Willingness-to-pay for Warnings: Main Tables

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December 31, 2021

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!
- 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 Discrepancy Regressions

- Regressing the difference between WTP and theoretical value for a risk-neutral subject
- Coefficients should be zero

WTP Discrepancy 1

Table: WTP for Information (Discrepancy)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
False pos. costs	.17	.207	.062	.447
	(1.6)	(1.5)	(0.4)	(1.0)
False neg. costs	.3***	.297***	.329***	.169
	(4.8)	(3.4)	(3.3)	(0.8)
Constant	-.111	-.143	-.139	.289
	(-1.2)	(-1.0)	(-1.0)	(0.8)
N obs.	744	336	354	54
AIC	2814	1243	1361	214
p(coeffs=0)	5.45e-06***	.00125***	.00434***	.468

t statistics in parentheses

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

WTP Discrepancy 2

- Controlling for the prior probability of a black ball with dummies

Table: WTP for Information (Discrepancy)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
False pos. costs	.213**	.292**	.0744	.125
	(2.3)	(2.3)	(0.5)	(0.3)
False neg. costs	.246***	.188**	.314***	.216
	(4.2)	(2.3)	(3.4)	(1.0)
Constant	.413***	.232	.463***	1.51**
	(3.4)	(1.3)	(2.6)	(2.3)
N obs.	744	336	354	54
AIC	2673	1169	1296	212
p(coeffs=0)	.0000248***	.00525***	.00367***	.576

t statistics in parentheses

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

WTP Discrepancy 3 (Beliefs Accuracy)

Table: WTP for Information (Discrepancy)

	(1) All	(2) Accur. beliefs	(3) Inaccur. beliefs
False pos. costs	.17	-.0437	.338**
	(1.6)	(-0.3)	(2.3)
False neg. costs	.3***	.234***	.367***
	(4.8)	(2.9)	(4.0)
Constant	-.111	-.0405	-.173
	(-1.2)	(-0.3)	(-1.2)
N obs.	744	372	372
AIC	2814	1389	1425
p(coeffs=0)	5.45e-06***	.0153**	.0000787***

t statistics in parentheses

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

WTP Discrepancy 4

- Positive signal costs include costs of responding to true positive signal and the costs of responding to false positive signals

Table: WTP for Information (Discrepancy)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
Pos. signal costs	.191***	.335***	.0629	-.0304
	(2.6)	(3.3)	(0.6)	(-0.1)
False neg. costs	.291***	.276***	.325***	.135
	(4.7)	(3.2)	(3.3)	(0.7)
Constant	-.342**	-.6***	-.21	.562
	(-2.4)	(-3.0)	(-1.0)	(0.9)
N obs.	744	336	354	54
AIC	2810	1235	1361	215
p(coeffs=0)	7.97e-07***	.000017***	.00419***	.772

t statistics in parentheses

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

WTP Discrepancy 5 (by Risk Aversion)

- 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) $\theta = 2.5$
False pos. costs	.0431	.127	.0752	-.0231	-.166
	(0.3)	(1.2)	(0.8)	(-0.2)	(-1.6)
False neg. costs	.385***	.49***	.666***	.829***	.996***
	(5.4)	(8.1)	(11.2)	(13.8)	(15.3)
Constant	-.148	-.383***	-.5***	-.608***	-.581***
	(-1.2)	(-3.9)	(-5.1)	(-6.0)	(-5.3)
Observations	594	744	744	744	744
Adjusted R^2	0.04	0.07	0.13	0.18	0.22

t statistics in parentheses

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

Tobit Regressions

- Regressing the WTP on its theoretical components
- Censoring at 0 and at 5 USD
- Coefficients should be one in absolute value
- No constant in regressions

WTP Tobit 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 Tobit 2: Splitting Protection Costs

