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:

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

- 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!
- If a switcher becomes non-switcher after a single change, calculate the risk aversion based on the total number of switches
- 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	10
0.15	1.216	13
0.2	0.573	29
0.25	0	16
0.3	-0.539	15
Never protect	$<$-0.539	14

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 (Tobit)

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

Table: WTP for Information (Tobit Estimation)

	(1) All	(2) Risk-averse	(3) Risk-loving
model			
BP costs	.688***	.625***	.72***
	(12.0)	(7.9)	(8.2)
Pos. signal costs	-.373***	-.233	-.486**
	(-3.0)	(-1.4)	(-2.5)
False neg. costs	-.587***	-.569***	-.578***
	(-6.7)	(-4.9)	(-4.2)
N obs.	744	336	354
AIC	2726	1213	1312
p(coeff=1)	6.68e-09***	1.04e-06***	.00357***

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

WTP for the Signal (Tobit, Conservative Classification)

- Any crossing from protection to no protection=switcher

Table: WTP for Information (Tobit Estimation)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
model				
BP costs	.688***	.635***	.704***	.74***
	(12.0)	(6.3)	(7.2)	(7.5)
Pos. signal costs	-.373***	-.326	-.492**	-.329
	(-3.0)	(-1.5)	(-2.3)	(-1.6)
False neg. costs	-.587***	-.619***	-.534***	-.625***
	(-6.7)	(-3.9)	(-3.4)	(-4.6)
N obs.	744	240	276	228
AIC	2726	868	1026	841
p(coeff=1)	6.68e-09***	.0028***	.00569***	.0000643***

t statistics in parentheses

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

WTP for the Signal (Tobit, Splitting Protection Costs)

- Any crossing from protection to no protection=switcher

Table: WTP for Information (Tobit Estimation)

	(1) All	(2) Risk-averse	(3) Risk-loving
model			
BP costs	.464***	.389***	.463***
	(6.9)	(4.2)	(4.5)
True pos. costs	.411**	.582**	.425
	(2.3)	(2.4)	(1.5)
False pos. costs	-.779***	-.649***	-.978***
	(-5.5)	(-3.5)	(-4.4)
False neg. costs	-.477***	-.442***	-.458***
	(-5.5)	(-3.8)	(-3.3)
Observations	744	336	354
AIC	2693.20	1193.95	1295.00

t statistics in parentheses

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

WTP for the Signal (Tobit, by Belief Accuracy)

- Accurate beliefs=total abs. belief elicitation error<median
- Subject with accurate beliefs are more sensitive to signal characteristics (but diffs are insignificant at 5%)

Table: WTP for Information (Tobit Estimation)

	(1) All	(2) Accur. beliefs	(3) Inaccur. beliefs
model			
BP costs	.688***	.77***	.613***
	(12.0)	(9.7)	(7.4)
Pos. signal costs	-.373***	-.538***	-.224
	(-3.0)	(-3.1)	(-1.3)
False neg. costs	-.587***	-.749***	-.422***
	(-6.7)	(-6.2)	(-3.3)
N obs.	744	372	372
AIC	2726	1356	1372
p(coeff=1)	6.68e-09***	.0202**	1.44e-07***

t statistics in parentheses

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

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 (-0.48)
  - Significance: $p = 0.12$ (standard), $p = 0.08$ (1000 bootstrap)
- Linear regression has lower variances (so that respective $p = 0.008$ and $p = 0.023$)

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

Table: 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	.00139	-.103**	.101**	.355***	.574***
	(0.0)	(-2.1)	(2.1)	(7.5)	(11.7)
False pos. costs	.0436	.0909	.111	.101	.0346
	(0.3)	(0.9)	(1.1)	(1.0)	(0.3)
False neg. costs	.384***	.534***	.623***	.677***	.75***
	(5.1)	(8.2)	(9.8)	(10.7)	(11.3)
Constant	-.153	.0119	-.888***	-1.98***	-2.79***
	(-0.6)	(0.1)	(-4.5)	(-10.1)	(-13.6)
Observations	594	744	744	744	744
Adjusted R^2	0.03	0.08	0.13	0.24	0.34

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:

Table: Actual Exp. Costs vs Theoretical Costs

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE
Optimal exp. costs	.979***	.549***	.987***	.733***	1.06***
	(13.1)	(2.9)	(11.5)	(6.0)	(10.2)
Prior prob.	-.689	-3.3**	-.607	-2.15**	-.18
	(-0.9)	(-2.5)	(-0.8)	(-2.5)	(-0.2)
False neg. rate		-2.48***		-1.88***	
		(-3.4)		(-3.1)	
False pos. rate		-1.04			.71
		(-1.4)			(1.0)
Constant	-.707***	-.542***	-.711***	-.637***	-.754***
	(-6.2)	(-4.5)	(-7.4)	(-6.6)	(-6.8)
Observations	743	743	743	743	743
Adjusted R^2	0.38	0.39	0.43	0.44	0.43

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

Table: Informed Protection

	(1) All	(2) All	(3) Smart	(4) Smart
Informed protection				
Posterior prob.	2.15***	.656***	2.26***	.632***
	(19.0)	(3.3)	(17.7)	(2.9)
Prior prob.		1.13***		1.17***
		(4.1)		(3.8)
Gremlin says Black		1.34***		1.47***
		(8.8)		(8.9)
Constant	-.661***	-1.03***	-.716***	-1.1***
	(-14.2)	(-11.2)	(-14.2)	(-10.9)
Observations	1488	1488	1260	1260
AIC	1468.48	1394.60	1212.73	1138.15

t statistics in parentheses

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

Informed Protection: Do Subject's Beliefs Matter?

Table: Informed Protection: Response to Reported Beliefs

	(1)	(2)	(3)
	All	All	Good quiz
Informed protection			
Belief	2.17***	1.1***	1.39***
	(18.5)	(7.3)	(7.9)
Posterior prob.		1.52***	1.41***
		(11.5)	(9.3)
Constant	-.76***	-.879***	-.96***
	(-14.3)	(-15.7)	(-15.8)
Observations	1488	1488	1260
AIC	1568.58	1414.72	1148.36

t statistics in parentheses

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

Belief Updating: Correlation

Table: Belief Elicitation: Belief vs Posterior

	(1) All	(2) Not_honest	(3) Good quiz
Posterior prob.	.644***	.693***	.524***
	(37.5)	(39.2)	(21.8)
Constant	.175***	.15***	.236***
	(21.7)	(19.8)	(23.4)
Observations	1488	1260	992
Adjusted R^2	0.53	0.60	0.38

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

Table: Belief Elicitation: Decomposition

	(1) OLS	(2) FE	(3) Good quiz, FE
lt_prior	.237***	.182***	.187***
	(3.9)	(4.0)	(4.0)
signalB	.426***	.865***	.992***
	(5.1)	(6.4)	(6.7)
signalW	.439***	0	0
	(5.7)	(.)	(.)
Constant		-.54***	-.632***
		(-6.0)	(-6.6)
Observations	332	332	288
Adjusted R^2	0.29	0.29	0.34

t statistics in parentheses

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