# APPENDIX

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 $<sup>^{*}</sup>$  This is the document intended as online appendix for the manuscript  $Eliciting\ Beliefs\ as$   $Distributions\ in\ Online\ Surveys$ 

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## A1 Question Formats

#### • Quantile Question

- 1. We have just shown you election results for similar districts. Now, we want to know what your expectations are.
  - Can you determine the median? This is the value where the vote share of party A is equally likely to be less than or larger than this value.
- 2. Imagine you were told that the actual result was below your median value. Can you determine a new value, such that the vote share of party A is equally likely to be between 0 percent and the new value or between the new value and the median value?
- 3. Imagine you were told that the actual result was above your median value. Can you determine yet another value, such that the vote share of party A is equally likely to be between the median and this new value or between this new value and 100 percent?
- 4. At the end, respondents are shown the four ranges (0-25th, 25th-50th, 50th-75th, 75th-100) and asked whether a random draw is equally likely to occur in each of them. If not, respondents can go and adjust their responses.
  - (a) Consider the following four intervals:  $[0,P_{25}]$ ,  $[P_{25}, P_{50}]$ ,  $[P_{50},P_{75}]$ ,  $[P_{75}, 100]$ .

Is it equally likely that party A's vote share will fall in any of these intervals?

 $(P_{XY} \text{ indicates the respondent's XY percentile.})$ 

- Interval Question (Narrow and Wide) This question comes in two versions a wide and a narrow version.
  - 1. We have just shown you election results for similar districts. Now, we want to know what your expectations for party A's vote share are.
    - What is the most likely vote share of party A? Please give your response in percentage points.
  - 2. What is the probability that party A will receive a vote share of less than 40 percent? (45% in narrow format)
  - 3. What is the probability that party A will receive a vote share of more than 60 percent? (55% in narrow format)

#### • Manski Question

- 1. We have just shown you election results for similar districts. Now, we want to know what your expectations for party A's vote share are.
  - What is the most likely vote share of party A? Please give your response in percentage points.
- 2. What do you think is a likely range of the vote share that party A will receive? Please indicate the lower bound in percentage points.
- 3. Now, please indicate the upper bound in percentage points.

- 4. What is the probability that party A will get a vote share of less than (lower value indicated by R) percent?
- 5. What is the probability that party A will get a vote share of more than (upper value indicated by R) percent?

#### • Bins and Balls

We implemented this question by inserting Java script into the survey software - a step that should be easily replicated by anybody. We also provide the JS code here (link) and have annotated it so that it can be adapted easily.

Figure A1 shows the full question as it is presented to respondents. By clicking on + and - buttons, the various bins can be filled or emptied. Each respondent allocates 100 balls into these bins.



Figure A1: Screenshot of Balls and Bins

## A2 Estimation

To estimate beliefs form the different question formats, we develop statistical models that permit us to estimate the parameters of respondents' belief distributions. In the following, we describe the Likelihoods that model the observed outcomes given parametric belief distributions for the different question formats.

#### A2.1 Likelihood for the Quantile Question

For the quantile question, we observe three outcomes for each respondent: The lower quartile, the median value, and the upper quartile of the respondent's belief. We denote them with  $y_i = [y_{i1}, y_{i2}, y_{i3}]$ , where  $i \in (1, ..., N)$  are respondents and k refers to the different quartile questions  $k \in (1, 2, 3)$ . We assume that these values are observed with measurement error, such that:<sup>1</sup>

$$y_{ik} \sim \mathcal{N}(\mu_{ik}, \sigma^2).$$
 (1)

