protect in the BP task significantly correlates with their likelihood to protect in the IP task conditional on posteriors, but this explains only a very small part (<1%) of variation in the IP decisions.[7]

Figure 2: Average Protection Response



(a) The bars show 95% confidence intervals for the mean proportion of subjects choosing protection at each prior probability.



(b) The bars show 95% confidence intervals for the mean proportion of subjects choosing protection at each posterior probability.

Table 2 presents the average protection decisions by signal type and tester characteristics. The first three columns summarize the tester accuracy information by the signal produced. Column 4 shows the posterior probability of a black ball averaged across all the treatments

[5]As a reference, switching at the probability 0.1 corresponds to a CRRA risk aversion $\theta = 2$, while switching at 0.2 corresponds to $\theta = 0.57$.

[6]That is, subjects do not protect for some treatments with posterior probability P while protecting for a posterior probability $P' < P$.

[7]We use a linear probability model to estimate this relationship, and while the coefficient on the total number of protection choices is significant at the 1% level, the R^2 only increases from 0.295 to 0.3.

within a group. Column 5 shows the subjects' share of empirical protection responses, next to the theoretical optimum for risk-neutral subjects in Column 6. Column 7 presents the p-value for a test of equality between empirical and theoretical protection responses.

We make three notable observations. First, regardless of the tester's FP and FN rates, black signals substantially increase the likelihood of protection. Second, subjects' protection decisions deviate significantly from what is optimal for risk-neutral subjects in most treatments, as evidenced by column 7. Subjects tend to overprotect when facing white signals (rows 1–4). Subjects underprotect when facing black signals, except if the signals were produced by a tester with positive FP rates (rows 5–8).

Third, we find that some deviations cannot be explained by the expected utility maximization for any degree of risk aversion. For example, consider rows 1 and 3: even though an increase in the tester's FP rate does not change the posterior (because the signal is white), the protection rate increases by 6 percentage points (pp). Similarly, row 4 shows that when both FP and FN are positive, the protection rate increases to 56 percent — even though the average posterior probability given the tester characteristics is merely 13 percent. As a benchmark, with no signal in the BP task, only 13 (32) percent of subjects choose to protect when the probability is 10 (15) percent.

Table 2: Average Protection by Signal Type

Row	**Tester Characteristics**		**Signal**	**Posterior**	**Share Protect**	**Share Optimal**	**P-val** (H_0 : (5) = (6))
	False Positive	**False Negative**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	No	No	White	0.000	0.067	0.000	0.000
(2)	No	Yes	White	0.100	0.333	0.000	0.000
(3)	Yes	No	White	0.000	0.130	0.000	0.000
(4)	Yes	Yes	White	0.131	0.564	0.121	0.000
(5)	No	No	Black	1.000	0.846	1.000	0.000
(6)	No	Yes	Black	1.000	0.841	1.000	0.000
(7)	Yes	No	Black	0.550	0.833	0.870	0.355
(8)	Yes	Yes	Black	0.483	0.886	0.871	0.685

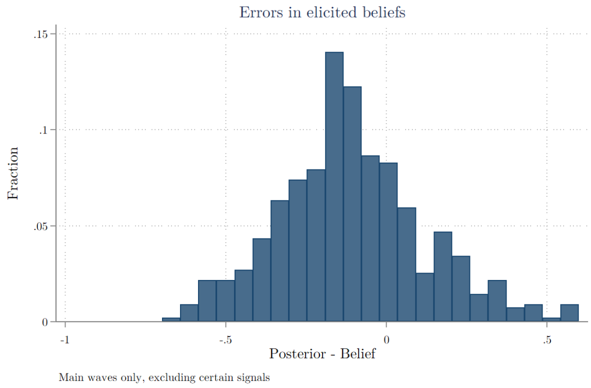
Notes:

4.3 Belief Elicitation

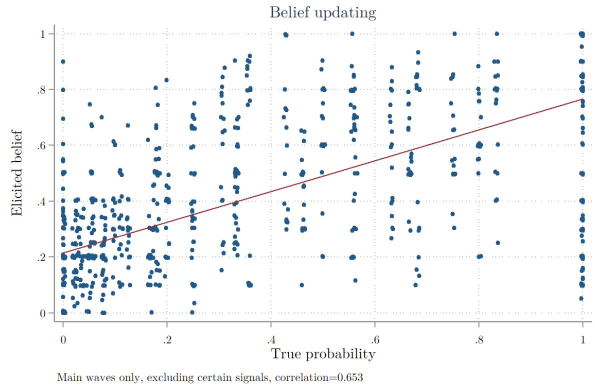
Subject decisions in the IP task capture the use of signals in protection decisions, but decisions reflect but risk preferences and (potentially erroneous) beliefs. The BP task can be used to construct a measure of the former; the BE task to measure the latter.

Figure 3: Errors in Bayesian Updating

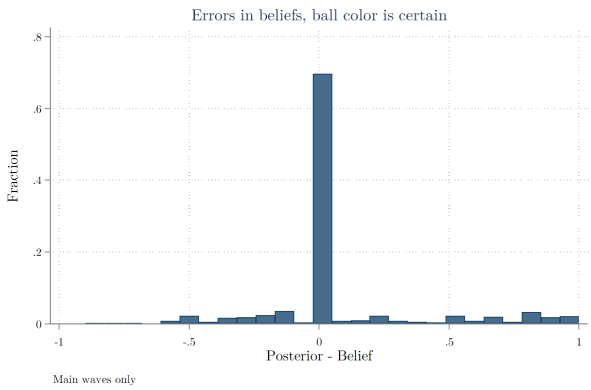
(a) Error Distribution



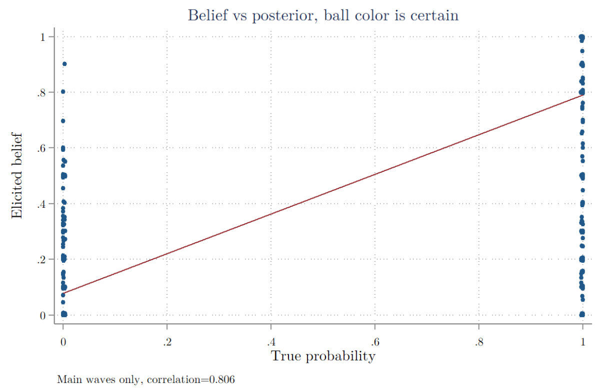
(b) Error v. Posterior



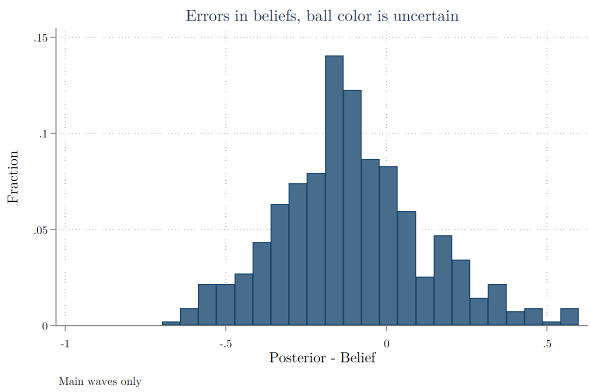
(c) Error Distribution, Certain Posterior



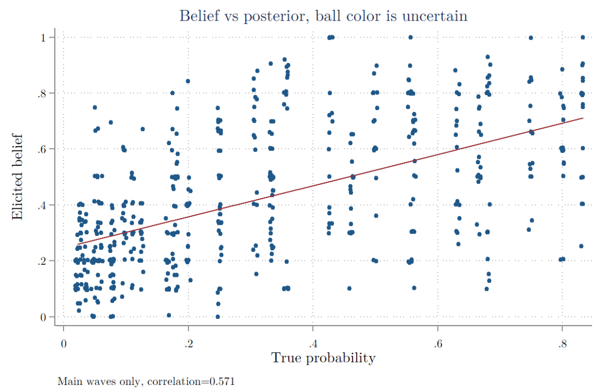
(d) Error v. Posterior, Certain Posterior



(e) Error Distribution, Uncertain Posterior



(f) Error v. Posterior, Uncertain Posterior



We define updating errors as the difference between the subjects' elicited belief and the actual posterior probability of drawing a black ball for a given signal. The left-hand column of Figure 3 shows the distribution of the updating errors, while its right-hand column presents a scatter plot of the elicited beliefs against the true posterior with a fitted line. Panel A uses all observations and suggests that, while errors occur, beliefs are still sensible. The distribution of updating errors is centered at 0, with roughly one-half (51%) concentrated within +/- 0.1 interval around zero. Overall, the correlation between the elicited beliefs and the true posteriors was 0.653.

