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Analysis

Fat tails and truncated bids in contingent valuation: An application to an endangered shorebird species☆

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ABSTRACT

A yes-response function in a contingent valuation study is said to have fat tails if it has a high and slowly declining yes-response rate at high bid levels. Truncated bids refer to the practice of dropping high bid offers before a yes-response rate of near zero is reached. This is a common practice in contingent valuation. We explore the extent and implications of fat tails and truncated bids in a study of an endangered shorebird species. We find, among other things, that mean willingness to pay is quite sensitive to the highest bid offered – so much so that the choice of highest bid nearly dictates outcomes.

1. Introduction

Fat tails in contingent valuation (CV) refers to the phenomena of a yes-response function having a high and slowly declining yes-response rate at high bid levels offered in a CV survey. So, for example, a yes-response rate might hold at 20% or greater over the three or four highest bids offered in a survey. The "tails" of the yes-response function are said to be "fat" in this case. A truncated bid refers to a circumstance where high-bids are not offered over a range where it appears as though the survey instrument would produce a non-zero percentage of yes responses – essentially ignoring the behavioral response to high bids or "truncating" the yes-response function.

Fat tails has been recognized and discussed in the CV literature for more than two decades (Desvousges et al., 1993). Analysts have also recognized that fat tails can create problems for parametric estimators (e.g., logit and probit), wherein the estimators are sensitive to the highest bids offered in a survey (Cooper and Loomis, 1992; Desvousges et al., 1993). In part because of this problem and in part because of the problem of negative willingness pay estimates from parametric estimators, the field has turned toward non-parametric estimators, especially the Turnbull lower bound (Kriström, 1990; Haab and McConnell, 1997). This paper shows that fat tails also create problems for non-parametric estimators. The real issues present in the data do not go away by simply changing estimators.

The tail of a yes-response function is equivalent to the portion of a conventional demand curve nearest the choke price, which is where much of consumer surplus for valuation lies. For this reason, it is important to have a good measure of the yes-response function over the high-bid range; the accuracy of willingness-to-pay estimates hinge upon it. Yet, it seems common to truncate bids, forcing analysts to either ignore or to infer the yes-responses over the high-bid range from response data over low-range bids. Whether this is intentional to avoid the complications of fat tails is uncertain, but it is common.

A search over the recent CV literature shows that many studies have truncated yes-response functions. Table 1 is a list of 86 CV studies along with their yes-response rate at the highest bid. This list includes studies published in eight of the leading environmental economics journals from 1990 to 2015 for which there was sufficient data to make the calculation.[1] Approximately 60% of the studies have at least one scenario in their analysis where the yes-response rate at the highest bid is 20% or greater. Nearly 50% have at least one scenario above 30%.

In this paper, we explore the implication of fats tails in the context of a contingent valuation (CV) survey designed to value the protection of a relatively unknown migratory bird species whose population has declined in recent years. Our analysis is in three steps. First, we provide a review of the relevant literature. Second, we document the extent of fat tails in the response data. To do this we purposefully seek to pin down the tail of the yes-response function by offering high, what seem like unusually high, bid levels to find the choke price and explore behavioral response to high bids. We do this using an internet-based survey and follow the standard protocol for state-of-the-art CV studies – a clear and balanced description of the good, budget reminders, follow-up certainty questions, referendum format, reinforcing consequentiality,

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[1] *JEEM*, *AJAE*, *LE*, *ERE*, *ARER*, *JARE*, *JAERE*, and *MRE*.

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Table 1
Yes-response rates to highest bid in referendum-style CV studies published in eight environmental economics journals from 1990 to 2015.