To estimate a respondent's average belief, we assume a parametric distribution and estimate the parameters of the distribution to closely mimic the expected observed indicators. To map the beliefs of/about? the measured values, we require the quantile function of the belief distribution. Because the sampling space of our experiment is bound between 0 and 1, we employ a Beta distribution as our parametric distribution. We denote  $Q^{-1}(q_k, \alpha, \beta)$  as the quantile function of the beta distribution. The two shape parameters  $\alpha$  and  $\beta$  define the expectation and the variance of the belief. The distribution is then linked to the expectation of the observed values. If we denote the three quartiles with  $q_k = [0.25, 0.5, 0.75]$ , we can write:

$$\mu_k = Q^{-1}(q_k, \alpha, \beta) \tag{2}$$

With this model, we define the likelihood of a respondent's observed answers as:

$$L(\alpha, \beta, \sigma^2 \mid y_i) = \prod_{k=1}^{3} \frac{1}{\sqrt{2\pi\sigma^2}} exp\left[\frac{-(y_{ik} - \mu_k)^2}{2\sigma^2}\right]$$
(3)

Maximizing the Likelihood for each individual would involve minimizing the squared distance between the observed quartile measurements and the shape parameters of the beta-distribution that generate the expected quartiles. If we assume that individual responses are identical and independently distributed, we can further write the Likelihood for the full sample as:

$$L(\alpha, \beta, \sigma^{2} \mid \mathbf{Y}) = \prod_{i=1}^{N} \prod_{k=1}^{3} \frac{1}{\sqrt{2\pi\sigma^{2}}} exp\left[\frac{-(y_{ik} - Q^{-1}(q_{k}, \alpha, \beta))^{2}}{2\sigma^{2}}\right],$$
 (4)

<sup>&</sup>lt;sup>1</sup>We assume that the measurement errors are normally distributed with the same error variance and no covariance between the errors.

where Y is a  $(N \times K)$  matrix with all respondents' responses  $[y_1, \ldots, y_N]'$ . The function is maximized with respect to the parameters  $\alpha, \beta, \sigma$  using R's optim function.

#### A2.2 Likelihood for the Interval Question

We observe three values for the interval question. Respondents report the mean value of their beliefs and the probabilities of observing a value below and above a certain threshold. We denote the mean with  $y_i$  and the two  $(k \in (1,2))$  probabilities with  $p_{i1}, p_{i2}$ . The interval values depend on the question format and are denoted with  $c = [c_1, c_2]$ , where in the wide version c = [40%, 60%] and in the narrow version c = [45%, 55%]. We assume that the values are measured with normal measurement error.

$$y_i \sim \mathcal{N}(\mu_y, \sigma_y^2)$$
 (5)

$$p_{i1} \sim \mathcal{N}(\mu_{p_1}, \sigma_p^2)$$
 (6)

$$p_{i2} \sim \mathcal{N}(\mu_{p_2}, \sigma_p^2) \tag{7}$$

The expectations  $\mu_y$  are calculated from the assumed parametric belief distribution. Here, we use the same distribution as in the data-generating process - a beta distribution. The beta distribution is relatively flexible and well-suited for our example with vote shares being constrained on the unit interval. It is generally possible to use other parametric distributions, like a normal distribution, instead. In practical applications, it would be sensible to try different distributions and compare their relative fit. The expectation for the mean from the beta are given by the two shape parameters  $\alpha$  and  $\beta$ :

$$\mu_y = \frac{\alpha}{\alpha + \beta} \tag{8}$$

The expected probabilities are given by the CDF of the beta distribution, which we denote with  $Q(\cdot, \alpha, \beta)$ .

$$\mu_{p_1} = Q(c_1, \alpha, \beta) \tag{9}$$

$$\mu_{p_2} = 1 - Q(c_2, \alpha, \beta) \tag{10}$$

With this model, we can define the Likelihood for the observed data of N respondents  $Y = [[y_1, p_{i1}, p_{i2}]', \dots, [y_N, p_{N1}, p_{N2}]']'$ . We assume that all responses are identically and independently distributed, which yields the following Likelihood:

$$L(\alpha, \beta, \sigma_y^2, \sigma_p^2 \mid \mathbf{Y}) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma_y^2}} exp\left[\frac{-(y_i - \mu_y)^2}{2\sigma_y^2}\right] \prod_{k=1}^{2} \frac{1}{\sqrt{2\pi\sigma_p^2}} exp\left[\frac{-(p_k - \mu_{p_k})^2}{2\sigma_p^2}\right].$$
(11)

To obtain MLE estimates of the parameters, the function is also maximized using R's optim function. The obtained estimates yield an estimate of the average beliefs under a specific condition. The goal is to identify the question format that will yield estimates that come closest to the true values.

