CAN ALTERNATIVE NON-MARKET VALUE ELICITATION METHODS REVEAL THE SAME VALUES?

Christian A. Vossler
University of Tennessee

Ewa Zawojska
University of Warsaw

Non-market value elicitation methods

- Provide estimates of economic value of non-market goods (e.g., clean air)
- Evaluate benefits needed for cost-benefit assessments
- Are based on preferences stated in surveys
- Use various formats for value elicitation

Non-market value elicitation methods

- Provide estimates of economic value of non-market goods (e.g., clean air)
- Evaluate benefits needed for cost-benefit assessments
- Are based on preferences stated in surveys → **Stated preference methods**
- Use various formats for value elicitation

Non-market value elicitation methods

- Provide estimates of economic value of non-market goods (e.g., clean air)
- Evaluate benefits needed for cost-benefit assessments
- Are based on preferences stated in surveys → **Stated preference methods**
- Use various formats for value elicitation

Would you be willing to pay $5 annually for the proposed program?

Yes / No

What is the maximum amount you would be willing to pay annually for the proposed program?

____

Elicitation effects: A threat to validity

- Common finding: Different formats generate different value estimates.

→ **"elicitation effects"**

- This signals a failure of convergent validity.
- Many explanations for elicitation effects:
  - Incentive properties, strategic responding (Carson and Groves, 2007)
  - Response uncertainty (Welsh and Poe, 1998)
  - Anchoring (Green et al., 1998)
  - Social norms and quality signals (Hanemann, 1995)
  - Statistical methods (Huang and Smith, 1998)
- Hundreds of studies document elicitation effects, but far from consensus.

Elicitation effects: A puzzle

- Induced-value experiments find little evidence of elicitation effects.
  - Vossler and McKee (2006): compare SBC, PC and MBDC
  - Carson, Chilton and Hutchinson (2009): compare SBC and DB
  - Collins and Vossler (2009): compare two- and three-option choice tasks
  - Messer et al. (2010): compare SBC and OE
- This is in stark contrast to field (and other lab) studies based on home-grown values, which usually evidence elicitation effects.

How to explain the puzzle?

- The induced-value experiments were incentive compatible, while home-grown value studies were typically not.

Incentive compatibility means truthful preference revelation is the dominant strategy.

- Respondents should view a survey as consequential (not entirely hypothetical).
- A **single binary choice** (yes-no) question is the gold standard for incentive compatibility.
- (But there are efficiency losses related to the use of this format.)
- …

How to explain the puzzle?

- The induced-value experiments were incentive compatible, while home-grown value studies were typically not.

Incentive compatibility means truthful preference revelation is the dominant strategy.

- Respondents should view a survey as consequential (not entirely hypothetical).
- A **single binary choice** (yes-no) question is the gold standard for incentive compatibility.
- (But there are efficiency losses related to the use of this format.)
- …

Can we obtain the same (home-grown) values under incentive compatible conditions?

Our study

- A lab experiment that incorporates important properties of field studies:
  - Elicitation of **home-grown values**
  - Evaluation of a **public**, environmental **good** with a large share of **passive-use value**
  - Ambiguity over cost of the good's provision
- **Four popular elicitation formats** compared:
  - Single binary choice
  - Double-bounded binary choice
  - Payment card
  - Open-ended
- Held fixed:
  - incentive properties (**incentive compatibility** assured)
  - framing, the decision rule, and the payment method

Experimental design: Valuation scenario

- We partnered with organization GreenTrees, who carries out tree-planting projects in the Mississippi River Valley.
- The proposal is for the session group to fund the planting and maintenance of 160 trees.
- Participants are provided with an overview of reforestation benefits and specific estimates of what 160 trees means in terms of increased water storage, avoided nutrient runoff and captured CO_2.

GreenTrees

ONE ACRE AT A TIME

Our study: A referendum

- In each session, participants vote in a referendum.
- If it cost you $x, are you in favor of funding the tree planting project?

- Each session is a separate referendum.
- The cost is coercive for everyone upon the referendum passing.

Experimental design: Treatments

- A continuum from no explicit cost to several possible costs

no cost — *several costs*

Open-ended	Single binary choice	Double-bounded binary choice	Payment card

- Held fixed across treatments:
  - Framing as a majority-vote referendum
  - Ambiguity as to whether the individual cost varies across participants
  - Pre-negotiated total cost; the cost share in place as needed
  - Incentive compatibility – all mechanisms translate into a single binding yes-no vote (Azrieli, Chambers and Healy, 2018)

Experimental design: Single binary choice

- “If passage of the referendum cost you \$x, are you in favor of funding the tree planting project?”
- Cost randomly drawn from vector {\$1, \$2, \$3, \$4, \$5, \$6}.
- Referendum passes if more than half vote “yes”.

