Willingness-to-pay for Warnings: Main Tables

A. Gaduh, P. McGee and A. Ugarov

May 28, 2022

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?

- 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

Figure: WTP for Information (Discrepancy)

	(1)	(2)	(3)	(4)	(5)	(6)
FP costs	.251*	.305**	.0991	.136	.404**	.439**
	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)	(0.2)
FN costs	.356***	.292***	.397***	.348***	.425***	.375***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Risk-averse			.0046	-.154		
			(0.3)	(0.4)		
Risk-averse × FP costs			.187	.227		
			(0.2)	(0.3)		
Risk-averse × FN costs			-.066	-.118		
			(0.2)	(0.1)		
Accur. beliefs					.212	.335
					(0.3)	(0.4)
Accur. beliefs × FP costs					-.361	-.339
					(0.2)	(0.2)
Accur. beliefs × FN costs					-.143	-.166
					(0.1)	(0.1)
Constant	-.233	.288	-.237	.336	-.331	.145
	(0.2)	(0.2)	(0.3)	(0.3)	(0.2)	(0.3)

WTP Discrepancy 5 (by Risk Aversion)

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

Figure: WTP for Information (different risk aversion)

	(1) $\theta = 0$	(2) $\theta = 0.5$	(3) $\theta = 1.0$	(4) $\theta = 1.5$	(5) $\theta = 2.5$	(6) Heterogeneous θ
FP costs	.295**	.322**	.316**	.271*	.151	.29**
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
FN costs	.243***	.346***	.46***	.559***	.69***	.343***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Constant	.254	-.146	-.664***	-1.32***	-1.81***	-.411
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)
Prior dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	504	504	504	504	504	504
Adjusted R^2	0.21	0.27	0.28	0.32	0.37	0.19

Standard errors 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

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) 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:

Figure: Expected costs discrepancy

	(1)	(2)	(3)	(4)	(5)	(6
FP costs	.0627	.0297	.153	.135	-.00302	-.07
	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)	(0.
FN costs	-.0285	.011	-.103	-.081	.134	.24
	(0.1)	(0.1)	(0.1)	(0.2)	(0.1)	(0.
Risk-averse			-.167	.121		
			(0.3)	(0.3)		
Risk-averse × FP costs			-.143	-.161		
			(0.3)	(0.3)		
Risk-averse × FN costs			.169	.198		
			(0.1)	(0.2)		
Accur. beliefs					.557*	.23
					(0.3)	(0.
Accur. beliefs × FP costs					.18	.27
					(0.3)	(0.
Accur. beliefs × FN costs					-.329**	-.46*

Actual Costs - Theoretical Costs Discrepancy 2

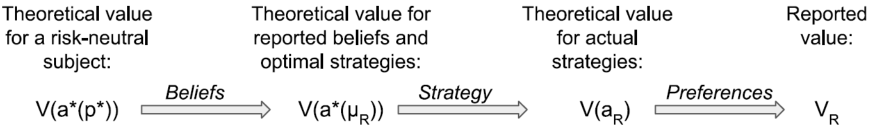
- Prior prob and false negative rates disproportionally affect expected costs:

Figure: Expected costs discrepancy (without 10% outliers)

	(1)	(2)	(3)	(4)	(5)	(6
FP costs	-.241***	-.217***	-.165*	-.137*	-.274***	-.12
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.
FN costs	-.112***	-.127***	-.0913**	-.116***	-.0678	-.10
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.
Risk-averse			-.128	.0384		-.11
			(0.1)	(0.1)		(0.
Risk-averse × FP costs			-.073	-.0708		-.08
			(0.1)	(0.1)		(0.
Risk-averse × FN costs			-.0302	-.0167		-.03
			(0.1)	(0.1)		(0.
Accur. beliefs					.219***	.259
					(0.1)	(0.
Accur. beliefs × FP costs					.0905	
					(0.1)	
Accur. beliefs × FN costs					-.0851	

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



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

Figure: Belief Elicitation: Belief vs Posterior

	(1)	(2)	(3)
	All	Good quiz	Dishonest greml
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

Figure: Belief Elicitation: Decomposition

	(1)	(2)	(3)
	OLS	FE	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

Figure: 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?

Figure: Informed Protection: Response to Reported Beliefs

	(1)	(2)	(3)
	All	All	Good quiz
Informed protection			
Belief	2.18***	2.62***	2.8***
	(18.5)	(18.2)	(17.0)
Belief error		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?

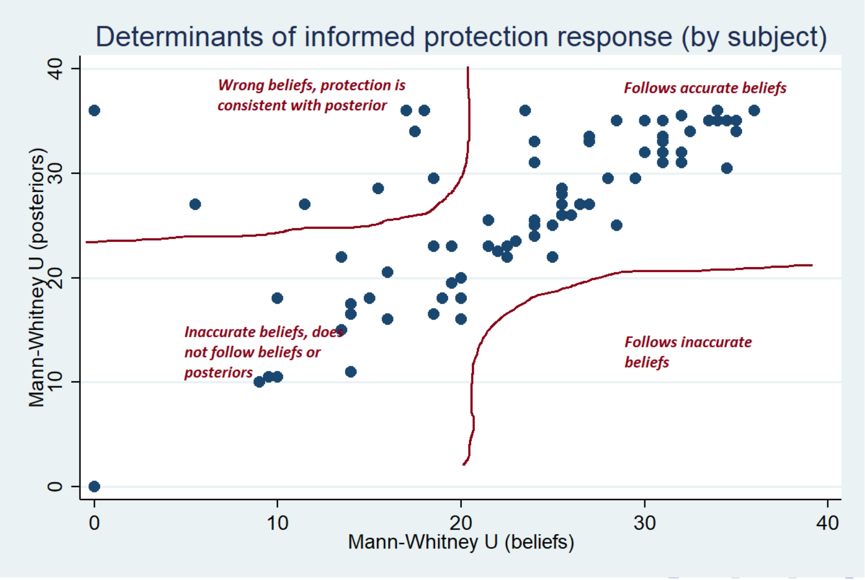
Figure: Informed Protection: Response to Reported Beliefs

	(1)	(2)	(3)	(4)
Informed protection				
Belief	2.36***	2.67***	2.63***	2.85***
	(0.2)	(0.2)	(0.4)	(0.4)
Belief error		1.3***	1.17***	1.44***
		(0.2)	(0.2)	(0.3)
Good quiz			.184	
			(0.2)	
Good quiz × Belief			.105	
			(0.5)	
Good quiz × Belief error			.34	
			(0.4)	
Stat. class				.0954
				(0.2)
Stat. class × Belief				-.287
				(0.5)

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 $\exists$ 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

Figure: 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

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