#### A2.3 Likelihood for the Manski Question

For the Manski Question, we observe five measures of respondents' beliefs. We measure three  $k \in 1, 2, 3$  values: the mean value (which we denote with  $y_{i1}$ ), and the lower and the upper bound values (which we denote with  $y_{i2}$  and  $y_{i3}$ , respectively). In addition, we measure two probabilities of observing values below and above the bounds (which we denote with  $p_{i1}$  and  $p_{i2}$ ). We assume that the values are measured with error and that the errors are identical and independently normally distributed.

$$y_{ik} \sim \mathcal{N}(\mu_k, \sigma^2)$$
 (12)

the expectations  $\mu_k$  are calculated from the assumed parametric distribution of respondents' beliefs. In our analysis, we work with the beta distribution, which yields a simple expression for the mean value. Given the assigned probabilities, the observed lower and upper bounds can be calculated from the quantile function of the Beta distribution, which we denote as  $Q^{-1}(\cdot, \alpha, \beta)$ . The expectations of the measurement model are given by:

$$\mu_{i1} = \frac{\alpha}{\alpha + \beta} \tag{13}$$

$$\mu_{i2} = Q^{-1}(p_{i1}, \alpha, \beta)$$
 (14)

$$\mu_{i3} = 1 - Q^{-1}(p_{i2}, \alpha, \beta) \tag{15}$$

The Likelihood is given by the normal measurement error and the respective expectationgenerating functions. We collapse the measured values and the probabilities in a matrix  $(\mathbf{Y} = [[y_{11}, y_{12}, y_{13}, p_{11}, p_{12}]', \dots, [y_{N1}, y_{N2}, y_{N3}, p_{N1}, p_{N2}]']'$ . Assuming that the observed values are independent allows us to write the Likelihood as:

$$L(\alpha, \beta, \sigma \mid \mathbf{Y}) = \prod_{i=1}^{N} \prod_{k=1}^{3} \frac{1}{\sqrt{2\pi\sigma^2}} exp \left[ \frac{-(y_{ik} - \mu_{ik})^2}{2\sigma^2} \right], \tag{16}$$

which is numerically maximized with respect to the parameters using R's optim function.

## A2.4 Likelihood for the Bins and Balls Question

The bins and balls question has a slightly different structure compared to the quantile questions. For this question, we observe the number of balls a respondent decides to place into K bins that each covers an exclusive interval. The intervals are given by ordered cut points  $c_1, \ldots, c_C$ . There is one cut-point more than categories C = K + 1, as the question format can have lower and upper bounds.<sup>2</sup> The number of balls out of B = 100 that a respondent places in a bin is denoted with  $y_{ik}$ . We assume that the measured placements are binomially distributed, with a certain probability  $\pi_k$ .

 $<sup>^2</sup>C$  is the number of cut-points which, in our question format, is C=13, and the corresponding cut points are  $0.25, 0.3, 0.35, 0.4, 0.45, \dots, 0.85$ .

$$y_{ik} \sim \mathcal{B}(\pi_k, B)$$
 (17)

The probabilities are calculated from the CDF of the assumed parametric belief distribution. The CDF of the Beta distribution is given by  $Q(\cdot, \alpha, \beta)$ . With this, we calculate the probability that a respondent places balls in each bin, as:

$$\pi_k = Q(c_{k+1}, \alpha, \beta) - Q(c_k, \alpha, \beta). \tag{18}$$

Assuming that the observed values are conditionally independent, combining all observed placements  $\mathbf{Y} = [[y_{11}, \dots, y_{1K}]', \dots, [y_{N1}, \dots, y_{NK}]']'$  yields the following Likelihood:

$$L(\alpha, \beta \mid \mathbf{Y}) = \prod_{i=1}^{N} \prod_{k=1}^{K} {B \choose y_{ik}} \pi_k^{y_{ik}} (1 - \pi_k)^{B - y_{ik}}$$
(19)

We numerically maximize the likelihood of obtaining MLE estimates of the shape parameters.