AUTHOR (journal publication year)[a]	Resource valued	% yes at highest bid amount[c]
Adamowicz et al., 2014	Heart disease risk reduction for self and children	18–32
Alberini et al., 1997	Wetland and wildlife protection, wilderness area protection, oil spill prevention	34–46 (14–43)
Andersson et al., 2013	Car safety	3–24
Balistreri et al., 2001	Insurance game	11[b]
Banzhaf et al., 2006	Ecological condition of Adirondack lakes	34–52
Berrens et al., 1996	Endangered species	8–22
Berrens et al., 1997	Expansion of cultural center programs	13–23
Blamey et al., 1999	Salinity in soil	17–69
Blomquist et al., 2009	Health management programs	0–19[b]
Boman et al., 1999	Wolf preservation & forest protection	6–11
Brown et al., 1996	Unpaved road removal	33
Brown et al., 2003	Scholarship fund	25–69[b]
Cameron and Quiggin, 1994	Wilderness area protection	54 (41)
Carson et al., 2003	Prevent oil spill	34 (14)
Champ and Bishop, 2001	Wind generated electricity	31[b]
Champ and Bishop, 2006	Wind generated electricity	7
Champ et al., 1997	Unpaved road removal	28
Champ et al., 2002	Open space	28–30
Champ et al., 2009	Whooping crane	15–36
Chien et al., 2005	Air quality	51(17)–63 (42)
Cook et al., 2012	Cholera and typhoid vaccines	7–20
Cooper and Loomis, 1992	Hunting, wildlife viewing & risk reduction	6–42
Corrigan et al., 2008	Water quality	32–35
Desvousges et al., 2015	Water quality	15–45
Egan et al., 2015	Water quality	40–42
Farmer and Lipscomb, 2008	Emissions test waiver	21
Frykblom, 1997	Environmental education book	17[b]
Frykblom and Shogren, 2000	Environmental education book	5–8[b]
Gerking et al., 2014	Leukemia vaccine	21–67
Giraud et al., 2001	Endangered species	39
Giraud et al., 2005	Local food product	10–33
Guria et al., 2005	Risk reduction	7–13
Haab and McConnell, 1997	Wolf recovery, beach cleaning	15–53
Haab and McConnell, 1998	Beach cleaning	15
Hammitt and Zhou, 2006	Treatment of illnesses caused by air pollutants	8–33
Harrison and Lesley, 1996	Oil spill prevention	35
Herriges et al., 2010	Water quality	35
Hite et al., 2002	Water quality	13–14
Holmes and Kramer, 1995	Forest protection	5
Huth and Morgan, 2011	Cave diving	16–19
Ivehammar, 2009	Urban scenic view	5–36
Johnston, 2006	Public water supply	33[b]
Koford et al., 2012	Curbside recycling	17
Kovacs and Larson, 2008	Open space	12(6)–25(17)
Kramer and Evan Mercer, 1997	Rain forest protection	0(0)
Kriström, 1990	Forest protection	11
Labao et al., 2008	Endangered species	9–13
Landry and List, 2007	Sports memorabilia	20–75[b]
Langford et al., 1998	Flood prevention and wetland protection	18
Leiter and Pruckner, 2009	Prevention of death in avalanche	24(5)–25(6)
Leon and Arana, 2012	Reconstructing natural feature	6–19
Lindberg et al., 1997	Traffic/noise reduction	24
Longo et al., 2012	Climate change mitigation	45–49
Longo et al., 2015	Cutting greenhouse gas emissions	24–58
Loureiro et al., 2009	Oil spill prevention	15
Lunander, 1998	Movie preview	11–91[b]
Lusk, 2003	Genetically engineered rice	62–72
Michael and Reiling, 1997	Outdoor recreation and congestion	0
Moore et al., 2011	Water quality	25
Morrison and Brown, 2009	Meal for disadvantaged children	27–53[b]
Murphy et al., 2005	Sign placement & endangered species	0[b]
Myers et al., 2010	Recreational bird watching	8–13
Nahuelhual et al., 2004	Open space	28–47
Nunes and van den Bergh, 2004	Algal bloom and water quality	13 (4)
Petrolia and Kim (MRE 2009)	Barrier island restoration	18–65
Polome et al., 2006	Natural mudflat for birds	32–50 (22–39)
Poor, 1999	Wetland preservation	11–14 (1–6)
Popp, 2001	Air and water quality	42
Ready and Hu, 1995	Preservation of horse farms	29
Ready et al., 1996	Food borne risk	13–18
Reaves et al., 1999	Red-cockaded woodpecker	0
Richardson et al., 2013	Reduce symptom days caused by wildfires	13
Riddel and Loomis, 1998	Spotted owl protection	9–60
Roach et al., 2002	Recreational moose hunting	5–11

(continued on next page)

Table 1 (*continued*)

AUTHOR (journal publication year)[a]	Resource valued	% yes at highest bid amount[c]
Ropicki et al., 2010	Eco-label for seafood	4–13[d]
Saz-Salazar and Garcia-Menendez, 2001	Improved waterfront area	24
Scarpa et al., 2001	Speed reduction	8–14
Smith, 1996	Tire recycling and wildflower enhancement programs	44
Tuan and Navrud, 2007	Visitation to cultural heritage price	12–13
Wang, 1997	Environmental quality	12
Weldesilassie et al., 2009	Improved wastewater irrigation	49 (31)
Welsh and Poe, 1998	Dam releases	19[b]
Whitehead et al., 2001	Saltwater fishing	13–50
Whitehead, 2002	Water quality, agriculture	36–53[b]
Whittington, 2002	Water services	23–38
Zhang et al., 2010	Anjou pears with ethylene treatment	21–76 (6–47)

[a] The table in includes all CV studies with sufficient information to calculate yes-response rate at the highest bid from the following journals: American Journal of Agricultural Economics (AJAE), Agricultural and Resource Economics Review (ARER), Environmental and Resource Economics (ERE), Land Economics (LE), Marine Resource Economics (MRE), Journal of the Association of Environmental and Resource Economists (JAERE), Journal of Agriculture and Resource Economics (JARE), Journal of Environmental Economics and Management (JEEM).
[b] The study was done all or in part in an experimental setting but we only include hypothetical payment responses from the study.
[c] For studies reporting more than one result, the range of outcomes is shown. For studies that use double-bounded dichotomous choice, we use percent yes at initial highest bid. The numbers in parentheses are the percent yes at the highest second bid amount and when the initial bid was the highest bid possible – or percent responding yes-yes beginning at the highest initial bid.
[d] Four percent of respondents would always pay the highest bid and 13% of respondents would sometimes pay the highest bid.

and so forth. Third, we analyze the implications of including high bids on mean willingness to pay. We simulate this impact by calculating willingness to pay assuming different maximum bid offers and use nonparametric measures of willingness to pay throughout our analysis.