Experimental design: Double-bounded binary choice

- "If passage of the referendum cost you $x, are you in favor of funding the tree planting project?"
- Participants face two referenda, which vary only by cost.
  - Cost randomly drawn from vector {$1, $2, $3, $4, $5, $6}.
  - Participant receives higher (lower) cost in the second referendum if she voted "yes" ("no") in the first one.
  - For the first referendum, the two extreme costs are excluded.
- One of the two referenda is selected at random as binding.
- The randomly selected referendum passes if more than half vote "yes".

Experimental design: Payment card

- "If passage of the referendum cost you \$x, are you in favor of funding the tree planting project?"
- On a single decision screen, participants vote yes/no separately for 11 different cost amounts (separate referenda): \$0, \$1, \$2, … , \$10.
- One of the costs (referenda) is selected at random as binding.
- The randomly selected referendum passes if more than half vote "yes".

Experimental design: Open-ended

- “What is the highest amount that you would pay and still vote in favor of funding the tree planting project?”
- Described as a way to learn the range of possible costs for which the person would vote “yes” or “no”.
- Random Price Voting Mechanism (Messer et al., 2010)
  - It translates the open-ended response to a yes/no vote at a specific cost.
  - Cost is randomly drawn from a distribution ambiguous to participants.
  - If the open-ended response is equal to or higher than the drawn cost, this is a “yes” vote.
- Referendum passes if more than half vote “yes”.

Experimental design: Procedures

1) Two "real effort" tasks:
   - Counting zeros in large zero-one matrices (Abeler et al., 2011)
   - Encoding words into numbers (Erkal et al., 2011)
   - Scores added up and rank-ordered
   - Participants paid according to their performance quintile: from $15 to $25
2) **Valuation task**
3) Post-experiment questionnaire

- Experiment programmed using the software z-Tree (Fischbacher, 2007)
- 410 students of the University of Tennessee; 18 sessions; 16-24 participants per session
- 40 minutes; Average earnings $19.79
- Referendum passed in 7 sessions

Summary statistics by treatment

No significant differences across treatments

	Single binary choice	Open-ended	Double-bounded binary choice	Payment card
Age	20.65	20.79	20.80	20.53
	(3.31)	(1.51)	(2.79)	(2.29)
Female	0.45	0.48	0.41	0.37
	(0.50)	(0.50)	(0.50)	(0.49)
Earned income	19.77	19.79	19.84	19.79
	(3.54)	(3.49)	(3.49)	(3.49)
Employed	0.46	0.48	0.58	0.47
	(0.50)	(0.50)	(0.50)	(0.50)
GPA	3.19	3.36	3.34	3.22
	(0.57)	(0.43)	(0.50)	(0.50)
Number of participants	130	94	92	94

Note: Standard errors given in brackets.

Empirical survival functions

Shares of “yes” votes for each cost amount

Cost	Single binary choice	Open-ended	Double-bounded binary choice	Payment card
$0				82.98
$1	79.17	84.04	87.32	74.47
$2	72.73	71.28	75.00	67.02
$3	61.90	59.58	56.58	56.38
$4	50.00	42.55	50.67	41.49
$5	33.33	35.11	31.94	36.17
$6	25.00	17.02	20.55	20.21
$7		13.83		17.02
$8		9.58		12.77
$9		8.51		12.77
$10		8.51		12.77

Empirical survival functions

Shares of “yes” votes for each cost amount

Cost	Single binary choice	Open-ended	Double-bounded binary choice	Payment card
$0				82.98
$1	79.17	84.04	87.32	74.47
$2	72.73	71.28	75.00	67.02
$3	61.90	59.58	56.58	56.38

- To non-parametrically test for differences across the distributions, we use two-sample Kolmogorov-Smirnov tests.
- The test statistic is the absolute value of the largest difference in the observed probabilities across two distributions.
- The largest observed difference, across all pairwise comparisons, is between the double-bounded and payment-card treatments at $1.
- But we cannot reject the equality of the distributions.