## A3 Balance

The following four tables present balance checks in terms of covariate averages and standard deviations for each experimental condition. These checks are based on the full data before reducing the data set only to observations which passed both attention checks. Please note that we refrain from the ill-advised practice of statistically *testing* for mean differences (Mutz, 2011). Overall, we find treatment conditions to be well balanced.

Format	n	Female	Age	University	Political Interest
Quantile	196	0.45	41.40	0.61	3.03
		(0.50)	(11.73)	(0.49)	(0.76)
Interval (Wide)	205	0.44	40.33	0.60	3.00
		(0.50)	(13.76)	(0.49)	(0.82)
Interval (Narrow)	205	0.48	41.39	0.57	3.09
		(0.50)	(12.26)	(0.50)	(0.78)
Manski	201	0.49	41.69	0.60	3.04
		(0.50)	(11.64)	(0.49)	(0.81)
Bins and Balls	189	0.49	40.81	0.61	2.99
		(0.50)	(11.63)	(0.49)	(0.81)

Table A1: Balance Check for a Symmetric Distribution. Means and Standard Deviations in Parentheses.

Format	n	Female	Age	University	Political Interest
Quantile	100	0.43	38.04	0.67	2.93
		(0.50)	(11.74)	(0.47)	(0.84)
Interval (Wide)	102	0.40	39.29	0.53	2.92
		(0.49)	(12.29)	(0.50)	(0.86)
Interval (Narrow)	97	0.40	40.66	0.60	2.95
		(0.49)	(12.66)	(0.49)	(0.85)
Manski	106	0.42	41.20	0.56	2.93
		(0.50)	(12.39)	(0.50)	(0.80)
Bins and Balls	102	0.41	41.35	0.65	3.08
		(0.49)	(13.58)	(0.48)	(0.83)

Table A2: Balance Check for a Symmetric Distribution with a Large Variance. Means and Standard Deviations in Parentheses

Format	n	Female	Age	University	Political Interest
Quantile	201	0.48	41.29	0.63	3.00
		(0.50)	(12.24)	(0.48)	(0.73)
Interval (Wide)	197	0.40	40.43	0.59	3.04
		(0.49)	(11.61)	(0.49)	(0.77)
Interval (Narrow)	206	0.47	39.47	0.59	3.02
		(0.50)	(12.13)	(0.49)	(0.80)
Manski	203	0.46	39.93	0.59	3.04
		(0.50)	(12.30)	(0.49)	(0.78)
Bins and Balls	196	0.43	41.44	0.64	3.10
		(0.50)	(12.07)	(0.48)	(0.80)

Table A3: Balance Check for an Asymmetric Distribution. Means and Standard Deviations in Parentheses.

Format	n	Female	Age	University	Political Interest
Quantile	102.00	0.54	41.49	0.72	3.09
		(0.50)	(12.40)	(0.45)	(0.76)
Interval (Wide)	104.00	0.44	38.80	0.72	2.88
		(0.50)	(10.72)	(0.45)	(0.75)
Interval (Narrow)	101.00	0.45	39.73	0.65	2.99
		(0.50)	(12.18)	(0.48)	(0.83)
Manski	98.00	0.48	41.00	0.68	2.91
		(0.50)	(13.26)	(0.47)	(0.90)
Bins and Balls	95.00	0.53	42.15	0.49	3.00
		(0.50)	(12.26)	(0.50)	(0.77)

Table A4: Balance Check for an Asymmetric Distribution with Large Variance. Means and Standard Deviations in Parentheses.