2. Related Literature

As mentioned in our introduction, several authors have called attention to the issue of fat tails in the context of estimation with a parametric model. Cooper and Loomis (1992), for example, analyzed ten discrete-choice CV questions from three surveys (covering valuation of wildlife and hazardous waste cleanup). When the top four bid levels and associated data were removed and the models re-estimated, mean willingness to pay declined on average to about 75% of its initial level. Most of the underlying data exhibited yes-response rates above 20% at the maximum bid.

Desvousges et al. (1993) have a similar, but more dramatic, finding. In a study of migratory bird valuation, they tested the effect of dropping the highest bid on mean willingness to pay. The highest bid was $1000; the next highest was $250. Both bids had yes-response rates close to 30%. Estimated mean willingness to pay declined to 48% of the initial value in one case and to 34% of its initial value in another.

McFadden and Leonard (1993) found the same. In a study valuing the preservation of wilderness areas, they drop respondents who received a bid of $2000 (where the next highest is $200) and mean willingness to pay declined to 54% of its initial value.

Brown et al. (1996) conducted a survey to value the removal of abandoned roads in the Grand Canyon to provide more wilderness area. In the course of their analysis they write.

> … 33 percent of the respondents to highest bid level ($50) chose 'yes', providing a less-than-ideal bid distribution for the purpose of estimating WTP.

In an ensuing footnote they write.

> …[i]n order to provide a more accurate estimate of hypothetical WTP, in the fall of 1994 we sent the hypothetical dichotomous choice survey to a comparable sample at higher bid levels (up to $200). However, there was no large drop in percent 'yes' at these higher bid levels. Including the additional data tended to *increase* mean WTP compared with the estimate based only on the 1993 data.

Their effort to pin down the tail of the distribution fell short and their recognition that having limited response data around the highest bids as "less than ideal" is consistent with our own concern.

Haab and McConnell (2002) present a nice discussion of how binary choice models (in many forms) fit and don't fit yes-response data with truncation at high-end and low-end bids. They show the extreme sensitivity of willingness to pay to the choice of functional form and the nature of the yes-response data. In one case, the same data are shown to generate mean willingness to pay estimates of less than zero or greater $1000 depending on the chosen functional form. A low yes-response rate at low bids and a high yes-response rate at high bids seem to cause a breakdown in binary choice models. In a concluding section they write.

> … [t]he set of offered bids should be designed to ensure that the tails of the distribution are well defined. Undefined tails can lead to unreliable measures of central tendency of WTP …

One of Haab and McConnell's criteria for a valid measure of willingness to pay is that "[e]stimation and calculation are accomplished with no arbitrary truncation." This would seem to apply whether one is using parametric or nonparametric methods for estimating value.

The sensitivity of functional form and, in turn willingness to pay, to response data with fat tails discussed by Haab and McConnell (2002) is, no doubt, one reason we see *intentional* bid truncation in much of the literature. Kanninen (1995) and Kanninen and Kriström (1993) found that binary response models fit yes-response data better if the bid design concentrates bids around the expected mean and drops bids in the tails. There is no doubting their statistical finding. However, it does involve ignoring or truncating real response data over high bids in favor of predicting responses for high bids based on how people responded to lower or closer to "average" bids. When response data to high bids are truncated, binary choice models smooth out the tails in a statistically satisfying way but do so by censoring response data over the very range where we would like to know more about true behavioral response.

Herriges et al. (2010) conducted a contingent valuation survey for valuing water quality improvements on lakes in Iowa. Their focus was on exploring the implications of policy consequentiality on the results of dichotomous-choice contingent valuation surveys. In the course of their analysis they write.

> …34.5 percent of individuals are willing to pay the maximum bid value of $600. As such, the posterior predictives *must* place considerable mass to the right of this largest bid point. The problem here is that we do not observe any outcomes to the right of the maximum bid of $600 to inform the shape of this distribution over that region; instead, its shape is determined by estimating a mean, a variance and other statistics to purely form a sequence of binary responses, which are then used (together with our parametric assumptions) to characterize the entire WTP predictive.

This is a nice explanation of the extrapolation required to predict the shape of the yes-response surface over the truncated range.

3. Survey

Our inquiry centers around a CV survey designed to value the protection of the red knot – a migratory bird species whose population has declined in recent years. The red knot is one of many species of shorebirds that makes a stop on the Delaware Bay during its annual ten-thousand-mile migration from South to North America. The stopover in May/June is timed during the horseshoe crab spawning season. The red knot relies on the horseshoe crab eggs to regain weight lost during their long-distance flight before proceeding north to breed. Over the past decade, annual counts of the red knot indicate a decline in numbers, which scientists have attributed to the overharvesting of horseshoe crabs and habitat loss. This has triggered an interest in regulations to protect the red knot such as beach/habitat preservation measures, horseshoe crab harvest limitations, and listing as an endangered species.