For some combinations of priors and signals, updating should be trivial and posteriors are completely certain. Panel B plots such cases, which account for 56% of the sample and include: (i) treatments with all-honest gremlins; and (ii) treatments with obviously irrelevant dishonest gremlins (e.g., a group gremlins comprising honest and white-swamp gremlins announcing that the ball is black — or vice versa). Reassuringly, 69% of reported beliefs are correct. About half of the errors involve reporting a probability of one when it should have been zero.

Meanwhile, Panel C plots the remaining observations (i.e., with uncertain posteriors). The median error in Panel C is -0.12, with with 90% of errors lying between -0.48 and 0.3, suggesting that, on average, subjects overestimate the likelihood of adverse events for uncertain posteriors. The correlation between beliefs and posteriors in this sub-sample falls to 0.571.[8]

Table 3: Average Updating Error by Signal Type

Row	**Tester Characteristics**		**Signal**	**Posterior**	**Updating Error***	**P-val** (H_0 : $Error = 0$)
	False Positive	**False Negative**				
	(1)	(2)	(3)	(4)	(5)	
(1)	No	No	White	0.000	0.050	0.000
(2)	No	Yes	White	0.100	0.122	0.000
(3)	Yes	No	White	0.000	0.122	0.000
(4)	Yes	Yes	White	0.131	0.218	0.000
(5)	No	No	Black	1.000	-0.163	0.000
(6)	No	Yes	Black	1.000	-0.279	0.000
(7)	Yes	No	Black	0.550	0.039	0.130
(8)	Yes	Yes	Black	0.483	0.048	0.021

Notes: *Updating error = $Belief - Posterior$.

Table 3 summarizes how updating errors vary with tester characteristics. We find that subjects overestimate the probability of a black ball when given a white signal. This upward bias for a white signal increases in the FP/FN rate of the tester. To illustrate, consider the change between rows 1 and 3, where introducing a FP rate would not change the posterior

[8]The overall pattern of belief updating is consistent with the existing literature which shows that despite updating in the correct direction, people tend to underreact both to the priors and to the signals. The effect of underweighting priors — first noted in the psychology literature (Phillips and Edwards, 1966; Tversky and Kahneman, 1971; Kahneman and Tversky, 1972) — is known as *representativeness bias* or *base-rate neglect*. Using the regression approach of Grether (1980), we find both base-rate neglect and signal underweighting. Our estimates of these parameters are significantly below one with $\hat{\alpha} = 0.43$ $\hat{\beta} = 0.25$ (see Column 1 in 9). These values are within the range found by the meta-analysis of Benjamin (2019) which calculates the average $\hat{\alpha}$ estimate to be around 0.22 (0.4 for incentivized studies only) and the average $\hat{\beta}$ to be 0.6 (0.43 for incentivized) for studies (like ours) that presented their signals simultaneously. Such experiments are known as *bookbag-and-poker-chip* experiments

because the signal is white. Yet, subjects update their posterior upward, magnifying their updating error. We find a similar effect for the introduction of the FN rate (row 1 v. 2).

The updating bias for black signals, however, varies by the information structure. Subjects slightly underestimate the probability with a perfectly accurate tester, but introducing FN rates exacerbates subjects' underestimation. Rows 5 and 6 suggest that the introduction of a FN rate without changing the posterior further reduces subjects' belief. With non-zero FP rate, subjects again overestimate the probability of a black ball. The difference in the updating errors for black signals coming from FP-only (row 7) v. FP-FN testers (row 8) is negligible. The magnitude of subjects' adjustments to their beliefs was smaller than the actual change to the posteriors due to the FP rates.

5 WTP and Signal Characteristics

5.1 Are Subjects Risk Neutral, Expected Utility Maximizers?

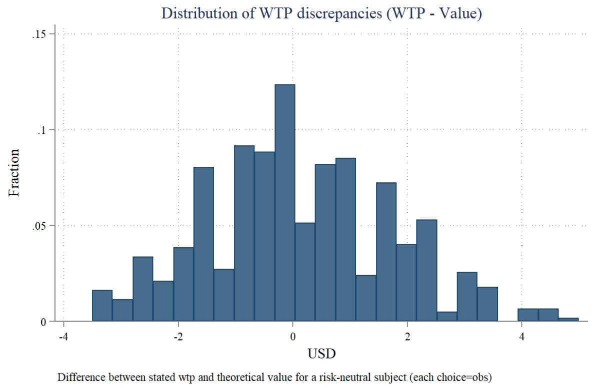
Hypothesis 1. *Subjects' WTPs for signals are equal to their value for risk-neutral agents.*

Result 1. *On average, there are no significant discrepancies between WTP and predicted value for risk-neutral agents. When splitting by a signal type, the difference emerges only for signals produced by testers with both false-positive and false-negative rates.*

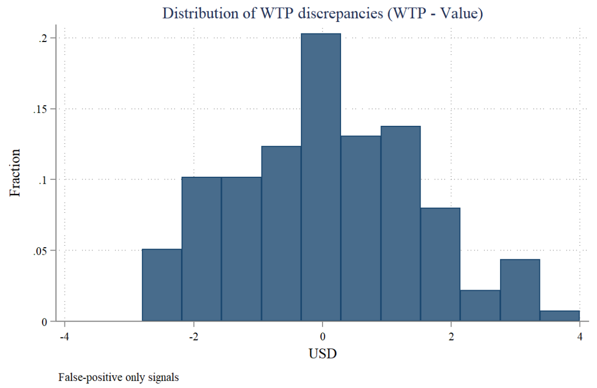
Overall, the theoretical value of a tester for a utility maximizing risk-neutral subject (hereafter, the risk-neutral WTP) in equation 2 is a useful benchmark of our subjects' WTP. Figure 4 plots the distribution of the differences between subjects' WTP and this value. The WTP is centered around the risk-neutral WTP, indicating that average choices do not fall far from the choices of a risk-neutral utility maximizer. However, there is substantial variation: only 25% of reported WTP are within \$0.50 of the risk-neutral signal value, and subjects overvalue signals by at least \$1.5 in 22% of cases and undervalue by at least \$1.5 in 19% of cases. Introducing FP and FN rates does not increase the range or variation of discrepancies, but introduces a long tail of positive discrepancies that shift the average upward.

Figure 4: Discrepancy (Observed WTP - Signal value) by Signal Type

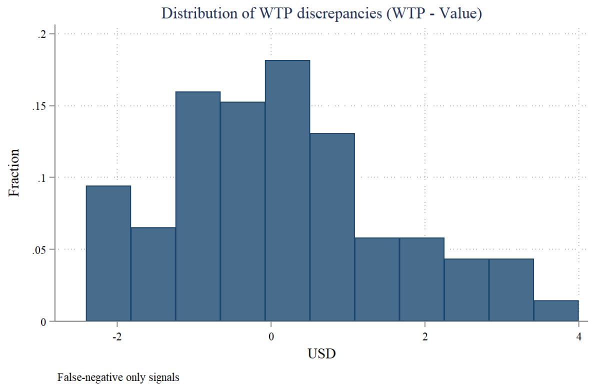
(a) All signals



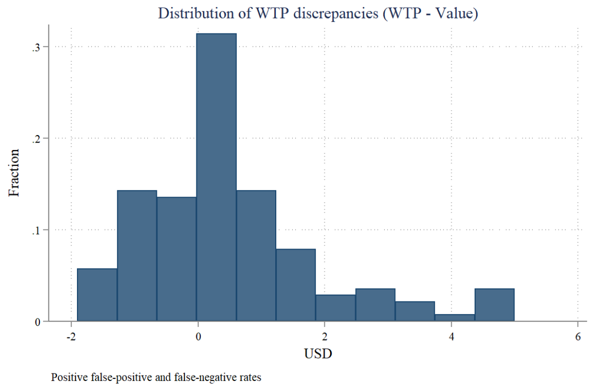
(b) FP only



(c) FN only



(d) Both FP and FN



Our non-parametric analysis in Table 4 also finds no differences on average between the observed WTP and the risk-neutral WTP for 3 out of 4 tester categories: honest (i.e., perfectly accurate), FP-only, and FN-only. With both FP and FN rates, however, subjects' WTPs are significantly higher than the risk-neutral WTP. Subjects overvaluations were similar for both low and high priors. Note, that these tester characteristics induce overprotection in the IP task. Subjects tend to overpay for testers with positive FP rates when the prior is low ($\in \{0.1, 0.2\}$), and for testers with positive FN rates when the prior is high ($\in \{0.3, 0.5\}$).

