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Willingness to Pay and Political Support for a U.S. National Clean Energy Standard

Joseph E. Aldy^{1,2,3}, Matthew J. Kotchen^{2,4,*} and Anthony A. Leiserowitz⁴

In 2010 and 2011, Republicans and Democrats proposed mandating clean power generation in the electricity sector [1,2,3]. To evaluate public support for a national clean energy standard (NCES), we conducted a nationally representative survey that included randomized treatments on the sources of eligible power generation and program costs. We find that the average American is willing to pay \$162 per year in higher electricity bills (95% confidence interval: \$128 – \$260), representing a 13% increase [4], in support of a NCES that requires 80% clean energy by 2035. Support for a NCES is lower among non-whites, older individuals, and Republicans. We also employ our statistical model, along with census data for each state and Congressional district [5], to simulate voting behavior on a NCES by Members of Congress assuming they vote consistent with the preferences of their median voter. We estimate that Senate passage of a NCES would require an average household cost below \$59 per year, while House passage would require costs below \$48 per year. The results imply that an “80% by 2035” NCES could pass both chambers of Congress if it increases electricity rates less than 5% on average.

The promotion of clean energy technologies for generating electricity has become an increasingly important priority in the United States. More than 30 states have established renewable and alternative energy mandates in the power sector [6]. A 2009 bipartisan Senate energy bill would mandate that 20% of the nation’s electricity come from renewable sources by 2020. [1] A 2010 Senate Republican energy bill would mandate 50% clean energy – renewables, nuclear, and fossil fuel with

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carbon capture and storage – by 2050. [2] In 2011, President Obama proposed an “80% by 2035” national clean energy standard and expanded the definition of clean energy to include natural gas. [3] All three policies set ambitious goals for expanding the share of U.S. electricity from clean energy sources relative to current and forecasted levels (Figure 1).

In the context of greenhouse-gas emissions mitigation, a NCES can serve as an alternative to implementing a federal cap-and-trade program or a carbon tax. [7] For example, one proposed NCES would reduce carbon dioxide (CO₂) emissions in the power sector by as much as 60% below 2005 levels by 2035 and mimic many of the attractive cost-effectiveness properties of market-based approaches. [6] Nonetheless, a recent analysis finds that implementing an 80% NCES would increase national average electricity rates by less than 5% through 2030, but ramp up to 11% by 2035. [8] Given the higher electricity costs associated with promoting clean energy, a critical economic and political question is whether the American public – and their representatives in Washington – support passage of a NCES.

To address this question, we collected data through a nationally representative survey of 1,010 Americans between April 23 and May 12, 2011. Respondents were asked, *inter alia*, whether they would “support” or “oppose” a NCES with the goal of 80% clean energy by 2035. We randomized two elements of this question across the entire sample. First, respondents received one of three randomized definitions for clean energy: (1) renewables only; (2) renewables and natural gas; and (3) renewables and nuclear. Second, respondents received randomized amounts for how much the NCES would increase annual household electricity bills. Using higher electricity bills as the payment vehicle in the survey instrument serves as a salient cost measure. The randomly offered “bid” amounts varied by \$20 increments between \$5 and \$155 per year (with the exception of a \$30 difference between the \$105 and \$135 bids).

To provide context for the bid amounts, the average American household spent \$1,250 on electricity in 2009. [7] Table 1 reports how selected bid amounts translate into percentage increases in

household electricity bills for different U.S. regions. Note the significant variation in the percentage increase in electricity bills across regions, which reflects the heterogeneity in electricity rates across the nation. [4]

Table 2 reports the percentage of respondents that supported the NCES by bid amounts, pooled and for each of the technology treatments. In nearly all cells the majority of respondents support passage of the NCES. Across all treatments, there appears to be a modest decline in support as costs increase. We test for such a cost effect more rigorously with a binary logit model for the probability of support that includes all respondents and accounts for the randomized bid amount (i.e., bill increase), the randomized technology treatment, and sociodemographic characteristics taken from the survey (i.e., education, gender, household size, income, ethnicity, and political affiliation). The accompanying Methods section provides details about the survey, the statistical approach, and the reason for pooling all data into one model.