In our application we attempt to value the protection of the red knot via a hypothetical resource conservation program. We used an internet-based survey and sampled households in New Jersey and Delaware. We follow standard guidelines for conducting a CV survey.[2] We began with a series of introductory warm-up questions about the environment and migratory birds in the region. Then, we described the historic and current condition of the red knot using maps, pictures, and graphs. Next, we laid out a hypothetical resource conservation program to be conducted jointly by the states of New Jersey and Delaware to protect the red knot. People were then asked to vote for or against the program at some cost to their household in a referendum-style CV question (Fig. 1). We used a one-time tax as the payment vehicle. Each person was asked to vote once. Our survey included a budget reminder, a statement to encourage respondents to treat the survey as consequential, and a clear description of the voting mechanism. Again, see footnote 2 for a link to the entire survey. Various versions of the survey and the valuation question in particular were pretested and discussed in focus groups until we felt confident that respondents understood the resource and the vote.

The bid design used in our survey was motivated by an interest in pinning down the tails of our yes-response function. As noted earlier, this is a region of the distribution that captures those with the highest willingness to pay and, no doubt, will figure importantly in any calculation of mean willingness to pay for use in a benefit-cost or natural resource damage assessment. We are also interested in the implications of truncating bids at the higher end of the distribution. For these reasons, our bid design is heavy on bids at the higher end and uses sample sizes that are sufficient to accurately capture the yes-response rate to high bids. Our bids included the following one-time state tax in dollars: 25, 50, 100, 150, 200, 300, 500, 1000, 2000, 3000, 5000, and 10,000.

We drew our sample from two sources: Qualtrics and Knowledge Networks (now GfK). The Qualtrics sample is an opt-in internet sample that matches the New Jersey and Delaware populations along the lines of income, age, and gender. The Knowledge Networks (KN) sample is probability-based and comes with probability weighting needed to adjust the sample to be representative of the underlying population. We apply these throughout our analysis. Our sample size is 1382 and is split 775 opt-in and 607 probability-based.[3] Table 2 shows some descriptive statistics for our sample.

4. Results

In this section we present our results including the yes-response function, willingness to pay estimates, and some tests of the robustness of our results.

4.1. Yes-Response Function

Our yes-response function is shown in Fig. 2. Please note that the scale on the x-axis is inconsistent – the same increment represents significantly more money as you move to the right. The actual shape of the curve is much longer and flatter than shown. We have a downward slope but there are some instances of non-monotonicity at bids $150, $500, $3000, and $10,000. Table 3 shows the yes-response rates for bids $200 to $10,000 along with other data. At bids between $200 and $500, about 30% to 40% of the sample is voting yes for red knot protection. At bids over $1000, about 20% to 25% vote yes. At $10,000, our highest bid, we still have 23% of the sample voting yes.[4] Our response data exhibit fat tails.

4.2. Willingness to Pay Estimates

Table 3 also presents our nonparametric mean estimates of willingness to pay assuming different maximum bids. For example, if we had used $2000 as our maximum bid, mean willingness to pay would have been $533 per household using a lower-bound nonparametric estimate. We used Vaughan and Rodriguez's (2001) lower-bound measure for this calculation. The estimate applies the yes-response probability over a given interval to the lower bound of that interval in each instance (e.g., if our smoothed function places 5% of the sample between $200 and $300, all 5% is assumed to have a willingness to pay of $200, even though some may be as high as $299). The formula for the lower-bound (see Vaughan and Rodriguez (2001, Table 1)) is

$$WTP_{LB} = \sum_{j=1}^{M+1} b_{j-1} \cdot p_j \tag{1}$$

p_j is the probability density in bid group j; b_j is one of M bid offers; $p_j = F_j - F_{j-1}$, where $F_j = N_j/(N_j + Y_j)$ is the cumulative density for bid group j; N_j is the number of no votes in bid group j, and Y_j is the number of yes votes in bid group j.[5] (Note: $b_0 = 0, F_0 = 0, F_{M+1} = 100$.)

Table 3 shows the dramatic effect of bid truncation on willingness to pay. If we had used $200 as a maximum bid instead of $10,000, our lower-bound mean willingness to pay would have been $102 per household. This ignores the density under the yes-response function in Fig. 2 for bids greater than $200 or what is essentially the demand curve over the high price range. Lower-bound mean willingness to pay doubles (versus $200) if $500 is used as the maximum bid, triples if $1000 is used, increases nine-fold if $3000 is used, and finally jumps as high as twenty times if $10,000 is used.[6,7]

To further appreciate the importance of the maximum bid selection, we have calculated the percent of the lower-bound mean willingness to pay accounted for by the highest bid, which is also reported in Table 3. Think of adding up the bid increments in the nonparametric calculation

[2] The survey may be viewed at https://delaware.qualtrics.com/SE/?SID=SV_cvXTegW9jXmVD5r.

[3] The sample was split this way to test for differences in willingness to pay in the two samples. Since the effects of splitting the sample have no affect on our basic finding, we focus on the combined results.

[4] Every yes-response percentage is statistically significantly different from zero at the 99% level of confidence.