Table 4: Average WTP discrepancy (WTP-Value) by Signal Type

Priors	**Honest**	**FN only**	**FP only**	**FP and FN**
All priors	-0.106	0.143	0.081	0.492***
Low priors	-0.135	-0.209	0.465**	0.437**
High priors (>0.2)	-0.077	0.496*	-0.303	0.547**

*The number of stars represents statistical significance (0.05, 0.01, 0.001)

Hypothesis 2. *Subjects' preferences demonstrate equal sensitivity to costs generated by false-positive and false-negative events.*

Result 2. *On average for our signal and sample structure, we cannot reject the hypothesis of equal sensitivity. However, we observe significant heterogeneity with respect to priors: subjects tend to overvalue false-negative costs for low probability events and overvalue false-positive costs for high probability events.*

Next, we examine how the WTP responds to tester quality. We estimate the relationship between WTP biases and signal characteristics with the following regression:

$$\Delta b_{is} = \beta_0 + \beta_1 FP + \beta_2 FN + \varepsilon_{is}$$

where $\Delta b_{is} = (b_{is} - b_s^*)$ is the difference between the WTP of individual i for signal s and b_s^* is the risk-neutral WTP; FP (FN) is the false positive (false negative) cost. All specifications include subject fixed effects, with standard errors clustered at the subject level. If subjects are risk-neutral expected-utility-maximizers, we expect $\beta_1 = 0$ and $\beta_2 = 0$. The result, reported in column 1 of Table 5, shows positive and statistically significant coefficients for both FP and FN costs. In other words, subjects deviate by overpaying for inaccurate testers.

The risk-neutral model predicts that subjects should value the marginal costs of false-negative and false-positive events symmetrically. Table 5 shows that the coefficient on FN costs is slightly larger indicating higher sensitivity to FP costs, but we cannot reject the hypothesis that the two coefficients are equal. However later we note that this equivalency breaks down when considering specific priors.

5.2 Risk Preference and Belief Accuracy

Our baseline estimation in column 1 indicates significant deviations from the model's predictions. Positive and significant coefficients on FP and FN costs indicate that subjects reduce their WTP with growing FP and FN rates by less than a risk-neutral decision-maker would, i.e., subjects' WTP did not adjust enough to decreasing tester quality.

As our benchmark model assumes both perfect updating and risk neutrality, assumptions which open two channels through which deviations could occur. First, Proposition 2 suggests that risk preferences can influence the sensitivity of WTP to these tester characteristics. Second, systematic biases during updating can also lead to deviations.

We find that risk preferences matter for sensitivity to tester quality. We use data from the BP task to categorize subjects by their risk preference. We classify all the subjects with internally consistent BP choices into three categories: risk averse, risk neutral, and risk loving.[9] Column 2 explores the heterogeneity of subject responses to FP and FN costs by their risk preferences, with risk-neutral as the default category. The WTPs of both risk-neutral and risk-loving subjects increase with FP/FN costs — suggesting that they did not downward-adjust

[9] We classify subjects based on the total number of protection choices made in the BP task with 2 or 3 choices corresponding to risk-neutrality (protecting starting from 0.2 or 0.25), but exclude subjects making more than one choice at odds with a consistent risk preference.

Table 5: Deviations from Signal Value (WTP - Value) and Signal Characteristics

	All			Prior	
				{.1, .2}	{.3, .5}
	(1)	(2)	(3)	(4)	(5)
FP costs	0.231	0.316	0.615	0.800	0.204
	(0.126)*	(0.195)	(0.252)**	(0.239)***	(0.488)
FN costs	0.319	0.425	0.426	0.150	0.407
	(0.070)***	(0.118)***	(0.127)***	(0.279)	(0.106)***
Risk-averse × FP costs		-0.297	-0.429	-0.491	-0.707
		(0.291)	(0.352)	(0.385)	(0.679)
Risk-averse × FN costs		-0.410	-0.367	-0.321	-0.264
		(0.174)**	(0.175)**	(0.343)	(0.151)*
Risk-loving × FP costs		0.053	-0.084	-0.431	0.253
		(0.339)	(0.413)	(0.449)	(0.718)
Risk-loving × FN costs		-0.016	0.027	0.083	0.035
		(0.166)	(0.192)	(0.387)	(0.142)
Constant	-0.182	-0.191	-0.443	-0.219	-0.332
	(0.083)**	(0.080)**	(0.135)***	(0.179)	(0.191)*
R^2	0.480	0.492	0.504	0.739	0.753
Obs	624	624	624	312	312
Risk-Averse Subjects:					
False Positive		0.019	0.186	0.309	-0.503
se		(0.216)	(0.246)	(0.302)	(0.472)
p-value		[0.928]	[0.451]	[0.309]	[0.289]
False Negative		0.014	0.060	-0.171	0.143
se		(0.127)	(0.120)	(0.200)	(0.108)
p-value		[0.910]	[0.621]	[0.393]	[0.189]
Risk-Loving Subjects:					
False Positive		0.369	0.531	0.369	0.457
se		(0.277)	(0.328)	(0.381)	(0.526)
p-value		[0.186]	[0.109]	[0.334]	[0.388]
False Negative		0.409	0.453	0.232	0.442
se		(0.117)	(0.143)	(0.267)	(0.094)
p-value		[0.001]	[0.002]	[0.387]	[0.000]
Subject FE	Yes	Yes	Yes	Yes	Yes
Inaccurate Belief Interactions	No	No	Yes	Yes	Yes
Prior Probability FE	No	No	No	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

their WTP enough to account for lower quality testers. In contrast, the WTPs of risk-averse subjects show hardly any sensitivity to FP and FN costs.

Accounting both for belief accuracy and risk preferences does little to explain the pattern of underreacting to FP and FN rates. We use data from the BE task to construct a measure of subjects' belief accuracy.[10] Column 3 presents the most flexible specification that controls for belief accuracy and risk preference by including triple interactions of belief accuracy, risk preference, and signal characteristics. The baseline group is the group of risk-neutral subjects with relatively accurate beliefs. We find a lower sensitivity to FP costs for risk-neutral subjects with accurate beliefs and very little change to the corresponding sensitivity to FN costs. This indicates that even relatively accurate Bayesians did not downward-adjust their WTP enough to increasing FP/FN costs.[11]

5.3 Heterogeneity by Prior

We motivate our experiment with a real-world problem of designing warning systems — often for events with low probabilities. With a low prior, the default action of risk-neutral subject would be not to protect, and vice versa with a high prior. The signal would help risk-neutral subjects decide whether to keep the default action or to switch. We split the prior by below/above 0.25 (= protection cost/potential loss). We incorporate prior-probability fixed effects to the aforementioned flexible specification.

Column 4 of Table 5 presents the results for low-prior WTPE tasks. With low priors, deviations from the risk-neutral WTP increase with FP costs: subjects overvalue testers that would induce them to overprotect. This overvaluation is similar for different risk preference profiles. It should be noted that while coefficients' magnitudes are relatively large, none of the coefficients or predicted sensitivities here (bottom panel) is significant due to relatively small sample size, so these results should be interpreted with caution.

Column 5 presents the results for high-prior WTPE tasks. With high priors, the deviations of risk-neutral and risk-loving subjects from the risk-neutral WTP increase with FN costs. These subjects did not downward-adjust their WTP enough to account for increasing FN rates and overvalue testers that would induce them to underprotect.