# A4 Evaluating Adequacy Check for the Quantile Question

Variance	Distribution	AdequacyCheck	alpha	beta	KL	N
Large Variance	Asymmetric	Yes	49.08	27.64	0.13	118
Large Variance	Asymmetric	No	158.50	91.07	0.98	130
Large Variance	Symmetric	Yes	48.41	47.90	0.01	119
Large Variance	Symmetric	No	34.21	34.59	0.07	115

Table A5: Estimates for the Elicited Beliefs. Comparing Quantile with and without Adequacy Check for the Large Variance Scenarios

# A5 No Screening

These two tables present the same information that is shown in Table 2. The data here is based on all results, i.e the raw data before reducing the data set only to observations which pass both attention checks.

method	alpha	beta	KL	lr	N	method
Quantile	45.54	47.29	0.07	0.14	100	Quantile
Bins and Balls	15.27	15.04	0.10	0.00	102	Manski
Manski	13.57	13.34	0.13	0.00	106	Bins and I
Interval (Wide)	8.80	8.53	0.27	0.00	97	Interval (V
Interval (Narrow)	7.13	6.78	0.36	0.00	102	Interval (N

method	alpha	beta	KL	lr	N
Quantile	59.69	60.15	0.00	0.85	196
Manski	50.73	49.12	0.02	0.04	201
Bins and Balls	26.76	26.82	0.13	0.00	189
Interval (Wide)	15.98	15.40	0.31	0.00	205
Interval (Narrow)	11.56	11.36	0.43	0.00	205

(a) Symmetric, Large Variance

(c) Symmetric, Small Variance

method	alpha	beta	KL	lr	N
Manski	22.79	13.46	0.12	0.00	98
Bins and Balls	11.49	7.16	0.24	0.00	95
Interval (Wide)	5.82	3.34	0.42	0.00	101
Quantile	60.58	35.75	0.54	0.00	102
Interval (Narrow)	3.40	1.82	0.67	0.00	104

method	alpha	beta	KL	lr	N
Manski	38.79	20.29	0.05	0.00	203
Quantile	56.95	31.47	0.10	0.00	201
Bins and Balls	18.27	12.45	0.54	0.00	196
Interval (Wide)	7.85	3.98	0.60	0.00	206
Interval (Narrow)	6.56	3.12	0.70	0.00	197

(b) Asymmetric, Large Variance

(d) Asymmetric, Small Variance

Table A6: Estimates for Elicited Beliefs. No Screen

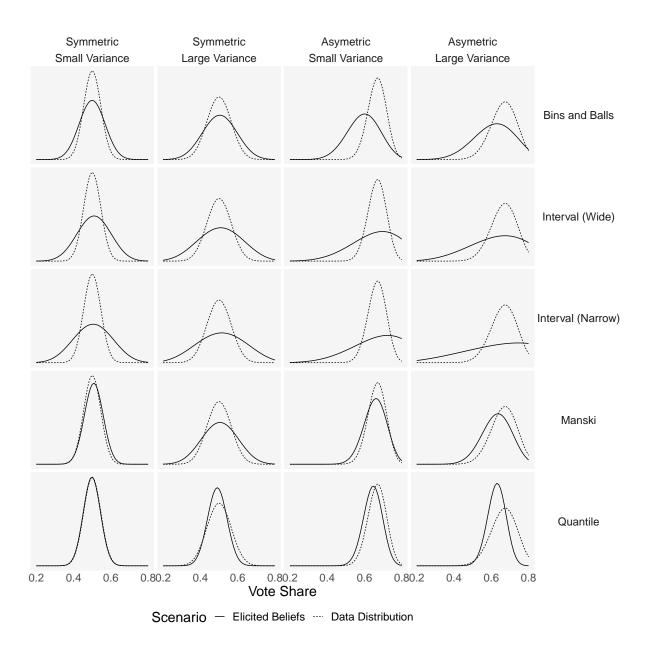


Figure A2: Comparison of Question Formats. No screen. The dotted line indicates the true distribution and the black solid line shows the average of the elicited distributions.