[5] This computation assumes no folding back of probabilities due to non-monotonicity. See Vaughan and Rodriguez (2001) or Haab and McConnell (2002) for folding back.

[6] We also calculated intermediate values of willingness to pay following Vaughan and Rodriguez (2001). As expected, these gave us even larger willingness to pay estimates. At $200, willingness to pay is $331 and at $10,000 it is $2706. The computed choke price in these cases played a large role in the final values.

[7] It is interesting to note that the median value ($89) does not change with the maximum bid. This may have implications for a voting outcome but it not useful in a benefit-cost or damage assessment setting where means are needed.

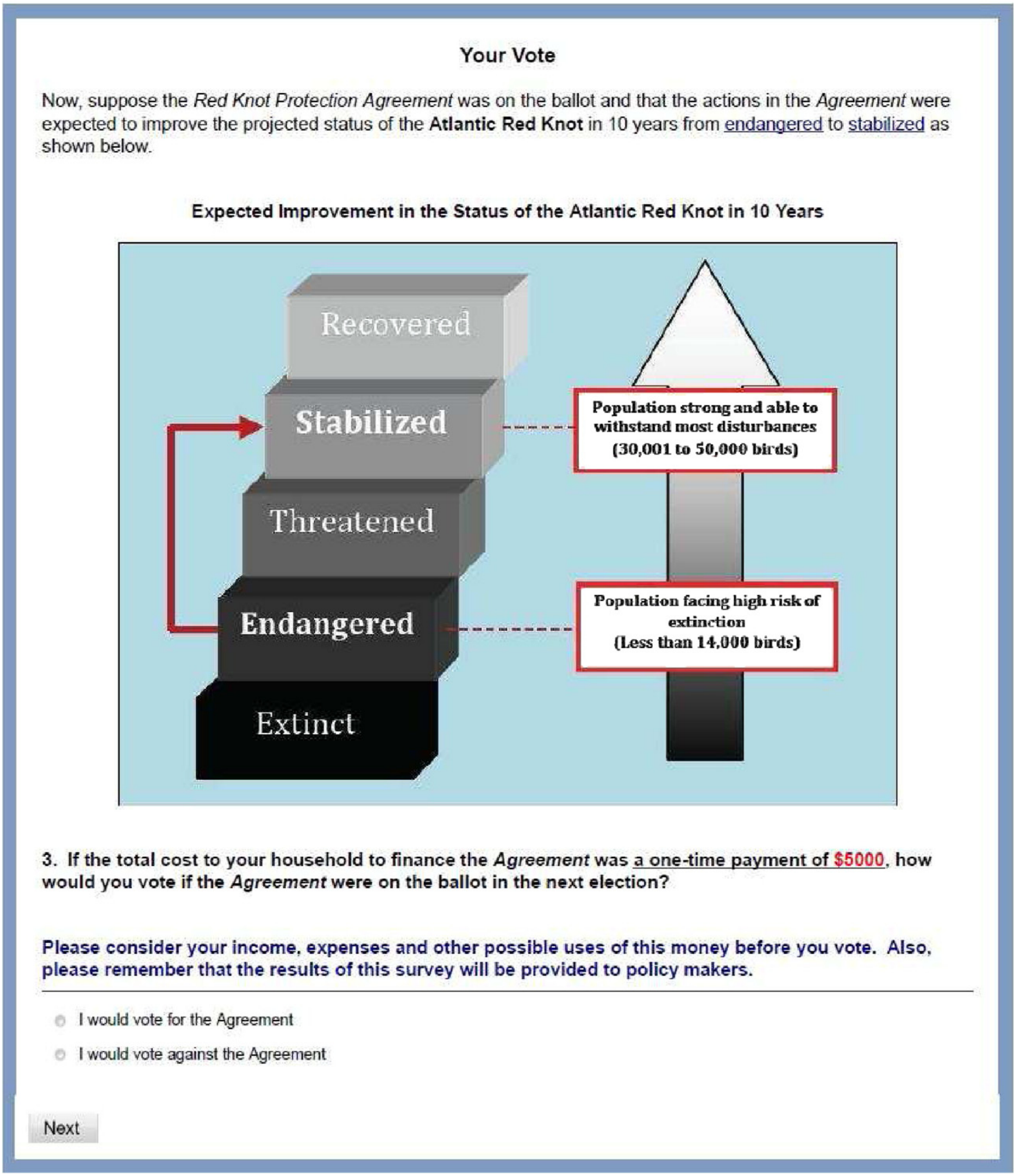

Fig. 1. Example voting question.

in Eq. (1). The increment over the final bid is the share attributed to the highest bid offer. For our lower-bound measure of willingness to pay, that share is $HB_{share} = \frac{b_M p_{M+1}}{WTP_{LB}}$, where b_M is the highest bid. As shown the share ranges from about 69% to 91% of the total value. In effect, a high yes-response rate at the highest bid places enormous weight on that bid and hence accounts for a large share of the value. This result emphasizes the importance of good resolution on the upper end of the distribution. If one believes the estimates, this result also suggests that concentrating bids near the upper end of the tail where most of the willingness to pay is located is a sensible research strategy, contrary to the current practice of truncating this range.