Parametric data analysis

- Non-parametric analysis is problematic for estimating mean willingness-to-pay (WTP) values.
- A model of WTP that interprets responses in an internally consistent way:
  - Treatments give rise to a mix of continuous, binary-censored and interval-censored data.
  - We assume WTP_i^* ~ *Normal*$(\mathbf{x}_i\boldsymbol{\beta}, \sigma_i^2)$.
  - We estimate an interval regression model.
  - Error variance is allowed to differ across treatments.

$$\ln \mathcal{L} = \sum_{i=1}^{N} \left\{ D_i \cdot \ln \Phi \left(\left(\frac{c_{i,u} - \mathbf{x}_i \boldsymbol{\beta}}{\sigma_i} \right) - \left(\frac{c_{i,l} - \mathbf{x}_i \boldsymbol{\beta}}{\sigma_i} \right) \right) + (1 - D_i) \cdot \ln \left(\frac{1}{\sigma_i} \phi \left(\frac{WTP_i - \mathbf{x}_i \boldsymbol{\beta}}{\sigma_i} \right) \right) \right\}$$

Parametric data analysis

	(1)	(2)	(3)
Open-ended	-0.25	-0.18	-0.36
	(0.65)	(0.61)	(0.62)
Double-bounded binary choice	-0.10	0.00	-0.09
	(0.68)	(0.62)	(0.62)
Payment card	-0.13	-0.03	0.07
	(0.65)	(0.56)	(0.55)
Age			0.25***
			(0.09)
Female			1.05**
			(0.44)
Earned income			-0.07
			(0.06)
Employed			0.15
			(0.44)
GPA			0.50
			(0.42)
Constant	3.94***	3.84***	3.89***
	(0.48)	(0.38)	(0.39)
Standard deviation function (σ)			
Open-ended		1.24	1.36*
		(0.81)	(0.79)
Double-bounded binary choice		0.89	0.81
		(0.99)	(0.96)
Payment card		0.65	0.47
		(0.81)	(0.78)
Constant	4.15***	3.23***	3.19***
	(0.23)	(0.73)	(0.71)
Log-L	-669.13	-667.92	-659.55
Number of observations	410	410	410

Parametric data analysis

	(1)	(2)	(3)
Open-ended	-0.25	-0.18	-0.36
	(0.65)	(0.61)	(0.62)
Double-bounded	-0.10	0.00	-0.09
	(0.68)	(0.62)	(0.62)
Payment card	-0.13	-0.03	0.07
	(0.65)	(0.56)	(0.55)
Age			0.25***
			(0.09)
Female			1.05**
			(0.44)
Earned income			-0.07
			(0.06)
Employed			0.15
			(0.44)
GPA			0.50
			(0.42)
Constant	3.94***	3.84***	3.89***
	(0.48)	(0.38)	(0.39)

	(1)	(2)	(3)
Standard deviation (σ)			
Open-ended		1.24	1.36*
		(0.81)	(0.79)
Double-bounded		0.89	0.81
		(0.99)	(0.96)
Payment card		0.65	0.47
		(0.81)	(0.78)
Constant	4.15***	3.23***	3.19***
	(0.23)	(0.73)	(0.71)
Log-L	-669.13	-667.92	-659.55
No. of observations	410	410	410

Parametric data analysis

No statistical evidence of elicitation effects

	(1)	(2)	(3)
Open-ended	-0.25	-0.18	-0.36
	(0.65)	(0.61)	(0.62)
Double-bounded	-0.10	0.00	-0.09
	(0.68)	(0.62)	(0.62)
Payment card	-0.13	-0.03	0.07
	(0.65)	(0.56)	(0.55)
Age			0.25***
			(0.09)
Female			1.05**
			(0.44)
Earned income			-0.07
			(0.06)
Employed			0.15
			(0.44)
GPA			0.50
			(0.42)
Constant	3.94***	3.84***	3.89***
	(0.48)	(0.38)	(0.39)

	(1)	(2)	(3)
Standard deviation (σ)			
Open-ended		1.24	1.36*
		(0.81)	(0.79)
Double-bounded		0.89	0.81
		(0.99)	(0.96)
Payment card		0.65	0.47
		(0.81)	(0.78)
Constant	4.15***	3.23***	3.19***
	(0.23)	(0.73)	(0.71)
Log-L	-669.13	-667.92	-659.55
No. of observations	410	410	410

Summary and discussion

- **Controlling for incentives, but allowing for possible behavioral factors, we find no evidence of elicitation effects** across a wide range of value elicitation formats.
- Possible implications:
  - Difference in incentive properties for field applications may be of first-order importance.
  - It may be possible to design field studies to eliminate or dampen incentive effects.
- Further extensions: Systematically relax controls to parallel field conditions
  - A majority-vote implementation rule (e.g., keeping the decision rule undisclosed)
  - Common knowledge of the random cost selection
  - Students vs. representative samples

Christian A. Vossler
University of Tennessee
cvossler@utk.edu

Ewa Zawojska
University of Warsaw
ezawojska@wne.uw.edu.pl