

Willingness-to-pay for Warnings: Some Tables

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November 1, 2021

- How much do people value alerts (signals) about potential preventable threats?
- How do signal's probabilistic characteristics affect the willingness-to-pay for it and the welfare gains from using it?
- Applications:
 - Natural disaster warnings (tornados, floods, earthquakes)
 - Medical tests for treatable conditions
 - Investing in research on likelihood of catastrophic events (rogue AI, global warming, pandemics)
- Note: most real-life applications provide little practice with using the signal

Overview of the Experiment

- An insurance experiment:
 - Two states of the world: bad ($\omega = 1$) and good ($\omega = 0$)
 - Probability of a bad state is $P(\omega = 1) = \pi$
 - Bad state \implies loss of $\$L$
 - A perfectly protective insurance can be purchased for $\$c$
- Subject can purchase a signal s before purchasing the insurance:
 - A signal is characterized by its true-positive ($P(s = 1|\omega = 1)$) and true-negative rates ($P(s = 0|\omega = 0)$)

Research objective

How do signal characteristics affect the WTP?

WTP for Signals

If losses are rare ($\pi L \ll c$)

- Theoretically, what should be the WTP for a signal?
- If bad states are a priori rare ($\pi L \ll c$) \implies never protect without a signal
- The theoretical WTP b for an expected utility maximizer given a signal s is a solution b^* to the following:

$$P(s=1)u(Y_0 - b^* - c) + \pi P(s=0|\omega=1)u(Y_0 - b^* - L) + \\ + (1 - \pi)P(s=0|\omega=0)u(Y_0 - b^*) = (1 - \pi)u(Y_0) + \pi u(Y_0 - L)$$

- A risk-neutral agent then pays:

$$b^* = \pi(1 - P(s=0|\omega=1))L - P(s=1)c$$

WTP for Signals

If losses are not necessarily rare

- The formulas become more complicated if subjects can protect without a signal (bad state are not rare enough)
- The theoretical WTP b for an expected utility maximizer given a signal s is a solution b^* to the following:

$$\begin{aligned} P(s=1)u(Y_0-b^*-c) + \pi P(0|1)u(Y_0-b^*-L) + (1-\pi)P(0|0)u(Y_0-b^*) &= \\ = \min[(1-\pi)u(Y_0) + \pi u(Y_0-L), u(Y_0-c)] \end{aligned}$$

- A risk-neutral agent then pays:

$$b^* = \min[\pi L, c] - \pi(1 - P(s=0|\omega=1))L - P(s=1)c$$

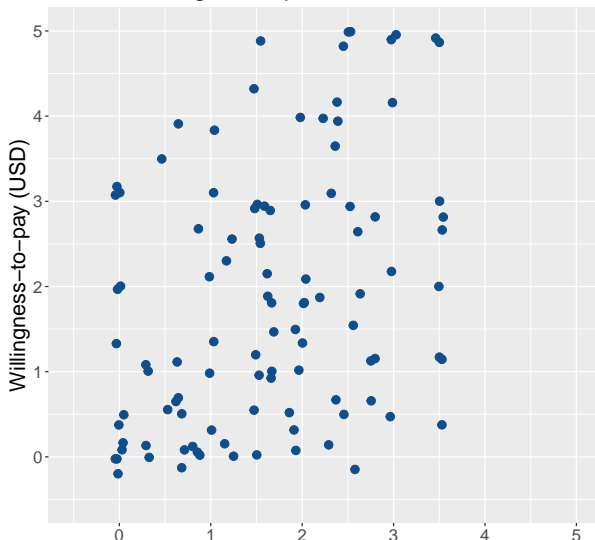
Hypotheses

- ① Conditional on the signal's value for risk-neutral subjects, false positive and false negative rates reduce the perceived value of the signal (WTP)
- ② Conditional on the signal's value for risk-neutral subjects, false positive and false negative rates increase expected costs
- ③ Extra: how much of these discrepancies result from belief updating issues or risk aversion?