Finally, consider the sheer size of the mean bids when high bid levels are introduced. The mean (lower-bound) willingness to pay is $2254 when the highest bid is used. Keep in mind that only 12% of the population was aware of the red knot before taking the survey. One would expect a greater awareness of a resource worth thousands of dollars per household. These estimates give an aggregate value for the states of New Jersey and Delaware over $15 billion. Since the contingent valuation question has the bird population increasing by 16,000 to 36,000 birds, the values translate to about $400,000 to $900,000 per "sustained" bird. For more perspective, the average household contributes about $4 to wildlife conservation programs. Although

Table 2
Respondent characteristics.

Variable (n = 1382)	Mean
Age	49.8
Gender (1 = Male)	0.47
Income (2010)	$82,033
Education (1 = College Degree or higher)	0.54
Heard of Red Knot (1 = Yes)	0.12
Knowledge about shorebirds (1 = Somewhat Knowledgeable or Very Knowledgeable)	0.28
Made a trip in past 5 years for primary purpose of bird watching (1 = Yes)	0.17
Belongs to a Bird Watching Group	<1%
Distance from the Delaware Bay	220.52
Number of years lived in DE or NJ	35.2

Fig. 2. Percent of Yes responses by bid amount.

suffering from free-riding effects (and hence understating full value), these include all wildlife, well beyond our single bird species. For all environmental causes this value is about $18 per household.[8] We made a similar calculation for environmental outlays per household in the United States and estimate that the average household implicitly pays about $2600. Again, this is for all federal and state environmental protection, fish and wildlife management, forest management, and several other "environmental" categories.[9] Viewed next to these numbers, our estimates are difficult to accept as true resource values.

We see fat tails as a manifestation of hypothetical bias, which has been an issue with contingent valuation response data since its inception – people not taking the survey seriously and not treating the willingness to pay question as a real trade off (with money) as intended. Seeing fat tails this way implies that it is a symptom of a larger problem present in contingent valuation data and not a separate, isolated issue to be dealt with on its own. Fat tails is consistent with many of the issues surrounding CV: yea saying, treating the survey as hypothetical, anchoring, voting simply to show support for a program, treating the good as some broader environmental purpose, and so on. All of these it would seem could generate fat-tailed response data. Boyle (2003), for example, sees the issue of fat tails as a demonstration of yea saying:

> Another problem has been termed "yea saying," which is the propensity of some respondents to answer yes to any bid amount presented to them. Here it seems that bid amounts are not acting as a quality or price cue. The manifestation of this problem has been the so-called "fat-tails" problem, with as much as 30% of a sample answering yes to any bid amount. When the inverse of the empirical cumulative distribution function (cdf) asymptotically approaches 0.30, rather than 0.00, the result is an extremely large estimate of central tendency with a large standard error. [Citations within the quote have been removed.]

Responses to extreme (high) bid offers in a CV survey are in a sense a test of the method itself – a way of revealing the reasonableness of responses that cannot be seen as easily over lower bid offers. If a survey is valid, one would expect a reasonable yes-response rate over the higher-end bids and an ability to pin down the tail of the distribution with plausible mean willingness to pay estimates.

4.3. Adjusting for Hypothetical Bias

We adjusted our yes-response function using a follow-up certainty question. This is one of several approaches commonly used to account for hypothetical bias (Champ et al., 2009). Immediately following our CV referendum question we asked respondents:

> On a scale of 1 to 10, where 1 means 'very uncertain' and 10 means 'very certain,' how certain are you that this is how you would vote if the Red Knot Protection Agreement were actually on the ballot?
>
> Please recall that you voted for/against the Agreement at a one-time cost to your household of [respondent's bid offer].

We used this variable to weight our response data. A person reporting a certainty level of 10 (very certain of their response) was assigned a weight of 1.0; a person with a certainty level of 9 was assigned a weight of 0.9; and so forth. In this way, responses with greater certainty were given a higher weight.

Fig. 3 shows the weighted and un-weighted yes-response functions. The weighted function is about the same as the un-weighted function until the bid reaches $2000. From there and up the weighted function has a lower tail. Yes responders tend to have a lower certainty level over the higher bids and this pulls the tail down. At $10,000, for example, the percent voting yes declines from 23% to 15% of the sample.

Table 4 shows the adjusted willingness to pay estimates. In line with the yes-response functions, there is little change in the lower-bound willingness to pay estimates for the weighted response data until the bid levels of $2000 and above are reached. At $10,000 mean willingness to pay using the lower bound data is reduced from $2254 to $1030. Still, the levels of willingness to pay, even after certainty-adjustment, are high.

Table 3
Non-parametric estimates by bid amount.

High end bid amounts	% of Yes responses	Sample size	Lower bound mean WTP	% of mean accounted for by highest bid
$200	41%	80	$102	91%
$300	32%	90	$134	76%
$500	35%	148	$204	81%
$1000	25%	132	$327	84%
$2000	21%	148	$533	78%
$3000	38%	144	$897	91%
$5000	16%	143	$1220	69%
$10,000	23%	136	$2254	84%

[8] These calculations were made using aggregate data from charity navigator (charitynavigator.org).
[9] These calculations were made using budgets from environmental-related agencies and include an RFF estimate of regulatory compliance cost (2% of GDP), which is the highest component of the value (Morgenstern et al., 1998).