To sum up, most subjects underreact to false-positive costs with low priors and underreact to false-negative costs for high priors. In practice, and given low priors implied by many alert systems, it means that users would tend to overpay for alert signals with high false-positive costs, while excessively discounting signals with significant false-negative rates. For example,

[10] We calculate a belief error as the absolute value of the difference between the subject's belief and the true posterior probability and then average these errors across all the decisions with identical priors, false positive and false negative rates. A subject's posterior belief for a decision is defined as accurate if its error is less than the median error across all the subjects making the same decision.

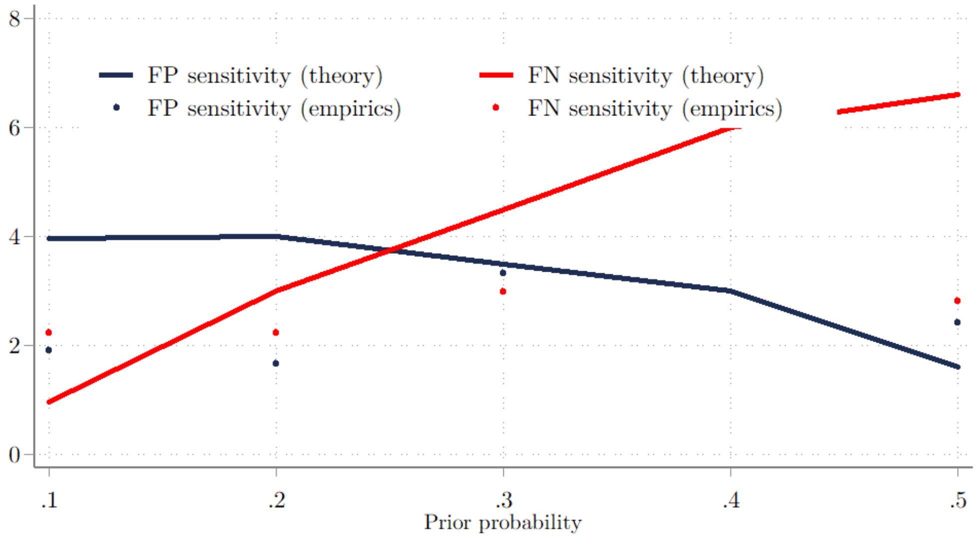
[11] Aside from these theoretically motivated individual differences, we investigate several other characteristics. Heterogeneity is not driven by demographic characteristics (e.g., age, gender) or prior statistical coursework. These results are in Appendix A Table A.

they would prefer a smoke alarm which never misses fires even if it involves higher expected costs of false alarms. Risk preferences seem to affect this pattern with risk-averse subjects moving closer to a risk-neutral benchmark, but most interaction coefficients are not statistically significant despite high magnitudes.

6 Discussion

Subjects' underreactions to false-positive (false-negative) costs for low (high) priors present a puzzle. These behaviors are inconsistent with our risk-neutral model: Equations 3 and 4 suggest that WTP should respond more to FP rates (relative to FN rates) for low priors and vice versa for high priors. Intuitively, for a given FN rate, false-negative events are much less likely with low priors and hence impose less costs on the agent. As priors increase, FN rates become more salient while FP rates become less salient. Instead, our subjects react very similarly to FP/FN rates for both low and high priors. The divergence between our subjects' WTP and the risk-neutral WTP explains changing signs on FP and FN costs in the previous regressions of WTP differences.

Figure 5: Theoretical and Empirical WTP Sensitivities to FP and FN rates



OLS estimates of sensitivity to FP and FN rates by prior probability of a black ball.

Figure 5 illustrates this puzzling behavior. This figure plots estimates from the regression of reported WTP — instead of its deviation from the risk-neutral WTP — on FP and FN rates. We find that the sensitivities of subjects' WTP to both FP and FN rates increase with priors and that the change occurs relatively smoothly. Two sensitivities are also surprisingly close to each other.[12]

We consider four candidate explanations. First, risk preference. Second, anchoring bias. Third, bias from valuation of non-instrumental information (Eliaz and Schotter, 2010; Masatli-

[12]For none of the priors can we reject the hypothesis that two sensitivities are equal to each other.

oglu et al., 2017). Finally, subjects may fail to distinguish how FP and FN error rates should affect how they calculate their posteriors differently.

Our evidence suggests that risk preference cannot explain this behavior. We test the risk preference hypothesis using subjects' BP choices. Columns 4–5 of Table 5 already show that, even after controlling for subjects' risk preferences, the coefficients on FP and FN costs remain very different for low and high priors. We augment this analysis in Table 12 (Appendix) by explicitly testing for interactions between risk-preferences, priors, and FP and FN rates. We find that these interactions are mostly insignificant, with the exception of interactions between FN rates and risk aversion for some specifications. The heterogeneity largely remains after controlling for risk preferences, but the interaction between high priors and FP rates becomes insignificant.

The evidence also does not support the anchoring hypothesis, to wit, that subjects anchored on previous priors. Each subject goes through two sets of treatments with two different priors and a fixed order of priors, so anchoring could be possible. We find, however, that most subjects (92 out of 104) change their decisions when going from one prior to another, and the average belief error in the BE task is actually *lower* for the second set of priors rather than the first, which suggests that changing priors does not increase subjects' confusion. Most importantly, the uniformity in coefficient ratio is present even if we limit our attention only to the first priors in each sequence.[13]

There is evidence in the literature of people valuing "non-instrumental information" that does not affect their decisions. For example, Eliaz and Schotter (2010) find that subjects are willing to pay to know the probability of their choice being correct even if this information cannot affect their choice. Similarly, Ganguly and Tasoff (2017) document that most people are willing to pay a small amount to know their pre-determined experimental payoffs at the beginning of the experiment rather than at the end. Most information in our experiment is instrumental by design (it helps to choose actions) and indeed enters into subjects' decisions as evidenced by choices in the IP task. Nonetheless, we find many subjects choosing positive WTP for signals that cannot affect their IP decisions (159 out of 624 total choices). It is therefore plausible that the reported WTPs includes some non-instrumental components.

However, we think that preferences for non-instrumental information cannot provide a full explanation of our results. First, the sensitivity of WTP to FP rates is much lower in the experiment compared to the theory when priors are low. Suppose that the information value $b = b(\pi, P_{01}, P_{10}) + n(\pi, P_{01}, P_{10})$ with $n(.)$ describing the non-instrumental component. If the discrepancy in sensitivities to FP rates with respect to theoretical value comes from the non-instrumental component n, it needs to be increasing in FP rates. In other words, subjects would have been putting higher non-instrumental values on worse testers — which seems implausible. Second, the closeness of coefficients for FP and FN rates seems also apriori implausible based

[13]Depending on session, the first 3 WTP treatments use either 0.1 or 0.2 as the prior, so there is no anchoring on the previous prior or something special about a particular prior.

only on the non-instrumental information value story.

Instead, we argue that subjects' observed behaviors arise from confusing FN and FP rates. We use as evidence subjects' own proffered explanation. At the end of the experiment, we asked subjects to explain to us how they made their protection choices. Out of 105 subjects in the main waves of the experiment, 39 refer to the *percentage* of dishonest gremlins as their rationale for choosing protection. For example:

- "*I took into consideration how many honest there were and looked at the chances of picking a ball.*"
- "*If there were only honest gremlins then I never protected but even if there was one white-swamp gremlin or one black-swamp gremlin then I payed for protection.*"

Among the other 66 subjects, some may use this heuristic without describing it. The closeness of the coefficient estimates for FP and FN rates in Table **??** are certainly consistent with these statements. If subjects neglect the difference between FP and FN risks when choosing their WTP, it would explain both the coefficients' similarity and their lack of variation with respect to priors. Indeed, if subjects treat FP and FN rates the same and consider only the total proportion of false signals, they would assign equal weights to each of them, and the best fit line of signal's value with the respect to the sum of FP and FN rates should be relatively flat because priors affect FP and FN costs in opposite ways. Note also that the equality of coefficients on FP and FN rates is a necessary prediction of this explanation, but can emerge only by chance with (some) heterogeneous risk preferences.