Based on the logit model results, Table 3 reports the estimated marginal effects of each independent variable on the probability of support for the NCES. There is a negative and statistically significant cost effect: a \$10 increase in the annual household cost of the NCES decreases the probability of support by 1 percentage point. Including natural gas or nuclear in the definition of clean power, decreases the probability of support between 7–8 percentage points. This result is not surprising given negative publicity regarding shale gas hydraulic fracturing and the Fukushima nuclear accident. After controlling for other sociodemographic characteristics, whites are 10 percentage points more likely than non-whites to support the policy. Republicans, Independents, and respondents having no party affiliation are significantly less likely – by 25, 13, and 25 percentage points, respectively – to support a NCES than self-identified Democrats.

Following standard methods, we use the logit model to derive estimates of mean (equal to median) willingness to pay (WTP) across households in support of the specified NCES, along with 95-

percent confidence intervals. [9,10,11,12] Note that mean WTP is interpreted as the amount that would, on average, make respondents indifferent between whether or not the NCES policy becomes law. Our statistical approach admits the possibility that respondents may have a negative WTP; that is, a respondent might be willing to pay to avoid passage of the proposed NCES. Averaging across the three technology treatments, we find that mean WTP in support of an “80% by 2035” NCES is \$162 per year, with a confidence interval of \$128 – \$260. When we estimate mean WTP separately for the technology treatments, we find a WTP of \$199 for renewables only, \$142 for renewables with natural gas, and \$147 for renewables with nuclear, although these WTP point estimates are not statistically different from each other. Even if a NCES cost nothing, 24% and 30% of respondents would oppose passage of a renewables-only NCES and NCES policies that include natural gas or nuclear, respectively.

We use the estimated WTP of \$162 per household per year to calculate the benefits of reducing CO2 emissions. To illustrate this, we assume a constant \$162 per household WTP through 2035, growth in the number of households consistent with population growth, emission reductions from an existing NCES proposal, [6] and a 3% discount rate. The present value benefit of this policy using our WTP measure is approximately \$15 per ton CO2. This estimate is moderately lower than the benefits estimated from an entirely different approach, based on the U.S. Government’s social cost of carbon measure. [13] This approach yields a present value benefit estimate of the NCES policy of about \$23.50 per ton CO2. By assigning all of the NCES benefits to CO2 emissions, this illustrative calculation should be considered an upper bound because some households are likely to value a NCES for reductions in conventional air pollutants and for other reasons.

From a political science perspective, a further implication of our WTP estimate is that *if* a national referendum were to determine the fate of an “80% by 2035” NCES, then the median voter would support passage even if it meant increasing annual electricity bills by 13%. Since the U.S. relies on a representative system of government, we employ a median voter model along with the estimated

logit results to simulate how members of the U.S. Senate and House of Representatives would vote on NCES legislation. We assume that elected officials would vote in line with the preferences of the median voter in their state or congressional district. [14,15,16] Our approach is consistent with the literature that seeks to explain Congressional votes based on the median voter, including recent work that considers the benefits of power sector environmental policies. [17,18,19] While the approach is also consistent with other studies that estimate WTP for goods specified in bills that subsequently become law, [20,21,22] a novel extension of our work is the use of benefit estimates combined with the median voter model to simulate political outcomes.

We construct characteristics of the median voter in each state and Congressional district using the U.S. Census American Community Survey, [5] and we assume that the political affiliation of elected officials in the 112th Congress reflects the affiliation of the median voter in the corresponding state or district. With this information, we can simulate votes for legislation creating a NCES with various cost estimates based on whether the predicted probability of support for the median voter falls above or below 0.5. We find that an “80% by 2035” renewable and natural gas NCES bill that increases annual electricity bills by \$162 per households (i.e., our mean WTP estimate) would not pass. We predict that 53 (out of 100) Senators and 194 (out of 435) Representatives would vote in support of the NCES, whereby the filibuster and cloture procedures in the Senate implies that the legislation would fail votes in both chambers of Congress. Note that these simulations closely mirror the political affiliations of Members of Congress, which is not surprising given the importance of political affiliation in the estimated logit model (Table 3).