Table: WTP for Information (Tobit Estimation)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
model				
BP costs	.464***	.389***	.463***	.989***
	(6.9)	(4.2)	(4.5)	(3.4)
True pos. costs	.411**	.582**	.425	-.825
	(2.3)	(2.4)	(1.5)	(-1.1)
False pos. costs	-.779***	-.649***	-.978***	-.648
	(-5.5)	(-3.5)	(-4.4)	(-1.1)
False neg. costs	-.477***	-.442***	-.458***	-.835**
	(-5.5)	(-3.8)	(-3.3)	(-2.5)
N obs.	744	336	354	54
AIC	2693	1194	1295	212
p(coeff=1)	1.51e-15***	1.44e-10***	1.70e-06***	.645

t statistics in parentheses

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

WTP Tobit 3: Controlling for Prior Probability

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

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

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

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

Actual Costs - Theoretical Costs Discrepancy

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

Table: Discrepancy: actual-theoretical Costs

	(1) OLS	(2) OLS	(3) FE	(4) FE
False pos. costs	.0438	.0142	.0336	.00252
	(0.4)	(0.1)	(0.3)	(0.0)
False neg. costs	-.0137	.0227	-.00554	.0221
	(-0.2)	(0.3)	(-0.1)	(0.3)
Constant	-.857***	-.706***	-.858***	-.823***
	(-8.9)	(-6.4)	(-11.2)	(-8.9)
Prior prob dummies	No	Yes	No	Yes
Observations	743	743	743	743
Adjusted R^2	-0.00	-0.00	-0.00	-0.00

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

Actual Costs - Theoretical Costs Discrepancy 2

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

Table: Discrepancy 2: actual-theoretical Costs

	(1) OLS	(2) OLS	(3) FE	(4) FE
False pos. rate	.443	.447	.657	.659
	(1.1)	(1.1)	(1.1)	(1.1)
False neg. rate	-.812**	-.814**	-.862*	-.864*
	(-2.0)	(-2.0)	(-1.9)	(-1.9)
Constant	-.803***	-.649***	-.823***	-.783***
	(-8.1)	(-6.3)	(-9.9)	(-8.1)
Prior prob dummies	No	Yes	No	Yes
Observations	743	743	743	743
Adjusted R^2	0.00	0.00	0.01	0.01

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

Value Formation

- What drives the difference between theoretical value and actual willingness-to-pay? Potential elements affecting the WTP:
  - Beliefs
  - Strategies
  - Preferences
- We recalculate the value after incorporating these elements one-by-one

Theoretical value for a risk-neutral subject:		Theoretical value for reported beliefs and optimal strategies:		Theoretical value for actual strategies:		Reported value:
$V(a^*(p^*))$	$\xrightarrow{\textit{Beliefs}}$	$V(a^*(\mu_R))$	$\xrightarrow{\textit{Strategy}}$	$V(a_R)$	$\xrightarrow{\textit{Preferences}}$	V_R

Value Formation

- Accounting for reported beliefs or strategies does not make the theoretical value closer to the WTP
- WTP is still more correlated with the (completely) theoretical value rather than with values accounting for beliefs μ_R or strategies a_R
- My hypothesis: subjects approach the tasks independently and/or do not report beliefs truthfully

	$V(a^*(p^*))$	$V(a^*(\mu_R))$	$V(a_R)$	V_R
$V(a^*(p^*))$	1	0.52	0.54	0.34
$V(a^*(\mu_R))$	0.52	1	0.63	0.29
$V(a_R)$	0.54	0.63	1	0.33
V_R	0.34	0.29	0.33	1

Additional Complementary Tables

1. Belief updating (slides are not updated)
2. Determinants of informed protection responses
3. Classifying informed protection strategies
4. Extra WTP tables

Belief Updating: Correlation

Table: Belief Elicitation: Belief vs Posterior

	(1)	(2)	(3)
	All	Not_honest	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

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

Informed Protection: Determinants

Table: Informed Protection

	(1) All	(2) All	(3) Good quiz	(4) Good quiz
Informed protection				
Posterior prob.	2.15***	.662***	2.26***	.638***
	(19.1)	(3.3)	(17.7)	(3.0)
Prior prob.		1.13***		1.17***
		(4.1)		(3.8)
Gremlin says Black		1.34***		1.46***
		(8.8)		(8.8)
Constant	-.662***	-1.03***	-.717***	-1.1***
	(-14.2)	(-11.2)	(-14.2)	(-10.9)
Observations	1487	1487	1259	1259
AIC	1467.25	1394.01	1211.48	1137.59

t statistics in parentheses

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

Informed Protection: Reacting to Own Beliefs or Posterior Probabilties?