In order to test this hypothesis, we use choices from the BE and IP tasks where subjects also face imperfect signals. If subjects systematically neglect the difference between FP and FN rates, we expect to find the pattern of unexplained reaction to FP and FN rates in cases when they do not affect the posterior. Namely, subjects would show sensitivity to FP rates when the signal is white and sensitivity to FN rates with black (positive) signals. This happens because some subjects react to FP rates as if they are FN rates, and vice-versa. If present, this pattern cannot be explained by any distribution of risk preferences or by anchoring on previous priors.

In Table 6 we estimate a linear regression of updating error (actual posterior - reported belief) on FP and FN rates by signal color. We use fixed effects to control for individual updating biases. Consistent with our conjecture, we observe that the FP rate has a significant positive effect on the error when the signal is white (negative), and that FN rate has a significant negative effect when the signal is black (positive).

In Table 7, we regress IP decisions on FP and FN rates and flexible controls of both posteriors and reported beliefs:[14]

$$Prob(s_{ij} = 1) = \alpha_i + \beta_1 P_{10} + \beta_2 P_{01} + Z(P_{ij}) + Z(\mu_{ij}) + \epsilon_{ij}$$

[14] Given that the true functional form is unknown, we use a linear probability model to get unbiased coefficient estimates.

Table 6: Updating Errors in BE Task

	All	Signal Received	
		White	Black
	(1)	(2)	(3)
FP rate	.6***	.292***	.908***
	(0.1)	(0.1)	(0.1)
FN rate	.0108	.273***	-.251***
	(0.1)	(0.1)	(0.1)
Constant	-.0784***	.314***	-.47***
	(0.0)	(0.0)	(0.0)
Subject FE	Yes	Yes	Yes
Observations	1248	624	624
Adjusted R^2	0.15	0.41	0.52
Subject FE	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Here s_{ij} is the protection decision of subject i in treatment j, α_i is subject FE, P_{10}, P_{01} are FP and FN rates and $Z(P_{ij})$ and $Z(\mu_{ij})$ are the splines of FP/FN rates and reported beliefs μ_{ij} to control for these variables in a flexible way. Each spline is a function $Z(x)$ which is just linear $x + C$ within one interval, and constant everywhere else. The splines are constructed so that their linear intervals cover the whole domain of probabilities and beliefs $[0, 1]$.[15] Columns 1 and 2 include only the flexible controls of the true posteriors. Columns 3 and 4 add further flexible controls to account for subjects' (often incorrect) beliefs, inferred from their BE responses.

Columns 1 and 2 show that even conditional on posterior and subject FEs that account for risk preferences, IP responses are still affected by FP and FN rates. For a white signal, FP and FN rates increase the tendency to overprotect while the FP rate had an opposite effect with comparable magnitude but without statistical significance for a black signal. Hence the first prediction of a conjecture of indiscriminate FP/FN rate use holds: FP rates increase protection when the signal is white conditional on the posterior. The effect holds if allowing for heterogeneity of sensitivities to FP and FN rates with respect to priors (Column 2), though the effect of the FN rate for black signals is small in magnitude and not statistically significant at conventional levels. Adding flexible controls for subjects' beliefs reduces the coefficient magnitude on FP rate for white signals (Columns 3 and 4), but the coefficients still remains significant. This indicates that while beliefs partially contribute to these protection anomalies, they cannot explain them completely.

Overall, we observe a striking uniformity in sensitivity of WTP to both false-positive and false-negative rates that cannot be explained by risk preferences or anchoring. This pattern

[15] We use Stata mkspline command to create 5 splines $z_1(x), z_2(x), ..z_5(x)$ of initial variable x over the range $[0, 1]$ such that $z_k(x) = \min[0, x - x_{k-1}, x_k - x_{k-1}]$ with x_k being equally spaced knot values. Splines account for potential nonlinear effects of posteriors and beliefs on protection decision with limited effect on degrees of freedom.

Table 7: Informed Protection Response

	(1)	(2)	(3)	(4)
FP rate x (S=White)	.461***	.494**	.282**	.286
	(3.3)	(2.4)	(2.0)	(1.4)
FN rate x (S=White)	.544***	.474**	.195	.125
	(2.9)	(2.1)	(1.0)	(0.5)
S=Black	.42***	.429***	.316**	.336**
	(2.7)	(2.7)	(2.0)	(2.1)
FP rate x (S=Black)	-.256	-.225	-.379	-.389
	(-0.5)	(-0.4)	(-0.8)	(-0.7)
FN rate x (S=Black)	.0494	-.027	-.00394	-.0879
	(0.5)	(-0.2)	(-0.0)	(-0.6)
p=0.2	.113***	.101***	.09***	.0723**
	(4.2)	(2.8)	(3.6)	(2.1)
FP rate x (p=0.2)		-.0363		.00218
		(-0.2)		(0.0)
FN rate x (p=0.2)		.122		.127
		(0.9)		(0.9)
N	1224	1224	1224	1224
Pseudo R-squared	.551	.552	.578	.578
Log-likelihood	-379	-378	-356	-356
Subject FE	Yes	Yes	Yes	Yes
Flexible controls for:				
Posterior	Yes	Yes	Yes	Yes
Beliefs	No	No	Yes	Yes

Notes: Coefficients are average marginal effects. t-statistics in parentheses. Standard errors are clustered at the subject level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

is, however, consistent with subjects neglecting the difference between false-positive and false-negative signals, a behavior that is supported by subjects' explanations explanations of their decision making and the odd sensitivities to false-positive and false-negative rates in other treatments in which they do not affect posterior probabilities.

7 Conclusion

We conduct an experiment to study people's preferences over false-positive and false-negative rates of signals aout rare events. These preferences matter in many real-life scenarios such as alarm systems, medical tests and extreme weather warnings, and hence measuring them should help to design better systems.

We observe that compared to a risk-neutral benchmark, subjects tend to pay more attention to false-negative rates rather than false-positive rates when the probability of an adverse event is low. In other words, users overpay for signals with frequent false alarms and heavily discount signals with frequent missed events. We find little evidence that risk preferences significantly affect the reported willingness-to-pay for signals.

Policy implications of our study depend on the source of the observed discrepancy. If users of signals for low probabilities pay more attention to false-negative rates rather than false-positive rates due to their preferences, then the designers of alarm systems should indeed minimize the false-negative rate even if it means slightly increasing the total expected cost of the system. In contrast, if the discrepancy emerges due to users miscalculating the future costs and benefits of signals, then improving well-being involves developing different ways to present information or educating users. This is similar to studies on Bayesian updating which find that medical professionals make better decisions if the information on medical tests is presented in the form of expected frequencies rather than a tuple of prior conditional probabilities. Hence more research is needed to understand the sources of the bias discovered in this paper.

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A Tables

Table 8: Demographic Characteristics of Subjects

	All		$p \in \{0.1, 0.3\}$		$p \in \{0.2, 0.5\}$	
	N	%	N	%	N	%
Male	43	41	22	41	21	41
Age>23yrs old	14	13	6	11	8	16
Students	88	84	46	85	42	82
Had statistics classes	63	60	37	69	26	51
Total	105	100	54	100	51	100

Table 9: Error Decomposition

	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Prior	.246***	.202***	.175***	.191**	.14**	.0403
	(5.5)	(4.0)	(3.1)	(2.5)	(2.3)	(0.6)
Signal	.43***	.43***	.327***	.327***	.539***	.539***
	(6.3)	(6.3)	(3.2)	(3.2)	(5.3)	(5.3)
Good quiz × Prior			.143*	.0207		
			(1.7)	(0.2)		
Good quiz × Signal			.193	.193		
			(1.4)	(1.4)		
Stat. class × Prior					.162*	.264***
					(1.9)	(2.8)
Stat. class × Signal					-.166	-.166
					(-1.2)	(-1.2)
Observations	280	280	280	280	280	280
Adjusted R^2	0.31	0.31	0.33	0.32	0.32	0.32

Decomposition works only for imperfect signals

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Informed Protection Response: logit with flexible control for posteriors

	(1)	(2)	(3)	(4)
FP rate	.365***	.472***	.593***	.573***
	(3.3)	(3.4)	(4.0)	(3.7)
FN rate	.168*	.611***	.15	.565**
	(1.8)	(2.8)	(1.5)	(2.5)
p>0.2	.0259	.0664***	.0471*	.0547*
	(1.5)	(2.8)	(1.8)	(2.0)
S=Black	.00422	.426**	-.0229	.473**
	(0.1)	(2.5)	(-0.3)	(2.4)
FP rate x (S=Black)		-.655		-.69
		(-1.4)		(-1.5)
FN rate x (S=Black)		-.561**		-.608**
		(-2.1)		(-2.2)
FP rate x (p>0.2)			-.293**	-.16
			(-2.3)	(-1.2)
FN rate x (p>0.2)			.0843	.264
			(0.5)	(1.6)
Observations	1248	1224	1224	1224
Adjusted R^2				

t statistics in parentheses

Reporting average marginal effects, subject FE, errors are clustered by subject.