We also conduct a retrospective analysis of our median voter model on the 111th Congress, which had significantly more Democrats. We find that the 111th House and Senate would pass a NCES that increases annual electricity bills by \$162 with 257 and 60 votes, respectively. Note that these results are broadly consistent with the actions on clean energy policy that occurred in the 111th Congress: the

House passed a comprehensive energy bill that included a greenhouse gas cap-and-trade program and a renewables-only NCES, [23] while the Senate passed a bipartisan renewables-only NCES in the Energy and Natural Resources Committee, [1] but then failed to engage in chamber-wide debate on energy policy.

For the final part of our analysis, we return to the current 112th Congress and simulate the “breakeven” cost of a NCES that gives a predicted probability of 0.5 for the median voter in each state and district. This represents the estimated median WTP of each political jurisdiction. With these results, we find that obtaining the vote of at least 60 Senators, and thereby securing cloture and passage, would require the NCES cost to fall below \$59 per year in higher household electricity bills. In the House, the cost would need to fall below \$48 per year to secure a majority of votes for passage.

Our results illustrate a stark contrast between the average American represented in our survey and the median voter constraining Senators and Representatives in the 112th Congress. The average American would support an “80% by 2035” NCES that increases annual electricity bills by \$162, representing an average increase of 13%. In contrast, in our Congressional median voter model, the 60th Senator voting “aye” and the median Representative in the House would support the same NCES only if it cost on the order of \$50–\$60 per year, representing a 5% increase in average electricity bills. One analysis of an 80% NCES suggests that utility bill increases would remain below 5% through 2030 while reducing utility sector carbon emissions by nearly 1 billion metric tons annually on average. [8]

This result may also reflect the fact that, in some contexts, models of special interest and partisan politics may better explain Congressional voting than the median voter. [24] Individual preferences may change over the course of political debate, and further survey evidence will be necessary to update public opinion on clean energy deployment policies. At present, however, the difference between public opinion and political support that we find is consistent with the observation that a majority of Americans support clean energy and climate-change policies, while the necessary

majorities in Congress do not. Importantly, the results also suggest that NCES policies that contain the cost impact on energy bills might succeed at generating the necessary political support to become law.

Methods

The survey was developed by the Yale Project on Climate Change Communication and the George Mason University Center for Climate Change Communication. The sample consists of 1,010 adults aged 18 and older from the nationally representative, probability-based online panel of Knowledge Networks, with a survey completion rate of 66%. Supplementary Table S1 includes descriptive statistics of the sociodemographic characteristics of respondents, including educational attainment, gender, household size, income, ethnicity, and political party affiliation. There were no statistically significant differences in the sociodemographic characteristics across randomized treatments (described below and in the main text).

Our analysis is based on a dichotomous-choice, contingent valuation question. This question format is recommended for the most reliable estimates of WTP based on survey responses. [25] In addition to the standard randomization of “bid” amounts, we randomized information about which technologies were to be included in the proposed NCES policy. The exact wording and structure of the question was as follows:

The federal government is considering a Clean Energy Standard that would require electric power companies to obtain 80 percent of their energy from clean sources by the year 2035. Eligible sources of clean energy would include [INSERT *randomize technology treatment*]. If this policy were to cost your household \$[INSERT *randomized bid amount*] more each year in higher electricity bills, would you support or oppose this policy?

