Willingness-to-pay for Warnings: Main Tables

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Research Question

- 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 ($\pi L << c$)

- Theoretically, what should be the WTP for a signal?
- If bad states are a priori rare ($\pi L << c$) $\implies$ 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:

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

$$= \min[(1-\pi)u(Y_0)+\pi u(Y_0-L), u(Y_0-c)]$$

- 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)
    - *The opposite is true: subjects underreact to false positive and false negative rates and overpay for bad signals*
2. Conditional on the signal's value for risk-neutral subjects, false positive and false negative rates increase expected costs
    - *No: FP and FN rates have no significant effects on costs besides their predicted theoretical effect*
3. Extra: how much of these disrepancies result from belief updating issues or risk aversion?

Risk Aversion Measurement

- Measure risk aversion based on blind protection choices:
  - Exclude obs from subjects switching back and forth
  - The lowest probability for which a subject chooses to protect is π^*
  - Calculate their coefficient of relative risk aversion θ as the solution to the following equation:

$$\pi^* u(Y_0 - L; \theta) + (1 - \pi^*) u(Y_0; \theta) = u(Y_0 - c; \theta)$$

  - Where $u()$ is the CRRA utility function:

$$u(x; \theta) = \frac{x^{1-\theta} - 1}{1 - \theta}$$

- Note: risk lovers have $\theta < 0$

Abnormal Protection Responses

- Roughly one third of subjects (33 in the sample) switch from protection to no protection at least once
- But only 6% (6 subjects) switch more than once!
- In order to keep more risk aversion measurements we "repair" switches if they require a single change (a single error):
  - "0 1 0" is replaced with "0 0 0"
  - "1 0 1" is replaced with "1 1 1"
  - "1 0" in last two rounds replace with "1 1"
  - Note: because the algorithm goes from through rounds in increasing order, the sequence "... 0 1 0 1 1 ..."changes to ".. 0 0 0 1 1 ..." and the switching round goes up
- Left with only 7 subjects where this approach doesn't work and no risk aversion measurement is possible

CRRA Estimates

- Most subjects are moderately risk averse:

Probability (π^*)	θ	N
Always protect	>2	1
0.1	2	9
0.15	1.216	14
0.2	0.573	24
0.25	0	15
0.3	-0.539	11
Never protect	$<$-0.539	24

WTP for the Signal

- Theoretical value of the signal for risk-neutral subject:

$$b^* = \underbrace{\min[\pi L, c]}_{\text{BP costs}} - \underbrace{\pi(1 - P(s = 0|\omega = 1))L}_{\text{False neg. costs}} - \underbrace{P(s = 1)c}_{\text{Protection costs}}$$

- Two potential approaches:

  1. Regress the discrepancy between WTP V and theoretical value b^*:
  $$V - b^* = \alpha_0 + \alpha_1 \text{FN costs} + \alpha_2 \text{Prot. costs} + \epsilon$$
  2. Regress WTP directly on its components and account for censoring at 0:
  $$V = \min[0, \beta_0 + \beta_1 \text{FN costs} + \beta_2 \text{Prot. costs} - \beta_3 \text{BP costs} + \gamma]$$
  3. Note: protection costs include costs due to false positive signals

WTP for the Signal (Approach 2, Tobit Estimation)

- Coeffs should be one in abs. value
- Coefs are significantly less than 1

Figure: WTP for Information (Tobit Estimation)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
model				
BP costs	.541***	.549***	.537***	.386
	(6.2)	(4.6)	(4.0)	(1.1)
Prot. costs	-.274**	-.292	-.186	-.78
	(-2.1)	(-1.6)	(-1.0)	(-1.4)
False neg. costs	-.471***	-.59***	-.357***	-.564
	(-5.1)	(-4.3)	(-2.7)	(-1.5)
Constant	.332	.325	.189	2.04
	(1.2)	(0.8)	(0.5)	(1.5)
sigma				
Constant	1.97***	1.91***	1.97***	2.18***
	(28.0)	(18.7)	(19.6)	(7.0)
Observations	630	288	300	42
AIC	2303.98	1038.72	1114.55	164.51

t statistics in parentheses

Risk-averse vs Risk-loving

- Estimate Tobit models separately for risk-averse and risk-loving subjects (includes risk-neutral)
- Then use Wald tests on coefficients (no assumpt. of equal variance); alternative - bootstrap
- Higher sensitivity to false negative rates for risk-averse subjects
- The difference is not stat. significant ($p=0.23$)
- The differences are even less significant for other coeffs
- **Cannot reject the hypothesis that coeffs completely match in two models ($p=0.58$)**