With flexible controls of posterior probability

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: WTP minus Value of Information: demographic determinants

	(1)	(2)	(3)	(4)	(5)	(6)
FP costs	.283	.352*	.117	.215	.248*	.291**
	(0.2)	(0.2)	(0.2)	(0.2)	(0.1)	(0.1)
FN costs	.322***	.247***	.395***	.303***	.303***	.249***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Male	-.193	-.157				
	(0.3)	(0.4)				
Male × FP costs	-.153	-.193				
	(0.2)	(0.2)				
Male × FN costs	.0791	.114				
	(0.1)	(0.1)				
Stat. class			-.24	-.142		
			(0.3)	(0.4)		
Stat. class × FP costs			.198	.124		
			(0.3)	(0.3)		
Stat. class × FN costs			-.0834	-.0226		
			(0.1)	(0.1)		
>23 yrs					-.366	-.647*
					(0.4)	(0.4)
>23 yrs × FP costs					-.0679	.0238
					(0.3)	(0.3)
>23 yrs × FN costs					.35	.277
					(0.2)	(0.2)
Constant	-.126	.391	-.0579	.419	-.157	.397*
	(0.2)	(0.3)	(0.3)	(0.4)	(0.2)	(0.2)
Prior dummies	No	Yes	No	Yes	No	Yes
Observations	624	624	624	624	624	624
Adjusted R^2	0.05	0.21	0.05	0.21	0.05	0.21

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: WTP minus Value of Information, risk aversion and sensitivity to FP and FN costs

	(1)	(2)	(3)	(4) FE	(5) FE
p>0.2	-.0942	-.11	-.0409	-.127	-.0578
	(0.2)	(0.2)	(0.3)	(0.2)	(0.3)
FN costs	-.229*	-.442*	-.327	-.385*	-.36*
	(0.1)	(0.2)	(0.2)	(0.2)	(0.2)
p>0.2 × FN costs	.716***	.977***	.889***	.949***	.914***
	(0.1)	(0.2)	(0.2)	(0.2)	(0.2)
FP costs	.558***	.69***	.78***	.652***	.672***
	(0.1)	(0.2)	(0.2)	(0.2)	(0.2)
p>0.2 × FP costs	-.933***	-.879***	-.899***	-.863***	-.91***
	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)
Risk-loving × p>0.2 × FN costs		.037	-.383	-.0593	-.276
		(0.1)	(0.2)	(0.2)	(0.2)
Risk-averse × p>0.2 × FN costs		-.245	-.279	-.372**	-.198
		(0.2)	(0.2)	(0.2)	(0.3)
Inconsistent × p>0.2 × FN costs		-.0735	-.181	-.066	-.297
		(0.2)	(0.4)	(0.2)	(0.4)
Risk-loving × p>0.2 × FP costs		-.287	.0971	.179	.259
		(0.4)	(0.5)	(0.6)	(0.5)
Risk-averse × p>0.2 × FP costs		-.323	.00169	-.52	.0291
		(0.4)	(0.5)	(0.5)	(0.5)
Inconsistent × p>0.2 × FP costs		.108	-.21	-.48	-.372
		(0.7)	(0.5)	(0.5)	(0.5)
Full risk pref interactions	No	No	Yes	No	Yes
Observations	624	624	624	624	624
Adjusted R^2	0.08	0.07	0.07	0.42	0.42

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Proofs

B.1 Proposition 1

Proof. If protection costs are low enough $c < \pi L$ than the risk-neutral decision-maker should always protect without a signal:

$$U = \max[\pi(Y - L) + (1 - \pi)Y, Y - c] = Y - c$$

It means that a strictly risk-averse decision-maker with a utility function $u()$ should also protect:

$$\pi u(Y - L) + (1 - \pi)u(Y) < u(\pi(Y - L) + (1 - \pi)Y) = u(Y - c)$$

Then denote stochastic payoff with a signal as X so that expected utility with a signal is $Eu(X - b)$

where b is the willingness-to-pay solving:

$$Eu(X-b) = u(Y-c)$$

Let b_0 be the willingness-to-pay for a risk-neutral decision-maker. By Jensen's inequality:

$$Eu(X-b_0) < u(EX-b_0) = u(Y-c) = Eu(X-b)$$

Because expected utility with a signal is a decreasing function of b_0 we obtain $b > b_0$. □

B.2 Proposition 2

Proof. Use the mean value theorem to rewrite the sensitivity as:

$$\frac{db}{dP_{01}} = -\frac{\pi u'(\zeta)(L-c)}{E[MU]}, \zeta \in (Y-c-b, Y-L-b)$$

Now let X denote a random payoff of the agent with a signal. A risk-averse decision-maker puts a positive value on the signal only if its expected payoff is higher than the payoff with full protection: $EX > Y-c-b$. If an agent is imprudent ($u''' < 0$) then $E[MU] \equiv E[u'(X)] < u'(EX)$. Next, u' being a strictly increasing function and $EX > Y-c-b$: $u'(\zeta) > u'(Y-c-b) > u'(EX)$. Hence $\frac{u'(\zeta)}{E[MU]} > 1$ and $\frac{db}{dP_{01}} < -\pi(L-c)$. □

However, risk aversion can both increase and decrease subject's sensitivity to false-positive rates depending on the utility function curvature and signal's characteristics. Intuitively, an expected marginal utility of a strongly risk-averse subject with a bad signal can be lower than the average slope of the utility function between $(Y-c-b)$ and $(Y-b)$ which reduces sensitivity to false-positive rates. It can also be higher if either the signal is good or the curvature is small. We can only say that it is very likely that for low protection costs and small priors π (leading to no automatic blind protection) the ratio of sensitivities to FP rates over FN rates should be lower for risk-averse subjects.

B.3 Proposition 3

Proof. The proof is approximate and relies on Taylor expansion to measure the effect of risk aversion on sensitivities to false-positive and false-negative rates. Start by rewriting the equilibrium condition for willingness-to-pay as the expected sum of utility differences:

$$\begin{aligned} P(0,0)(u(Y-b)-u(Y)) + p(0,1)(u(Y-b-L)-u(Y-L)) + P(1,0)(u(Y-c-b)-u(Y))+ \\ +P(1,1)(u(Y-b-c)-u(Y-L)) = 0 \end{aligned} \tag{5}$$

Here, $P(x,y)$ is a shorthand for the probability of an event that the signal equals x and the state equals y. Next, we expand the utility differences of $u(Y-b)-u(Y), u(Y-c-b)-u(Y)$ as Taylor series around Y and $u(Y-L-b)-u(Y-L)$ difference around $Y-L$ to get the following equation:

$$\begin{aligned} P(0,0)[u'(Y)(-b)+o(b)] + p(0,1)[u'(Y-L)(-b)+o(b)] + P(1,0)[u'(Y)(-c-b)+o(c+b)]+ \\ +P(1,1)[u(Y)-u'(Y)(b+c)+o(b+c)-u(Y-L)] = 0 \end{aligned} \tag{6}$$

Then we drop the terms $o(b), o(b+c)$ which we expect to be small enough to neglect to obtain:

$$\begin{aligned} P(0,0)u'(Y)b + P(0,1)(u'(Y) + [u'(Y-L) - u'(Y)])b + P(1,0)u'(Y)(c+b) + \\ + P(1,1)(-u'(Y)(b+c) - (u(Y-L) - u(Y)) = 0 \end{aligned} \tag{7}$$

