

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

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Non-market value elicitation methods

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

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Would you be willing to pay \$5 annually for the proposed program of reducing carbon concentrations?
Yes / No

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

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Yes / No

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

Do different formats lead to the same value estimates?

Stated preference methods

- **Wide range of applications**

- Transportation: vehicle choice, transportation mode choice
- Marketing: consumer satisfaction, demand for a new product
- Health: preferences for health programs, value of statistical life
- Environment: value of air quality improvements, recreation
- Culture: value of cultural heritage
- ...

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- **Advantages**

- Capture “use” and “passive-use” values
- Can go beyond the scope of the existing data
- Relatively clean identification of policy effects

- **Disadvantages**

- Not based on market behavior
- No direct financial consequences
- Incentive properties insufficiently understood

Elicitation effects: A threat to validity

- Different formats of eliciting values are very often found to generate different value estimates. → **so-called “elicitation effects”**
- Evidence of elicitation effects 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.
- A single binary choice question is seen as the gold standard, but myriad formats continue to be used.

Elicitation effects: A puzzle

- Induced-value experiments, conducted under incentive compatible conditions, 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 evidence from field (and other lab) studies based on home-grown values, where a finding of no elicitation effects is rare.

Elicitation effects: A puzzle

Incentive compatibility means that truthful preference revelation is the dominant strategy.

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- This is in stark contrast to evidence from field (and other lab) studies based on home-grown values, where a finding of no elicitation effects is rare.

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:
 - Open ended
 - Single binary choice
 - Double-bounded binary choice
 - Payment card
- Held fixed:
 - incentive properties (**incentive compatibility** assured)
 - framing, the decision rule, and the payment method

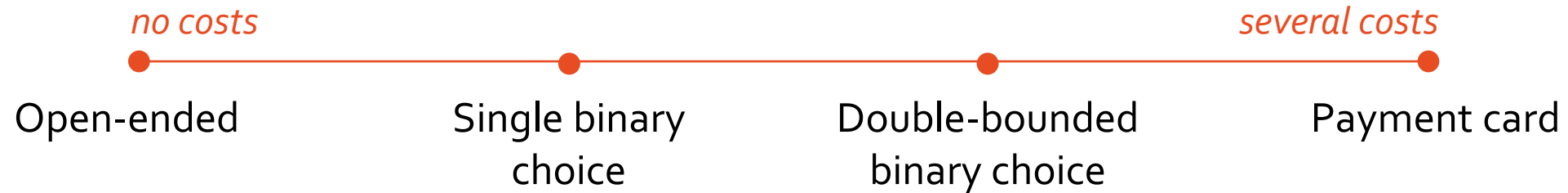
Experimental design: Valuation scenario

- 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 CO₂.



Experimental design: Treatments

- A continuum from no explicit cost to several possible costs



- Held fixed across treatments:
 - Framing as a referendum with a majority-vote implementation rule
 - 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}.
 - For the first referendum, the two extreme costs are excluded.
 - Participant receives higher (lower) cost in the second referendum if she voted “yes” (“no”) in the first one.
- 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: Cost levels and sample sizes

- To determine parameters, we undertook two pilot sessions, using the open-ended format.
- We ran Monte Carlo simulations to determine cost levels for the single binary choice, double-bounded binary choice and payment-card treatments, along with sample sizes.
- Design is powered to detect a treatment effect of 70 cents with 80% probability, based on a 5% significance level.

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) The 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 (3.31)	20.79 (1.51)	20.80 (2.79)	20.53 (2.29)
Female	0.45 (0.50)	0.48 (0.50)	0.41 (0.50)	0.37 (0.49)
Earned income	19.77 (3.54)	19.79 (3.49)	19.84 (3.49)	19.79 (3.49)
Employed	0.46 (0.50)	0.48 (0.50)	0.58 (0.50)	0.47 (0.50)
GPA	3.19 (0.57)	3.36 (0.43)	3.34 (0.50)	3.22 (0.50)
Number of participants	130	94	92	94

Note: Standard errors given in brackets.

Summary statistics by treatment

Assessed on a Likert scale from 1 to 5

	Single binary choice	Open-ended	Double-bounded binary choice	Payment card
Comprehension	4.90	4.79	4.88	4.79
5 – instructions well understood	(0.30)	(0.48)	(0.36)	(0.55)
Confusion	1.35	1.54	1.51	1.70
5 – not confused about the voting process	(0.73)	(0.99)	(0.88)	(1.13)
Need Information	1.89	1.96	1.77	2.10
5 – enough information provided	(1.12)	(1.15)	(0.89)	(1.31)
Certainty	4.08	3.78	4.14	4.02
5 – absolutely certain about the own vote	(0.99)	(1.13)	(0.91)	(1.14)

Note: Standard errors given in brackets.

Summary statistics by treatment

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	Single binary choice	Open-ended	Double-bounded binary choice	Payment card
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Confusion 5 – not confused about the voting process	1.35 (0.73)	1.54 (0.99)	1.51 (0.88)	1.70 (1.13)
Need Information 5 – enough information provided	1.89 (1.12)	1.96 (1.15)	1.77 (0.89)	2.10 (1.31)
Certainty 5 – absolutely certain about the own vote	4.08 (0.99)	3.78 (1.13)	4.14 (0.91)	4.02 (1.14)

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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

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- 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 $WTP_i^* \sim Normal(\mathbf{x}_i\boldsymbol{\beta}, \sigma_i^2)$.
 - 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)
<i>Open-ended</i>	-0.25 (0.65)	-0.18 (0.61)	-0.36 (0.62)
<i>Double-bounded binary choice</i>	-0.10 (0.68)	0.00 (0.62)	-0.09 (0.62)
<i>Payment card</i>	-0.13 (0.65)	-0.03 (0.56)	0.07 (0.55)
<i>Age</i>			0.25 ^{***} (0.09)
<i>Female</i>			1.05 ^{**} (0.44)
<i>Earned income</i>			-0.07 (0.06)
<i>Employed</i>			0.15 (0.44)
<i>GPA</i>			0.50 (0.42)
<i>Constant</i>	3.94 ^{***} (0.48)	3.84 ^{***} (0.38)	3.89 ^{***} (0.39)
Standard deviation function (σ)			
<i>Open-ended</i>		1.24 (0.81)	1.36 [*] (0.79)
<i>Double-bounded binary choice</i>		0.89 (0.99)	0.81 (0.96)
<i>Payment card</i>		0.65 (0.81)	0.47 (0.78)
<i>Constant</i>	4.15 ^{***} (0.23)	3.23 ^{***} (0.73)	3.19 ^{***} (0.71)
Log-L	-669.13	-667.92	-659.55
Number of observations	410	410	410

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No statistical evidence of elicitation effects

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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
 - Students vs. representative samples
 - A majority-vote implementation rule (e.g., keeping the decision rule undisclosed)
 - Common knowledge of the random cost selection

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