WTP for signals

- Higher average WTP for more valuable signals

WTP for a signal vs predicted value



- Extra effect of false positive and false negative rates

Table: WTP for Information

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
value	.475*** (5.1)	.24** (2.2)	.119 (0.9)	.109 (0.8)
Prior prob.		1.76*** (2.7)	1.85*** (2.8)	1.86*** (2.8)
honest_treatment		.759*** (2.7)		.306 (1.0)
False neg. rate			-2.13*** (-2.8)	-1.64** (-2.1)
False pos. rate			-2.34*** (-3.5)	-1.83*** (-3.0)
Constant	.54*** (3.6)	.214 (0.9)	1.19*** (3.1)	.981** (2.4)
Observations	150	150	150	150
Adjusted R^2	0.14	0.21	0.22	0.22

t statistics in parentheses

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

WTP for the Signal (Risk Aversion)

- Does accounting for risk aversion based on blind protection choices helps to explain WTP?

Table: WTP for Information (Accounting for Risk Aversion)

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
value	.475*** (5.1)				
value_ra		.236** (2.1)	.0615 (0.4)	.0615 (0.4)	-.112 (-0.7)
honest_treatment			.734* (1.7)	.734* (1.7)	.132 (0.3)
False neg. rate					-2.92** (-2.1)
False pos. rate					-2.13** (-2.3)
Constant	.54*** (3.6)	.793*** (3.6)	.886*** (3.8)	.886*** (3.8)	2.02*** (3.5)
Observations	150	78	78	78	78
Adjusted R^2	0.14	0.04	0.07	0.07	0.09

t statistics in parentheses

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

WTP for the Signal (Uniform Risk Aversion)

- Risk aversion measurements are noisy. What if we assume the same risk aversion for everybody?

θ	R^2
0	.17
0.5	.15
1	.1
1.5	.07
Observations	150

Actual Costs vs Theoretical Costs

- Calculate actual costs based on decisions made in the Informed Protection treatment and actual posterior probabilities of losses.
- Each reported participant's strategy s is a tuple of numbers (r_w, r_b) representing protection responses correspondingly to white and black hints
- Then the expected cost of each decision are:

$$EC(s) = \pi(P(0|1)(1 - r_w) + P(1|1)(1 - r_b))L + \\ + (P(s = 0)r_w + P(s = 1)r_b)c$$

- Regress expected costs on minimal theoretical costs and other signal characteristics

Actual Costs vs Theoretical Costs

Table: Actual Exp. Costs vs Theoretical Costs

	(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) FE	(6) FE
Optimal exp. costs	1.04*** (9.4)	.842*** (4.3)	.592 (1.3)	1.04*** (10.7)	.879*** (4.1)	1.13*** (9.3)
Prior prob.		-2.19 (-1.1)	-3.69 (-1.2)		-2.07 (-1.1)	
False neg. rate			-2.68 (-1.6)			-.696 (-0.6)
False pos. rate			.713 (0.4)			2.51 (1.4)
Constant	-.888*** (-3.3)	-.733** (-2.6)	-.662** (-2.2)	-.875*** (-4.0)	-.684*** (-3.3)	-.918*** (-4.3)
Observations	150	150	150	150	150	150
Adjusted R^2	0.34	0.35	0.36	0.41	0.42	0.43

t statistics in parentheses

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Additional Complementary Tables

- Factors affecting informed protection responses
- How well do participants update their beliefs?

Informed Protection: Correlation

Table: Informed Protection

	(1) All	(2) All	(3) Smart	(4) Smart
Posterior prob.	.663*** (8.5)	.114 (0.9)	.692*** (9.4)	.126 (0.8)
Prior prob.		.467*** (3.5)		.519*** (3.1)
Gremlin says Black		.497*** (5.8)		.506*** (5.0)
Constant	.235*** (7.3)	.0872** (2.2)	.233*** (7.7)	.0678 (1.6)
Observations	300	300	228	228
Adjusted R^2	0.35	0.41	0.36	0.42

t statistics in parentheses

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Informed Protection: Determinants

Table: Informed Protection: Response to Reported Beliefs

	(1) All	(2) All	(3) Smart
Belief	.746*** (7.8)	.358** (2.4)	.462** (2.5)
Posterior prob.		.424*** (3.5)	.367** (2.6)
Constant	.206*** (5.3)	.189*** (4.8)	.178*** (4.6)
Observations	300	300	228
Adjusted R^2	0.32	0.38	0.40

t statistics in parentheses

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Informed Protection: Do Subject's Beliefs Matter?