1. Support
2. Oppose

The randomized technology treatments were assigned with equal probability: “renewables, such as solar and wind power”; “natural gas and renewables, such as solar and wind power”; and “nuclear power and renewables, such as solar and wind power.” The randomly assigned bid

amounts were \$5, \$25, \$45, \$65, \$85, \$105, \$135, \$155, where the middle amounts \$45–\$105 were assigned with twice the probability as the two lowest and highest amounts.

In contrast to contingent valuation surveys that may include a significant amount of information about a proposed policy, [26] our survey provided only a limited amount of information on a national clean energy standard due to space constraints. But given the public's familiarity with the major categories of power generation and with paying utility bills, we do not believe this poses a risk that respondents had differing expectations about the policy being considered. In addition, this survey question was part of a larger survey instrument focused on clean energy and climate change policy. Survey respondents answered a broad array of questions regarding their attitudes about climate change, including its causes, anticipated impacts, and means of adaptation. The survey instrument posed a number of questions regarding various national energy policies that could impact greenhouse gas emissions, with associated costs (in terms of higher utility bills and gasoline prices). In total, the survey instrument provided the respondent with extensive information and questions to frame the issues of climate change and clean energy, and presented several opportunities for respondents to assess and express their preferences over the costs and benefits of clean energy and climate change policy proposals. Details about the range of questions included in the survey are reported elsewhere. [27,28]

We first estimated logit models separately for each treatment and using the pooled data. These results are shown in Supplementary Table S2. We conducted a likelihood ratio test to determine whether the set of sociodemographic variables explain the support/oppose responses differently across the technology treatments. We fail to reject the null hypothesis ($\chi^2 = 27.28, p = 0.201$), indicating that it is reasonable to estimate a pooled model, while also controlling for average treatment effects. This model, denoted pooled (2) in Table S2, is the one

we use to generate marginal effects, mean and median WTP, confidence intervals, and the voting simulations reported in the main text. Mean WTP is derived following standard methods for the logit model admitting the possibility for a negative WTP [9,10]. All explanatory variables other than bid amount are evaluated at their mean, multiplied by their respective coefficient, and added to the constant. Mean and median WTP are then simply the ratio of the “grand” constant over the coefficient on bid amount. Confidence intervals are derived using the simulation methods adapted for dichotomous-choice contingent valuation questions [11,12].

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Author contributions

All authors contributed equally to this work. M.J.K. developed the survey question and A.A.L. implemented the survey instrument. The statistical analysis of the survey data was undertaken by M.J.K. and J.E.A. The estimated carbon benefits calculation was undertaken by J.E.A. Authors J.E.A and M.J.K. developed the median voter model based on the survey results. All authors participated in the drafting of the text.

Additional information

The authors declare no competing financial interests.

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Tables and Figures

Table 1. Selected NCEs premiums as percentage increases in annual household electricity bills

Census Region	Bid amount			
	\$5	\$45	\$85	\$155
New England	0.4%	3.4%	6.5%	11.9%
Middle Atlantic	0.4%	3.7%	6.9%	12.6%
East North Central	0.5%	4.4%	8.3%	15.2%
West North Central	0.5%	4.4%	8.2%	15.0%
South Atlantic	0.3%	2.9%	5.6%	10.2%
East South Central	0.4%	3.2%	6.1%	11.1%
West South Central	0.3%	3.0%	5.6%	10.2%
Mountain	0.5%	4.2%	7.9%	14.5%
Pacific	0.5%	4.4%	8.3%	15.1%
United States	0.4%	3.6%	6.8%	12.4%

Notes: Percentage increases are based on 2009 residential electricity bills from data published by the Energy Information Administration. [4] The estimates assume that residential consumers do not adjust consumption in response to higher electricity costs. The percentage increases for other bid payments (\$25, \$65, \$105, and \$135) are available from the authors upon request.