#### A5.1 Individual Beliefs

The question formats and estimation method can also be used to obtain individual beliefs. We use the same Maximum Likelihood approach as described in section A2, but allow for individual shape parameters:  $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_N]$  and  $\boldsymbol{\beta} = [\beta_i, \dots, \beta_N]$ . To illustrate, consider the Individual Likelihood for the Quantile question:

$$L(\boldsymbol{\alpha}, \boldsymbol{\beta}, \sigma \mid \boldsymbol{Y}) = \prod_{i=1}^{N} \prod_{k=1}^{3} \frac{1}{\sqrt{2\pi\sigma^{2}}} exp\left[\frac{-(y_{ik} - Q^{-1}(q_{k}, \alpha_{i}, \beta_{i}))^{2}}{2\sigma^{2}}\right],$$
 (20)

where we now introduce a subscript for the shape parameters of the Beta quantile function  $Q^{-1}(q_k, \alpha_i, \beta_i)$ .

We obtain estimates for respondent-specific shape parameters by numerically maximizing the Likelihood function. We first estimate the shape parameters for each respondent, and afterwards estimate the error variance terms for the Likelihood function. We repeat until convergence in the error variances.<sup>3</sup>

<sup>&</sup>lt;sup>3</sup>Some response patterns do not yield estimates of sensible shape parameters. For example, if a respondent reports a lower quartile of 0.50 and a Median of 0.45, the maximization of the function will be impossible. We exclude respondents with such inconsistent answering behaviors.

## A5.2 Results

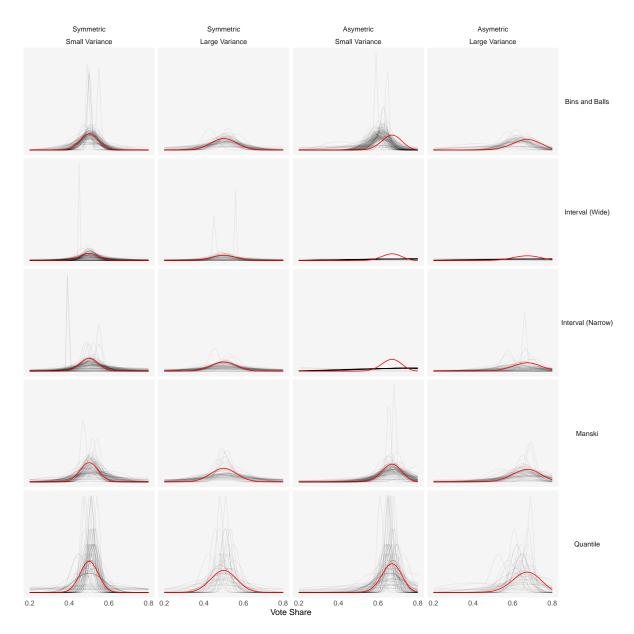


Figure A3: Individual Beliefs. The grey lines indicate individual elicited beliefs. The red line indicates the true distribution.

type	method	median	qlow	qhigh
Symmetric	Bins and Balls	0.13	0.06	0.26
Symmetric	Interval (Narrow)	0.27	0.05	0.81
Symmetric	Manski	0.36	0.23	0.66
Symmetric	Interval (Wide)	0.45	0.14	1.33
Symmetric	Quantile	0.50	0.15	1.92

type	method	median	qlow	qhigh
Symmetric	Bins and Balls	0.10	0.03	0.23
Symmetric	Manski	0.25	0.11	0.45
Symmetric	Interval (Wide)	0.36	0.12	1.27
Symmetric	Interval (Narrow)	0.37	0.11	1.11
Symmetric	Quantile	0.48	0.17	1.17