Table: Informed Protection: Response to Reported Beliefs

	(1) All	(2) All	(3) Smart
Belief	.746*** (7.8)	.358** (2.4)	.462** (2.5)
Posterior prob.		.424*** (3.5)	.367** (2.6)
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Belief Updating

- A bit more correlation with actual posterior probabilities!
- Even more if we exclude everybody scoring less than 7 out of 9 quiz questions

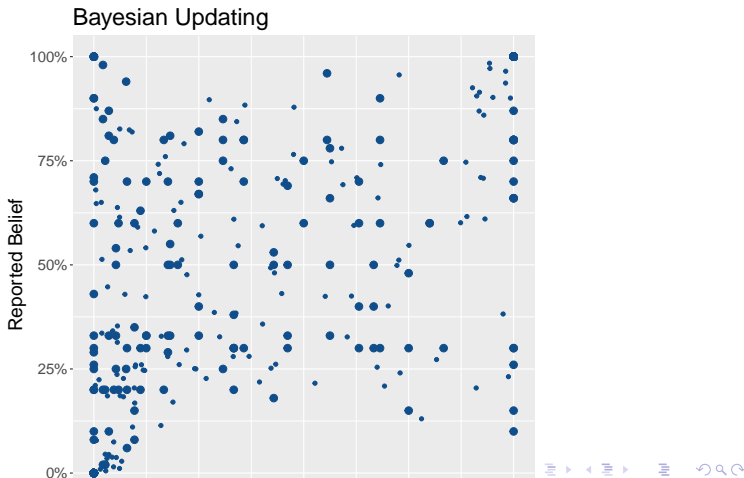


Table: Belief Elicitation: Belief vs Posterior

	(1) All	(2) Not_honest	(3) Good quiz
Posterior prob.	.649*** (16.6)	.68*** (15.6)	.477*** (8.5)
Constant	.138*** (9.7)	.128*** (7.9)	.212*** (10.5)
Observations	300	228	200
Adjusted R^2	0.55	0.57	0.34

t statistics in parentheses

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What Affects Beliefs?

Table: Belief Elicitation: Determinants

	(1) OLS	(2) FE	(3) Smart, FE
Posterior prob.	.0528 (0.4)	.114 (0.9)	.126 (0.8)
Prior prob.	.347** (2.0)	.467*** (3.5)	.519*** (3.1)
Gremlin says Black	.542*** (5.3)	.497*** (5.8)	.506*** (5.0)
Constant	.123** (2.3)	.0872** (2.2)	.0678 (1.6)
Observations	300	300	228
Adjusted R^2	0.34	0.41	0.42

t statistics in parentheses

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Belief Updating: Decomposition

- Posterior probability $\mu = P(B|S = x)$ that the ball is black conditional on a hint $S = x$ can be written as:

$$\ln \left(\frac{\mu}{1 - \mu} \right) = \lambda_0 + S_B + S_W$$

- With $\lambda_0 \equiv \ln(p/(1 - p))$ representing (transformed) prior beliefs
- And S_B, S_W describing the effect of new evidence:

$$S_B \equiv I(S = B) \ln(P(s = B|B)/P(s = B|W))$$

$$S_W \equiv I(S = W) \ln((1 - P(s = B|B))/(1 - P(s = B|W)))$$

Belief Updating: Decomposition

Table: Belief Elicitation: Decomposition

	(1) OLS	(2) FE	(3) Smart, FE
lt_prior	.178 (1.4)	.205** (2.5)	.231** (2.2)
signalB	-.0835 (-0.2)	.735** (2.5)	.988** (2.5)
signalW	.818*** (2.8)	0 (.)	0 (.)
Constant	.332 (0.9)	-.471** (-2.7)	-.577** (-2.6)
Observations	68	68	52
Adjusted R^2	0.16	0.20	0.25

t statistics in parentheses

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