Table 2: Percentage distribution of “support” responses at each bid amount, pooled and by clean energy technology treatment

BID amount	Technology treatment			
	Pooled	Renewables	Renewables & Natural Gas	Renewables & Nuclear
\$5	72%	86%	61%	72%
\$35	78%	81%	69%	83%
\$45	57%	65%	57%	49%
\$65	64%	68%	63%	60%
\$85	61%	70%	55%	61%
\$105	60%	58%	59%	64%
\$135	49%	57%	50%	41%
\$155	54%	56%	59%	57%
Observations	983	311	343	329

Notes: Table includes percentages for actual “support” responses compared to “oppose.” Not included are 27 respondents that refused to answer the question, although the refusals appear randomly distributed among the bid amount and technology treatments.

Table 3: Logit model marginal effects on the probability of supporting the NCES

	Marginal effect	Standard error	p-value	Variable mean
Bid amount	-0.001	(0.000)	0.000	78.136
Renewables only (omitted)	--	--	--	0.316
Renewables + natural gas	-0.080	(0.040)	0.047	0.348
Renewables + nuclear	-0.072	(0.041)	0.077	0.337
College degree	0.037	(0.038)	0.336	0.283
Male	-0.027	(0.032)	0.409	0.484
Household size (# people)	-0.014	(0.012)	0.218	2.912
Household income (\$10,000s)	0.004	(0.004)	0.304	6.793
Age (years)	-0.002	(0.001)	0.021	46.085
White	0.103	(0.041)	0.011	0.685
Democrat (omitted)	--	--	--	0.312
Republican	-0.247	(0.045)	0.000	0.249
Independent	-0.127	(0.047)	0.007	0.229
No party	-0.247	(0.050)	0.000	0.194

Notes: The dependent variable is an indicator for whether the respondents answered "support" for the NCES question. The model includes 983 observations. The pseudo R-squared for the model is 0.052. Marginal effects for continuous variables are evaluated at the variable means. Those for dummy variables are evaluated for the discrete change from 0 to 1.

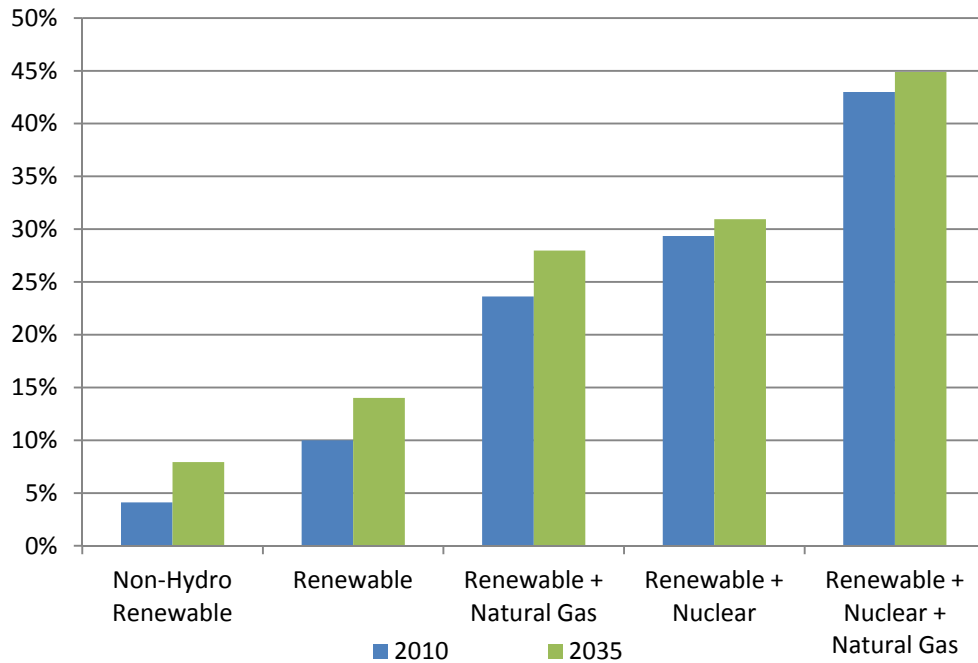


Figure 1: U.S. share of “clean power” from various technologies for 2010 and forecasted for 2035. The “clean power” share represented by natural gas reflects a weighting based on its carbon dioxide emission intensity relative to that of coal-fired generation. The 2035 levels represent a forecast reference scenario, i.e., no new policies to promote the deployment of clean energy technologies. The figure was constructed by the authors using data from the Energy Information Administration. [29]