Now we can express the equilibrium (approximate) WTP b as:

$$b = \frac{P(1,1)\frac{(u(Y)-u(Y-L))}{u'(Y)} - P(S=1)c}{D}$$

Where the denominator $D \equiv 1 - P(0,1)\left(\frac{(u'(Y)-u'(Y-L))}{u'(Y)}\right)$. Now we remember that $P(1,1) \equiv \pi P_{11} = \pi(1-P_{01}), P(S=1) = \pi(1-P_{01}) + (1-\pi)P_{10}$ and take derivatives of equilibrium (approximate) WTP b with respect to false-positive and false-negative rates:

$$\frac{db}{dP_{10}} = -\frac{(1-\pi)c}{D}$$

$$\frac{db}{dP_{10}} = -\pi\left[\frac{\frac{(u(Y)-u(Y-L))}{u'(Y)} - c}{D} - \left(\frac{P(1,1)\frac{(u(Y)-u(Y-L))}{u'(Y)} - P(s=1)c}{D^2}\right)\frac{(u'(Y)-u'(Y-L))}{u'(Y)}\right]$$

For a strictly risk-averse subject the sensitivity to false-positive rates should be lower than for a risk-neutral one because $u'(Y) - u'(Y-L) < 0$ by decreasing marginal utility leading to $D > 1$. The opposite is true for strictly risk-loving subjects. It is hard to say something more specific about the sensitivity to false-negative rates.

Dividing the sensitivity to FN rate to the sensitivities of FP rate, we also obtain that this ratio is greater than 1 for strictly risk-averse subjects and less than one for strictly risk-loving ones.

$$\frac{db/dP_{01}}{db/dP_{10}} = \frac{\pi}{(1-\pi)}\left[\frac{(u(Y)-u(Y-L))}{u'(Y)} - c + \frac{(P(1,1)\frac{(u(Y)-u(Y-L))}{u'(Y)} - P(s=1)c)}{D}\frac{(u'(Y)-u'(Y-L))}{u'(Y)}\right]$$

Note that the corresponding equation for the risk-neutral decision-maker puts the ratio of sensitivities to:

$$\frac{db/dP_{01}}{db/dP_{10}} = \frac{\pi}{(1-\pi)}[L-c]$$

Hence the question of comparison of two ratios is equivalent to the question of the sign of the following inequality:

$$\frac{(u(Y)-u(Y-L))}{u'(Y)} + \frac{(P(1,1)\frac{(u(Y)-u(Y-L))}{u'(Y)} + P(s=1)c)}{D}\frac{(u'(Y-L)-u'(Y))}{u'(Y)} >< L$$

However note that the first component in the left-hand sum is already greater $\frac{(u(Y)-u(Y-L))}{u'(Y)} > L$ for any strictly risk-averse decision-maker by a mean value theorem. Risk aversion also makes the second component positive as $u'(Y-L) - u'(Y) < 0$ and $P(1,1)\frac{(u(Y)-u(Y-L))}{u'(Y)} + P(s=1)c > P(1,1)L - P(s=1)c > 0$ is also positive as it equal the expected savings from using a signal. Hence the LHS is greater than the RHS L leading to the ratio of sensitivities to be greater than for a risk-neutral decision-maker. The same argument applied in reverse will show that for a strict risk-loving decision-maker the ratio of sensitivities will be lower. $\square$

C Subjects' Explanations

The list of responses to the question *"Please explain the strategy you used for Task 2 (Informed Protection)? This is the task in which you see a hint and when decide to protect or not."*:

1. if the hint was favorable not protection and vice versa
2. I always bought protection unless I was certain that I didn't need it (i.e. both gremlins were honest or it wasn't possible to get the black/white gremlin)
3. I trusted honest golems fully, and did not put much stock in the swamp golems.
4. my strategy was to just look at what the odds were
5. I looked at the percentages of white and black balls and made my guess off of that. Also, there was no big harm in buying protection, and there was a lot of harm if you did not buy protection and got a black ball.
6. I trusted my instinct.
7. If the entire panel of gremlins was honest and they told me that the selection was white, I did not buy protection, since I could be certain that I would not lose money. In any other scenario, I bought protection. In my case, better to guarantee a $25 return every time than risk $20 for a $5 reward.
8. if it is an honest one, i don't need to buy informed protection cuz i can't trust its hint.
9. I think the gremlins were confusing, but if you see how many gremlins were. Then from that how many of each type where and what they say, after that you based that to the actual percentage of balls you get close to the answer.
10. I am a little bit more risky so I chose to not get protection if any of the monsters said it was white because I felt the probability of one of the honest ones getting picked was higher and if they said it was black I bough protection.
11. i used probablity and if the odds were more in favor i would mae a decision based on that and the ball probabilty color
12. If the hint was from one of the honest gremlins then I didn't choose to protect because they could only tell the truth. If there were any just black or just white gremlins then I decided to protect because the information they give isn't helpful
13. See the quantity of hints and the percentage of drawing the colors of the balls.
14. I would calculate the probability that the gremlins were right. So in task two, I already did task 3. Like if there were two black/white gremlins, I would add the probability that they were right to the certainly that the honest gremlin was right.
15. I would see what the probability that they are telling the truth is and then see if they were saying black. if no one was the black swamp monster then I knew it was black and therefore it would be 100%
16. I looked at the box of balls and the box of gremlins. If the gremlins were honest or white, I would not use protection for a white ball. If the ball was black I would sometimes take my chances depending on the amount of white and black balls. If they were honest or black, I would use protection for a black ball. If the ball was white, I would not use protection since there were mostly honest gremlins.
17. I weighed the cost of loosing money and percentage difference with that chances of getting a white ball.
18. I weighed my odds. I knew they were in my favor.
19. When I paid attention to the composition of the box and saw the gremlins, that helped to inform my decision on whether to buy protection. For example, if I saw the box had equal numbers of both black and white ball and two honest gremlins were there, I did not buy protection. When I saw a box with

a larger amount of black than white balls and had a white-swamp gremlin with four honest gremlins, I opted to buy protection.

20. I would the probability of one of the balls being picked. If the chances were not likely than I would not protect it.
21. I looked at what percentage of gremlins were honest and used that info in my decisions.
22. Instinct and possibility of either white or black being picked
23. I took protection when there was a higher chance of drawing out black balls.
24. If all glimpses are honest, then choose not to protect on each color. If most are honest and one is black, then choose not to protect white color. If the one is white, then choose not to protect black because we know white one always say white, so black color should be the truth.
25. I based my decision on the probability of the honest gremlin being chosen.
26. I would base my answers off of how many honest goblins there were.
27. I chose the best odds
28. If it was more than approximately a 70% chance of drawing a black ball, I decided to protect. The cost to protect outweighed the potential loss of not protecting.
29. If the gremlin was honest then I did not buy protection because they were accurate in telling me the color of the ball.
30. If there were only honest gremlins then I never protected but even if there was one white-swamp gremlin or one black-swamp gremlin then I payed for protection.
31. If the gremlins were honest, I didn't buy protection. If there were swap gremlins, I calculated the chance of getting a hint from a swap gremlin and considered that along with the chance of getting a black ball. If the total chance of getting a black ball was more than 15% I get protection.
32. I determined what the probability was that the gremlin would tell the truth. The more honest gremlins in the lineup, the less likely I was to buy protection. However, I'm risk-averse, so I was more likely to buy protection than not because the risk was too high and the cost of protection was low.
33. I just used probability in my head
34. **I took into consideration how many honest there were and looked at the chances of picking a ball**
35. I was able to calculate the odds from the hints. It was not a measurement requiring me to calculate the chance of balls, but of variance between the hints. This made it easier to calculate the probability of what the chances the gremlins would give regardless of the actual odds (14/6 white-black balls)
36. I just took into note the goblins that were listed, and then the probability of which the information could be truthful or not.
37. I just relied on the number of honest gremlins to inform my decisions
38. If there were a white swamped gremlin, I would buy the protection if it said white ball. If it said black on a white swamped I would always not buy the protection. This is vice versa if there was a black swamped gremlin.
39. I used the strategy of using the "honest gremlin" to my advantage to know when I could get away with not paying for protection
40. I relied on understanding which type of gremlin was presented and then based my decision on their bias/lack of bias. Honest gremlin were a simple binary decision (white -¿ no protection, black -¿ protection). The white gremlin would default to no protection unless the probability of black was greater than 25%. The black gremlin defaulted to protection.