#### (a) Symmetric, Large Variance

## (c) Symmetric, Small Variance

type	method	median	qlow	qhigh
Asymetric	Bins and Balls	0.27	0.12	0.62
Asymetric	Manski	0.27	0.09	0.53
Asymetric	Quantile	0.51	0.16	1.48
Asymetric	Interval (Wide)	0.64	0.63	0.73
Asymetric	Interval (Narrow)	0.84	0.37	2.26

type	method	median	qlow	qhigh
Asymetric	Manski	0.15	0.05	0.38
Asymetric	Quantile	0.44	0.14	0.91
Asymetric	Interval (Wide)	0.96	0.95	0.96
Asymetric	Interval (Narrow)	0.96	0.95	0.96
Asymetric	Bins and Balls	0.99	0.55	1.54

(b) Asymmetric, Large Variance

(d) Asymmetric, Small Variance

Table A7: KL Divergence for Individual Beliefs in different Scenarios

method	median	qlow	qhigh
Manski	0.25	0.09	0.49
Bins and Balls	0.30	0.09	0.90
Quantile	0.48	0.14	1.20
Interval (Wide)	0.92	0.43	0.96
Interval (Narrow)	0.93	0.25	0.98

Table A8: KL Divergence for Individual Beliefs over different Scenarios

# A6 Sub-Samples Political Interest

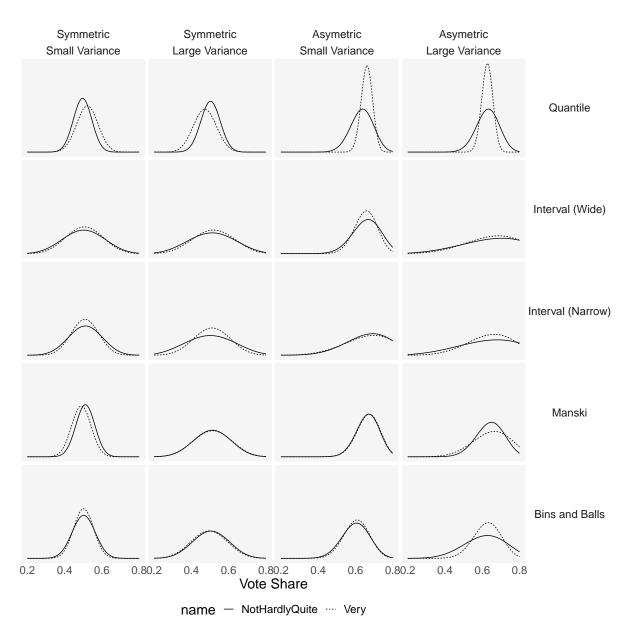


Figure A4: Estimated Beliefs for Sub-Groups of Political Interest

method	$Not Hardly Quite\_alpha$	$Not Hardly Quite\_beta$	$NotHardlyQuite\_KL$	$Very\_alpha$	Very_beta	$Very\_KL$
Quantile	46.80	46.33	0.06	31.01	34.63	0.10
Interval (Wide)	8.11	7.79	0.31	10.56	9.83	0.23
Interval (Narrow)	7.16	7.12	0.35	13.78	13.24	0.13
Manski	13.13	12.55	0.15	12.62	11.98	0.16
Bins and Balls	13.65	13.40	0.13	13.57	13.81	0.12

#### (a) Symmetric, Large Variance

method	$Not Hardly Quite\_alpha$	$Not Hardly Quite\_beta$	$Not Hardly Quite\_KL$	Very_alpha	Very_beta	Very_KL
Quantile	39.09	23.07	0.24	166.57	99.32	2.70
Interval (Wide)	5.01	2.68	0.49	6.75	3.60	0.36
Interval (Narrow)	5.04	2.90	0.48	9.27	5.17	0.25
Manski	25.16	14.05	0.06	13.69	7.38	0.12
Bins and Balls	10.98	6.91	0.26	26.79	16.02	0.16