Willingness to Pay and Political Support for a U.S. National Clean Energy Standard: Supplementary Information

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This supplementary information includes two supporting tables and the results of additional statistical analysis:

- Table S1: Descriptive statistics for socioeconomic characteristics
- Table S2: Logit models of contingent valuation question, pooled and by treatment
- Robustness Checks for Mean WTP and Voting Simulations
- Figure S1: The non-parametric survivor function
- Supplementary References

**Supplementary Table S1:
Descriptive statistics for socioeconomic characteristics**

Variable	Mean	Std. Dev.
College degree (1=yes)	0.277	(0.448)
Male (1=yes)	0.482	(0.500)
Household size (# people)	2.929	(1.718)
Household income (\$10,000s)	6.774	(4.720)
Age (years)	45.85	(16.95)
White (1=yes)	0.682	(0.466)
Democrat (1=yes)	0.307	(0.461)
Republican (1=yes)	0.242	(0.428)
Independent (1=yes)	0.225	(0.418)
No party (1=yes)	0.195	(0.396)

Notes: Statistics based on 1010 observations and weighted for sample representativeness. Exact dollar amounts for household income imputed as midpoints of 19 categorical responses. Political party affiliation is self-reported, and the no party category includes responses of “no party/not interested in politics” and the relatively few “other, please specify responses.”

**Supplementary Table S2:
Logit models of contingent valuation question, pooled and by treatment**

	Treatment				
	Renewables	Renewables & Natural Gas	Renewables & Nuclear	Pooled (1)	Pooled (2)
Bid amount	-0.010*** (0.003)	-0.004 (0.003)	-0.006** (0.003)	-0.006*** (0.002)	-0.006*** (0.002)
Renewables + natural gas	--	--	--	--	-0.338** (0.169)
Renewables + nuclear	--	--	--	--	-0.305* (0.171)
College degree	0.343 (0.309)	0.125 (0.280)	-0.080 (0.294)	0.172 (0.166)	0.159 (0.167)
Male	0.194 (0.254)	-0.136 (0.235)	-0.371 (0.242)	-0.098 (0.137)	-0.113 (0.137)
Household size	-0.093 (0.092)	-0.035 (0.082)	-0.051 (0.093)	-0.061 (0.050)	-0.062 (0.050)
Household income	0.031 (0.029)	-0.004 (0.026)	0.027 (0.029)	0.016 (0.016)	0.016 (0.016)
Age	0.003 (0.008)	-0.009 (0.008)	-0.026*** (0.008)	-0.011** (0.005)	-0.011** (0.005)
White	0.361 (0.306)	0.290 (0.300)	0.663** (0.293)	0.420** (0.168)	0.432*** (0.169)
Republican	-0.730** (0.366)	-1.252*** (0.317)	-1.135*** (0.334)	-1.020*** (0.190)	-1.025*** (0.191)
Independent	-0.427 (0.361)	-0.650* (0.345)	-0.524 (0.325)	-0.510*** (0.193)	-0.527*** (0.194)
No party	-0.616 (0.381)	-1.593*** (0.376)	-0.706** (0.353)	-0.997*** (0.209)	-1.014*** (0.210)
Constant	1.361** (0.679)	1.856*** (0.678)	2.330*** (0.709)	1.791*** (0.389)	2.015*** (0.405)
Pseudo R ²	0.069	0.062	0.066	0.048	0.052
Observations	311	343	329	983	983

Notes: Standard errors are reported in parentheses. Democrat is the omitted category for political party affiliation, and the renewables only treatment is the omitted category for the pooled (2) model. One, two and three asterisk(s) indicate statistical significance at the 90-, 95- and 99-percent levels, respectively.