41. I considered the probability of the computer selecting a white ball and a honest gremlin. If that probability was high (>70%), then I decided not to buy protection. When there were only honest and black gremlins and the hint was that the ball was white, then it was easier since that hint could only come from an honest gremlin.
42. I took into consideration which of the gremlins I got. If it were two honest ones, I would not buy protection if they said white because they were right. If they were two honest ones and a black one, and they said it was white, I would do the same thing because the black one would never say the ball is white. If any of the gremlins said the ball was black, I would buy protection because there would always be a chance that the ball was black.
43. It was really just similar to math and common sense.
44. I went with the odds. I didn't buy protection if the probability of picking a ball was really high in a situation
45. I would look at how many honest gremlins there were to see if i could trust it or not. ex: if there were only honest and white gremlins, and they said the ball was white, i would trust that.
46. If it was all honest then I 100% percent trusted it and went for no protection but if there was even a chance of dishonest gremlin then I went with protection
47. My strategy depended on the gremlins. I was willing to pay a higher price for more honest gremlins, while I was not willing to pay as much when there were not as many honest gremlins.
48. The higher the % of black balls the more likely I was to buy protection.
49. I based it off of the amount of different colored balls mainly. Because, if there was only 2 black balls and one black gremlin, then I would most likely have a white ball chose if the other two were honest.
50. I looked at the percentage and the chance of drawing which ball, and I compared it to the grimlin options/hints and made my decision based off of the numbers I was provided.
51. I am broke and I was willing to take risks to make more money.
52. I just hoped for the best and picked one
53. **If it was all honest gremlins I did not buy protection. Even if there was one un honest gremlin I was skeptical to buy protection. If there was more than one un honest gremlin I definitely bought protection.**
54. If there were more black balls I would decide to protect it because there was a higher chance it needed to be and if there were more white balls I didn't protect it because I assumed the chance of a black ball being chosen was lower.
55. My strategy in task two was primarily based on the gremlins. For example, if they were all honest then I would not buy protection if they said white but would if they said black. Furthermore, if four were honest and one was a white-choosing gremlin, then if the gremlins said the ball was black I would buy protection; Considering that the white gremlin could only say the ball would be white, then it is known that an honest gremlin said that the ball would be black and vise versa. I did not really consider the probability of the balls being chosen and rather focused on the likely hood that the hint given by the gremlins is correct.
56. I would first take into account how many white and how many black balls were in a box, and the chance of drawing each. With the gremlins then telling a hint I would not buy protection if the gremlin said white and the percent of drawing white was more than 75%. I used this kind of method for the whole task.
57. my strategy for this task was to only buy protection if there was a white or black gremlin and not if there was a truth gremlin

58. the percentages of black and white balls and which gremlins I would get to give a hint.
59. I took my chances that the gremlins telling the truth would be selected
60. If the goblins were all honest I would buy protection if they say the black was the ball chosen and not if the ball was white. If 1 of the goblins was saying the ball was black or white exclusively I would buy protection if they say it was black and not if the ball was white. If 2 of the goblins was saying the ball was black or white exclusively I would buy protection no matter what they said
61. How likely it was that it would be white
62. I mainly looked at the probability percentage of the computer choosing a white ball. If it was greater than or equal to 70%, then I would not choose protection.
63. It was pretty simple, actually. I basically based my decision off of the amount of honest gremlins there were. If there were 4/5 honest, then there was an 80% chance the hint was correct. On a situation with 50% white and 50% black, this strategy proved to be helpful.
64. I based my decision off of the makeup of the gremlins if they were all honest and said the ball was white I would not buy protection and if they said it was black I would buy protection. If there was a 1/3 chance of an honest gremlin being picked for the hint I would just buy protection because I did not like the odds of the hint being true. If the chance of an honest gremlin being picked was 2/3 I would look at the probability of a white/black ball being chosen and then make my decision to protect or not off of that.
65. I based my chances solely on the honest Gremlins.
66. I mostly would buy protection if there was an over 50 percent chance to get a black ball.
67. I thought of how many un honest gremlins there were and tried to guess the percent of accuracy I would be given based on the colors.
68. If it was mostly Honest Grimlins I took the hint
69. I looked at the different types of gremlins in each group to make my decision. If it was all of the honest gremlins, I would go from there, but even if it were 2 honest and 1 black or white swamp gremlin that would inform my decision better than if it was an equal mix of all three types
70. I looked at the % of white vs black balls then looked at how many honest grimlins there were. If there were a majority of white balls and honest grimlins I would do no protection for a white ball but buy protection for black.
71. Always went with the honest ones. When there was one white or one black, I would know it was an honest one when they said the opposite of the color. For example, two honest and one white, when it said the ball was black, I knew it would be black because the white can't say that.
72. I compared the number of balls to the gremlins hints and if the chances were higher than 50% ish I wouldn't get protection
73. I would always take the hints from honest and be skeptical of non-honest
74. I looked at the gremlins and then looked at their hint. depending on what gremlins I had, i looked at the combination of balls to see if I should risk it or not. If I had a lot of white balls and quite a few honest gremlins, I did not buy the protection plan
75. I decided weather or not to buy protection based on the gremlins
76. I am basically gambling so I would not pay attention to the Gremlins and look at the percentages
77. Sorry. My strategy was same through-out, except the very first question of task1. Risk-averse, not worried about losing $5. Also, not trusting even honest gremlins or perhaps myself if I had mis-read.
78. Just went with my gut guess. I didn't really use a strategy for any of them tbh

79. there was no need to protect if the hint were made by all honest gremlins. also no need to protect if i had a combination of honest and black gremlin and the prediciton said it's white cos a black gremlin will never give a white answer
80. I had two honest gremlins, so the hint was 100% accurate.
81. I measured my decision based off of the type of gremlin giving the hint. If I felt that the gremlin or group was highly trustworthy, I would follow the advice.
82. If it was highly likely that the gremlin was going to be correct, I chose no protection. I aimed for the highest payout each round based on the amount of black to white balls there were.
83. If there were all honest ones I would not buy protection if it was white. I bought protection on all the others so that I would not lose more money.
84. I just created a pattern in my head and looked at the percentage of the likeliness of a black ball being drawn or not.
85. I based it off the amount of honest gremlins presented
86. If the color said was the opposite of black or white eyed gremlin then I knew it was true because the rest were honest gremlins
87. Based off how many white ball there was
88. I decided what to do based on both probability of selecting a ball of off composition of colors, and the used the gremlins to add an extra level of certainty.
89. Simply used the projection of likelihood for how much risk I was willing to take.
90. If i was feeling lucky or not
91. Based off of the number of gremlins would help me determine to use protection or not
92. I used the gremlins as my strategy, i took more risks if it was the honest gremlins
93. I payed attention to the honest gremlins and I used my answers based off how many there were.
94. I would observe which of the gremlins informing me were honest and make my decision there.
95. I just tried not to risk it. I prefer getting a little bit less than the total amount than actually reducing $20
96. I figured out what the gremlins were saying and used that to calculate the probability
97. I just guessed.
98. I thought about which option would make me the most amount of money based on protection or not.
99. I just decided which ones wanted protection and not.
100. Basically if the white balls had a higher rate than the black balls I wouldn't buy protection
101. I looked mostly to whether or not I had an honest gremlin in my group. If I had gremlins which could be dishonest, I then evaluated my chances based on the percentage of black vs. white balls in the box.
102. If I knew the ball would be white then I would not protect, everything else I protected
103. I was a little more clueless about it, I tried to make sense of the question first and then see the number of balls that were black and if they were less, then I would not buy protection.
104. If the goblins were guaranteed to be honest, I followed their hint. If there was a white goblin at all, I ignored the hint completely. If there was only a black goblin, I wouldn't buy protection if the hint was white since that couldn't be correct.