Fig. 3. Comparison of percent Yes responses vs. responses adjusted for certainty.

4.4. Belief in Bid Offers

Respondents are told that if more than half of the population votes in favor of the Red Knot Agreement their household will pay a tax of $X into a Red Knot Protection Fund and the program described will be implemented. Respondents may or may not believe the $X presented in the survey. People may use another amount they find more believable. For example, people may make a mental calculation of what a reasonable per household cost for the program is and adjust the amount given in the survey up or down accordingly. Or, people may look for some historical context of what a realistic tax in their state might be for the program and use that expected level. In our case, particularly with regard to the high bid levels shown, people may not believe that a tax for a bird protection program would ever reach such heights. Similarly, people may be skeptical of a low tax on the valuation question, thinking in the real world that the cost the government will incur to achieve success will actually be higher. Whether respondents accept the bid they are told and then vote based on that bid is simply unknown.

To explore this issue, we asked the following follow-up question

When you voted, did you think that your household would actually end up paying the tax amount stated, or did you think you would pay more or less than that amount?

Table 5 shows the response frequencies for this question. About 17% of all voters thought they would have to pay less than the amount stated in the survey and about 21% thought they would pay more. Fig. 4 shows how the sample responded by bid levels. As the bid level increases more people believe that they would pay less than the stated amount. This suggests that people who received high bids may simply reject the plausibility of the bid and insert one of their own. At $10,000, for example, about 33% of the sample believed that would actually pay less than the amount stated. At $25 only 11% believe they would pay less. In contrast, as the bid increases the share of people saying they would pay more declines. Surprisingly, even at the highest bid levels 10% believed they would pay more and most believed the stated amount.

Following this question, we asked the respondents who believed that they would pay something other than the stated amount in the survey (about 38% of the sample) to report the amount they actually thought they would pay. We used this amount to recode the data and reconfigure the yes-response function. For example, if someone was asked if they would vote yes at $5000 but believed they would actually pay only $100, we recoded this respondent as a yes at $100. This presumes that the person voted using $100 as the tax. It is entirely possible that a person may have voted using the amount stated even if they found the amount implausible. Our adjusted yes-response curve is shown in Fig. 5. Our mean willingness to pay estimates using the same nonparametric procedure reported earlier are shown in Table 6. Again, we report the values assuming truncation at each bid shown. The estimates fall versus the raw data as expected. The decline over the higher end bids is largest. At $10,000, for example, the mean lower-bound WTP declines from $2254 using the raw data to $1508 using the newly configured data. But again, the values after adjusting are still high.

Table 4
Non-parametric estimates by bid amount and adjusted for hypothetical bias.

High end bid amounts	% of Yes responses	Sample size	Lower bound mean WTP	% of mean accounted for by highest bid
$200	38%	58	$103	81%
$300	31%	65	$134	75%
$500	35%	117	$204	84%
$1000	22%	105	$311	71%
$2000	19%	113	$497	84%
$3000	29%	102	$774	83%
$5000	11%	126	$993	56%
$10,000	15%	98	$1030	71%

Table 5
Responses to follow-up question about the tax amount in vote.

When you voted, did you think that your household would actually end up paying the tax amount stated, or did you think that your household would pay more or less than that amount?	Percent of total		
	Yes voters n = 493	No voters n = 879	Entire sample n = 1372
The amount stated	32%	42%	39%
More than the amount stated	24%	19%	21%
Less than the amount stated	21%	15%	17%
Unsure	23%	24%	24%

4.5. Follow-up Questions

Finally, we included a number of other follow-up questions to explore respondent behavior at high bids. The results are mixed on explaining why the tail of the yes-response function is fat. On one hand, we found a tendency of respondents to mentally scale down high bids and to vote simply to show support (so dollars were maybe largely ignored), which may explain why the yes-response rate stays

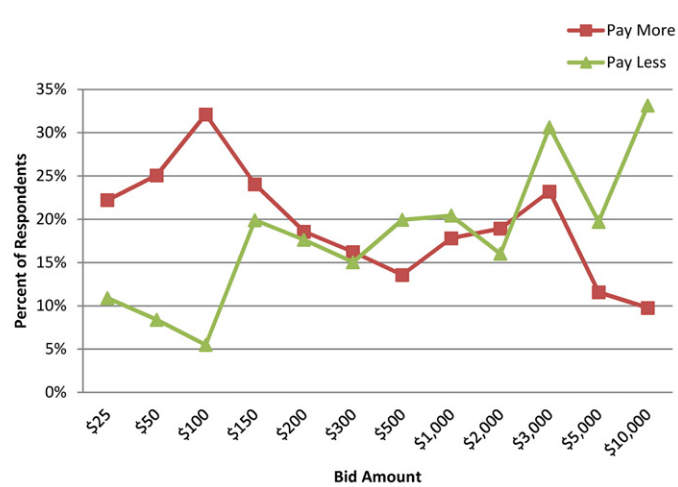

Fig. 4. Percent of respondents who believed would pay more or pay less than offered bid amount.