Robustness Checks for Mean WTP and Voting Simulations

We conducted robustness checks of our mean willingness to pay (WTP) estimates and voting simulations. Throughout our analysis we found no statistically significant differences in mean WTP among treatments. Thus, we focus the robustness checks on the pooled estimate of \$162 (95% confidence interval: \$128 – \$260) that we employed in our simulated voter model and used to estimate the benefits per ton of carbon dioxide abated. We explain in the methods section how this estimate is based on a logit model with mean WTP derived using the standard method in the contingent valuation literature. Our approach admitted the possibility for negative WTP. In what follows, we consider two alternative distributional assumptions, one non-parametric and one parametric.

Part of the motivation for these robustness checks is that our main estimate of mean and median WTP (\$162) lies just above the highest Bid amount that was offered to respondents (\$155). This implies that our estimate of mean WTP relies on our logistic functional form assumption outside the range of data. While it would have been desirable from a statistical standpoint to have higher Bid amounts, this was only known *ex post*. In what follows, however, we demonstrate that the main results are robust to several alternative distributional assumptions. To begin, note that with the probability of accepting a bid slightly greater than 50% over the highest two Bid amounts in aggregate (nearly 52%, reflecting the 49% at \$135 and 54% at \$155), and greater than 50% for all lower Bid amounts, then \$155 bounds from below the median without relying on any distributional assumption.

We now turn to a non-parametric approach for estimating willingness to pay, the Turnbull empirical distribution estimator [1,2]. The Turnbull estimator allows for “spikes” in the data (i.e., a probability mass of respondents with zero WTP) without any ad hoc distributional assumptions. In other words, if there are unidentified “indifferent” respondents in the sample, the Turnbull lower-bound estimate of WTP is robust to their inclusion in the analysis [3]. The first step in this process is to convert the sequence of responses at different Bid amounts into a monotonically decreasing function using the pool-adjacent-violator algorithm. Then, a lower- and upper-bound estimate of WTP is calculated as follows. The lower-bound is based on multiplying each offered Bid amount by the probability that WTP falls between that Bid amount and the next highest bid amount. The upper-bound is based on multiplying each offered Bid amount by the probability that WTP falls between that amount and the next lowest amount. For the upper-bound estimate, we assume a maximum WTP of \$465 (three times the highest Bid amount offered in the survey). Using these approaches, we estimate a lower bound WTP of \$80 and an upper bound of \$260. These estimates clearly bound our mean estimate of \$162.

As a third non-parametric estimate, one that is more directly comparable to our estimate of mean WTP, we employ the method described in Kristrom [4]. For this, we use the same monotonically decreasing function, estimate the probability density function through linear interpolation between Bid amounts, and take the integral of the area under this function. These probability density functions are plotted as survival functions in Figure S1 for the pooled data and separately for each policy treatment. The corresponding estimate of mean WTP is based on the areas under these curves. For the pooled data, we derive mean WTP of \$177, which is relatively close to our estimate of \$162. Estimates for each of the policy treatments separately are \$192 for renewables only, \$177 for renewables and natural gas, and \$172 for renewables and nuclear. All of the estimates are reasonably close to those reported in the main text for the logit model.

The parametric approach that we take also seeks to address the potential impact of indifferent respondents. One method would be to estimate a spike model based solely on the dichotomous-choice

contingent valuation question, but this approach has undesirable econometric properties because statistical identification of the indifferent respondents relies entirely on the assumed form of the conditional distribution of WTP [5,6]. Instead, we take advantage of another question in our survey to estimate the well-known spike model of Kristrom [7].