False-positive vs False-negative payoff

- Test equality of coefficients on false-positive (-0.27) and false-negative costs (-0.47)
- Currently insignificant ($p=0.18$)
- Linear regressions seem to produce slightly lower variances (so that respective $p=0.07$)

WTP for the Signal (Risk Aversion)

- Explaining the discrepancy between WTP and value with risk aversion:

Figure: WTP for Information (different risk aversion)

	(1) Heterogeneous	(2) $\theta = 0.5$	(3) $\theta = 1.0$	(4) $\theta = 1.5$	(5) $\theta = 2.5$
BP costs	-.257***	-.442***	-.208***	.114*	.443***
	(-3.4)	(-7.4)	(-3.5)	(1.9)	(6.9)
Prot. costs	.706***	.855***	.776***	.604***	.333***
	(6.3)	(9.3)	(8.5)	(6.6)	(3.4)
False neg. costs	.602***	.675***	.754***	.788***	.828***
	(7.1)	(9.7)	(10.8)	(11.1)	(11.1)
Constant	-.574**	-.14	-1.01***	-2.08***	-2.89***
	(-2.3)	(-0.7)	(-5.3)	(-10.9)	(-14.2)
Observations	444	630	630	630	630
Adjusted R^2	0.15	0.19	0.23	0.30	0.36

t statistics in parentheses

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

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:

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

$$+(P(s = 0)r_w + P(s = 1)r_b)c$$

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

Actual Costs vs Theoretical Costs

- Prior prob and false negative rates disproportionally affect expected costs:

Figure: Actual Exp. Costs vs Theoretical Costs

	(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) FE	(6) FE
Optimal exp. costs	1.05***	.986***	.586***	1.04***	.99***	1.03***
	(23.4)	(12.0)	(2.8)	(20.9)	(10.6)	(17.9)
Prior prob.		-.739	-3.17**		-.603	
		(-0.9)	(-2.2)		(-0.8)	
False neg. rate			-2.4***			-.8
			(-2.9)			(-1.4)
False pos. rate			-.874			.831
			(-1.1)			(1.2)
Constant	-.745***	-.693***	-.54***	-.776***	-.721***	-.809***
	(-6.4)	(-5.6)	(-4.1)	(-7.0)	(-6.8)	(-7.4)
Observations	629	629	629	629	629	629
Adjusted R^2	0.38	0.38	0.39	0.44	0.44	0.44

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional Complementary Tables

1. Factors affecting informed protection responses
2. The effect of beliefs on informed protection
3. How accurate are their beliefs?
4. Decomposition of belief updating: priors vs signals

Informed Protection: Determinants

Figure: Informed Protection

	(1) All	(2) All	(3) Smart	(4) Smart
Informed protection				
Posterior prob.	2.09***	.699***	2.24***	.642***
	(17.7)	(3.3)	(16.1)	(2.7)
Prior prob.		1.23***		1.3***
		(4.1)		(3.8)
Gremlin says Black		1.26***		1.44***
		(7.6)		(7.7)
Constant	-.668***	-1.06***	-.724***	-1.14***
	(-13.2)	(-10.6)	(-12.9)	(-10.0)
Observations	1260	1260	1020	1020
AIC	1263.29	1206.92	982.25	925.61

t statistics in parentheses

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

Informed Protection: Do Subject's Beliefs Matter?

Figure: Informed Protection: Response to Reported Beliefs

	(1)	(2)	(3)
	All	All	Smart
Informed protection			
Belief	2.36***	1.36***	1.35***
	(17.1)	(7.9)	(7.1)
Posterior prob.		1.3***	1.37***
		(9.4)	(8.3)
Constant	-.811***	-.912***	-.943***
	(-13.9)	(-15.0)	(-14.5)
Observations	1260	1260	1020
AIC	1289.25	1197.97	933.64

t statistics in parentheses

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Belief Updating: Correlation

Figure: Belief Elicitation: Belief vs Posterior

	(1) All	(2) Not_honest	(3) Good quiz
Posterior prob.	.655***	.711***	.546***
	(35.7)	(36.8)	(21.1)
Constant	.156***	.138***	.216***
	(20.9)	(17.5)	(22.0)
Observations	1260	1020	840
Adjusted R^2	0.56	0.61	0.42

t statistics in parentheses

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

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

Figure: Belief Elicitation: Decomposition

	(1) OLS	(2) FE	(3) Smart, FE
lt_prior	.216***	.202***	.165***
	(3.3)	(4.0)	(3.1)
signalB	.65***	.86***	1***
	(4.0)	(6.3)	(5.9)
signalW	.21	0	0
	(1.5)	(.)	(.)
Constant	-.279*	-.514***	-.642***
	(-1.7)	(-5.3)	(-6.0)
Observations	280	280	216
Adjusted R^2	0.26	0.31	0.34

t statistics in parentheses

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