Table: Informed Protection: Response to Reported Beliefs

	(1)	(2)	(3)
	All	All	Good quiz
Informed protection			
Belief	2.18***	1.1***	1.39***
	(18.5)	(7.3)	(7.9)
Posterior prob.		1.52***	1.41***
		(11.5)	(9.3)
Constant	-.762***	-.881***	-.963***
	(-14.3)	(-15.7)	(-15.9)
Observations	1487	1487	1259
AIC	1566.82	1413.23	1146.78

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) All	(2) Accurate beliefs	(3) Inaccurate beliefs
Informed protection			
Belief	1.1***	2.18***	.728***
	(7.3)	(6.9)	(3.8)
Posterior prob.	1.52***	.69**	1.55***
	(11.5)	(2.1)	(10.6)
Constant	-.881***	-.953***	-.807***
	(-15.7)	(-12.8)	(-9.4)
Observations	1487	744	743
AIC	1413.23	603.49	798.79

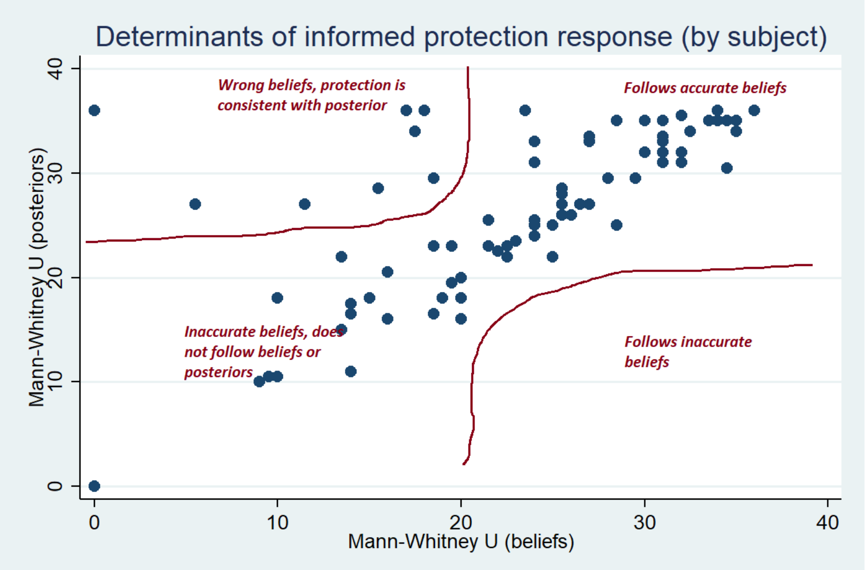
t statistics in parentheses

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

Informed Protection: Responding to Beliefs or Posterior Probabilities

- Calculate the subject-specific correlation between beliefs, posterior probabilities and protection responses
- Mann-Whitney U-test as a correlation measure with two "groups": signals answered with either protection or no protection responses
- No obvious clustering, but ∃ three groups:
  1. Sophisticated: protection decisions closely follow their accurate beliefs
  2. Clueless: protection decisions follow neither posteriors nor reported beliefs
  3. Amenders: have inaccurate beliefs, but behave consistently with posterior probabilities (small group)

Informed Protection: Responding to Beliefs or Posterior Probabilities



WTP Discrepancy 6

- Adding blind protection costs

Table: WTP for Information (Discrepancy)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
BP costs	-.519***	-.484***	-.534***	-.622**
	(-9.3)	(-6.2)	(-6.6)	(-2.5)
Pos. signal costs	.671***	.759***	.596***	.482
	(8.0)	(6.8)	(4.5)	(1.4)
False neg. costs	.475***	.423***	.542***	.371*
	(7.3)	(4.6)	(5.2)	(1.7)
Constant	.818***	.526**	.917***	2.06**
	(4.6)	(2.1)	(3.6)	(2.5)
N obs.	744	336	354	54
AIC	2738	1206	1326	210
p(coeffs=0)	3.83e-22***	2.00e-12***	8.46e-10***	.0958*

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

WTP Discrepancy 7

- Controlling for the prior probability of a black ball with dummies

Table: WTP for Information (Discrepancy)

	(1) All	(2) Risk-averse	(3) Risk-loving	(4) Switchers
False-neg. prob. x Loss	.044**	.0366	.0572**	.0162
	(2.5)	(1.5)	(2.1)	(0.2)
False-neg. prob. x Prot. cost	.13*	.176*	.0378	-.0058
	(1.8)	(1.8)	(0.3)	(-0.0)
Constant	.404***	.244	.417**	1.63**
	(3.1)	(1.3)	(2.2)	(2.5)
N obs.	744	336	354	54
AIC	2686	1174	1303	213
p(coeffs=0)	.00982***	.0542***	.109***	.969

t statistics in parentheses

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