Prior to the NCES question in the survey instrument, respondents were asked “Do you think that developing clean sources of energy should be a low, medium, high, or very high priority for the president and Congress?” The percentage frequency of responses was low = 11%, medium = 24%, high = 34%, and very high = 31%. For purposes of estimating the Kristrom spike model, we assume that all respondents answering “low priority” to this question and also answering “Oppose” to the valuation question are indifferent respondents. We know *ex ante* that this is an overly conservative assumption because low priority does not mean WTP = 0, and respondents may have answered “Oppose” because that were simply given bid amounts (i.e., annual increases in electricity bills) that exceeded their WTP. We know, for example, that among those answering “low priority,” 21% did answer “Support” to the valuation question.

We nevertheless estimate this model as a robustness check of our WTP estimate, recognizing in advance that it will be downwardly biased. For the pooled model, we estimate an intercept $\alpha = 2.040$ (SE = 0.092) and a coefficient on Bid amount $\beta = 0.19$ (SE = 0.001). Following the formulas derived in Kristrom [7], these estimates imply that 12% of the respondents have a WTP = 0 and the mean WTP estimate is \$116 (95% confidence interval: \$107 – \$124). While this estimate is indeed lower, the confidence interval nearly overlaps that for our primary estimate, and the mean WTP exceeds the Turnbull lower bound of \$80.

The question remains, however, about whether the voting simulations are sensitive to these alternative estimates of WTP. We find that even using the lower bound estimate from the Turnbull estimator (\$80) does not change the results for the 112th Congress. As we note in the paper, the cost of a proposed NCES would have to be about \$59 to elicit 60 “aye” votes in the Senate and \$48 to receive a majority in the House. The same lower bound of \$80 does not change the results for the 111th Congress. We predicted that a NCES would pass with an estimated \$162 increase in annual electricity bills, and thus it would obviously still pass with a lower bill increase of \$80, and we find that the number of votes is the same between these two estimates. The voting results, which are central to our analysis, are therefore robust to alternative distributional assumptions about WTP.

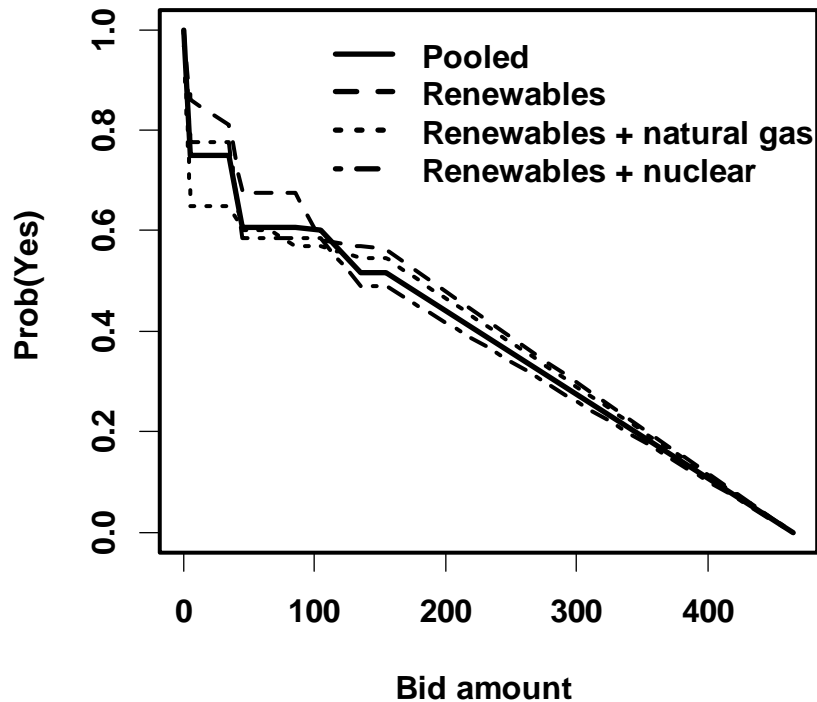


Figure S1: The non-parametric survivor function. For each policy treatment, the figure plots the probability of a “yes” response based on given Bid amounts after making the sequence monotonic with the pool-adjacent-violator algorithm and a linear interpolation between points. WTP is truncated at \$465.

Supplementary References

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