#### (b) Asymmetric, Large Variance

method	NotHardlyQuite_alpha	NotHardlyQuite_beta	NotHardlyQuite_KL	Very_alpha	Very_beta	Very_KL
Quantile	51.63	52.38	0.01	40.24	36.87	0.12
Interval (Wide)	10.18	10.08	0.48	13.15	12.84	0.38
Interval (Narrow)	15.88	15.20	0.32	23.63	22.84	0.18
Manski	49.91	47.72	0.03	45.31	47.19	0.03
Bins and Balls	33.50	33.21	0.07	44.41	44.11	0.02

#### (c) Symmetric, Small Variance

method	$Not Hardly Quite\_alpha$	$Not Hardly Quite\_beta$	$Not Hardly Quite\_KL$	Very_alpha	Very_beta	Very_KL
Quantile	39.07	22.54	0.17	159.98	82.26	0.38
Interval (Wide)	24.78	12.82	0.15	38.88	20.56	0.06
Interval (Narrow)	9.79	4.90	0.50	8.38	4.17	0.57
Manski	38.64	19.43	0.04	38.58	19.17	0.04
Bins and Balls	25.90	17.20	0.50	30.70	20.06	0.48

#### (d) Asymmetric, Small Variance

method	$Not Hardly Quite\_KL$	$Very_KL$
Quantile	0.12	0.83
Interval (Wide)	0.36	0.26
Interval (Narrow)	0.41	0.28
Manski	0.07	0.09
Bins and Balls	0.24	0.20

## (e) Summary Kullback-Leibler divergence over four applications

Table A9: Estimates for Sub-groups of Political Interest

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# A7 Additional Survey Trump Vote Share

In section 5 of the paper, we show the results from an additional survey where we ask respondents about their beliefs regarding Donald Trump's popular vote share in November. Table A10 shows the beliefs according to the different formats. In addition, the results are also shown for sub-samples of Republicans and Democrats.

Table A10: Parameter Estimates & Moments of Belief Distribution

	α	β	mean	variance
Manski	39.70	43.38	0.48	0.00
Manski (D)	49.47	62.74	0.44	0.00
Manski (R)	19.34	17.61	0.52	0.01
Quantile	19.91	22.81	0.47	-0.01
Quantile (D)	32.39	39.05	0.45	0.00
Quantile (R)	18.57	19.00	0.49	0.01
Bins & Balls	-5.57	-7.58	0.42	$  0.0\overline{2}$ $-$
Bins & Balls (D)	6.43	10.93	0.37	0.01
Bins & Balls (R)	7.46	7.35	0.50	0.02
Interval wide	3.36	3.46	0.49	$-0.0\bar{3}$
Interval wide (D)	3.70	4.67	0.44	0.03
Interval wide (R)	5.03	4.22	0.54	0.02
Interval narrow	3.94	4.40	0.47	0.03
Interval narrow (D)	4.47	5.56	0.45	0.02
Interval narrow (R)	2.39	2.19	0.52	0.04

# A8 Timing of Elicitation Methods

The time variable accounts for time for the *entire* survey. As all respondents have the same introduction questions and identical demographic questions, the remaining differences are due to the different belief elicitation question formats. Since these additional variables are constant in all elicitation methods, the timing variable gives us a sense of the relative performance of the five elicitation methods. However, a simple F-test reveals that these differences are not statistically significant.

Table A11: Median amount of time spent per elicitation in seconds

Elicitation Method	Experiment	Trump
		Vote
Manski Question	170.0	132.0
Quantile Question	200.0	162.0
Interval Question Wide	149.0	106.0
Interval Question Narrow	157.0	108.5
Bins and Balls	199.0	155.0
F-value	0.89	1.56
$\Pr(>F)$	0.4682	0.1833

# References

Mutz, Diana C. 2011. Population-Based Survey Experiments. Princeton University Press.