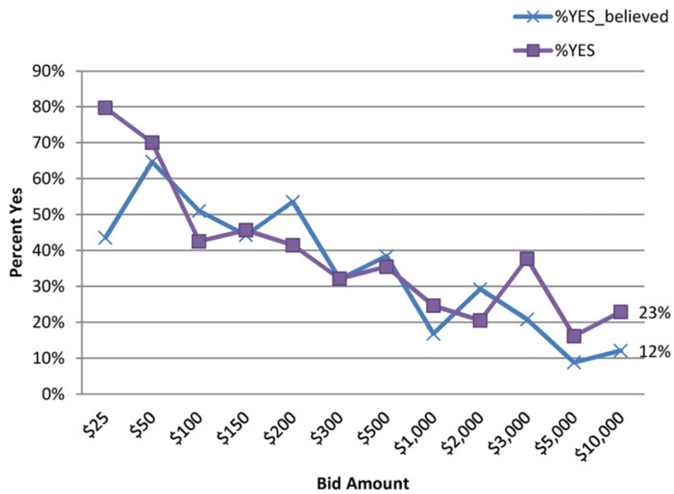

Fig. 5. Comparison of percent Yes responses vs. responses adjusted for "believed" bid amount.

high at higher bids. On the other hand, we found people to be more neoclassical (think in terms of money tradeoffs) at the high bid levels and more likely to think that the red knot funds would not be used solely for protecting the red knot. Both of these effects work to decrease yes responses at high bids. In short, we cannot say we found anything in the follow-up-question responses to "explain away" the presence of fat tails and the response to high bids.

5. Discussion

Consider Table 1 again. Based on our findings, we are left wondering what would have happened if higher bids had been considered in many of these studies where the yes-response function is truncated. While we cannot say for sure, we suspect they may have had findings similar to ours: a difficulty pinning down the tail of the yes-response function and a mean willingness to pay estimate that is highly sensitive to choice of maximum bid and perhaps implausibly high at extreme bids. It would be interesting to test their surveys.

Consequentially has become an important issue in contingent valuation (Herriges et al., 2010). In order for respondents to provide meaningful data, they need to believe that the survey is consequential and that their responses matter for policy purposes. At least two recent studies listed in Table 1 are designed to address consequentiality (Petrolia et al., 2014; Herriges et al., 2010). Both appear to have fat tails, suggesting that a lack of consequentiality may not be the issue. Obviously, more is need here to draw definitive conclusions.

Again, we see fat tails as a manifestation of hypothetical bias (the tendency of people to report a value other than their true value due to the hypothetical nature of a survey) and not an isolated contingent valuation issue. Fat tails is, after all, consistent with most contingent valuation phenomenon believed to cause hypothetical bias: yea saying, anchoring, using valuation questions to express emotive instead of trade-off values, using valuation questions to show support for a program, etc. Viewed in this way, fixing fat tails amounts to fixing the fundamental hypothetical bias presence in contingent valuation.

Table 6
Non-parametric estimates by bid amount and adjusted for believed bid.

High end bid amounts	% of Yes responses	Sample size	Lower bound mean WTP	% of mean accounted for by highest bid
$200	54%	104	$103	98%
$300	32%	93	$135	75%
$500	38%	153	$211	85%
$1000	17%	120	$295	59%
$2000	29%	131	$560	78%
$3000	21%	87	$779	80%
$5000	9%	138	$955	46%
$10,000	12%	124	$1508	60%

Truncating high-end bids is a tempting response to fat tails. If the tail of the yes-response surface is ignored over its high end, the analyst may offer truncated values using a lower-bound nonparametric estimator as a conservative value. But, this is not a real fix to the underlying problem of hypothetical bias, nor is the resulting willingness to pay truly conservative. Indeed, it "hides" the effects of fat tails. One may falsely believe that she has a reasonable estimate of value when in fact the survey instrument could produce vastly different values with only modest changes in the bid levels offered. Truncating offers nothing new for understanding underlying preferences, explaining why contingent valuation data yield fat tails, or dealing with hypothetical bias.

Perhaps our most startling finding is the sensitivity of mean willingness to pay to the largest bid. This is because so much of the willingness to pay is captured in the high-end tail of the yes-response function (or demand function over high prices). One can easily double or triple a mean willingness to pay by simply picking a larger bid. This lack of robustness is troubling.

We encourage more exploration into the causes and consequences of fat tails in contingent valuation response data. Follow-up questions similar to ours but perhaps more probative might shed some light on underlying behavior and intentions of respondents facing high bids. It should be kept in mind, however, that the behavioral anomalies present for people facing high bids is likely to exist for all respondents, since bids are assigned randomly. We are also interested in knowing whether there is a fat-tails-equivalent for choice experiments. This would manifest through sensitivity of willingness to pay estimates to the maximum bid level used for the payment attribute in the choice experiment. Finally, alternative behavioral models, along with tests, to better explain choice by respondents in a survey setting may lead to a better understanding of the unexpected responses we see to high bids.

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