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The effect of providing climate and health information on support for alternative electricity portfolios

Brian Sergi¹, Alex Davis¹ and Inês Azevedo^{1,2} 

¹ Department of Engineering and Public Policy, Carnegie Mellon University, United States of America

² Author to whom any correspondence should be addressed.

E-mail: iazevedo@cmu.edu

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Abstract

Support for addressing climate change and air pollution may depend on the type of information provided to the public. We conduct a discrete choice survey assessing preferences for combinations of electricity generation portfolios, electricity bills, and emissions reductions. We test how participants' preferences change when emissions information is explicitly provided to them. We find that support for climate mitigation increases when mitigation is accompanied by improvements to air quality and human health. We estimate that an average respondent would accept an increase of 19%–27% in their electricity bill if shown information stating that either CO₂ or SO₂ emissions are reduced by 30%. Furthermore, an average respondent is willing to pay an increase of 30%–40% in electricity bills when shown information stating that both pollutants are reduced by 30% simultaneously. Our findings suggest that the type of emissions information provided to the public will affect their support for different electricity portfolios.

Introduction

Reducing emissions from electricity generation in the United States is imperative to mitigating climate change and improving air quality. Well over half of the electricity generated in the US comes from fossil fuels, and the electricity sector is responsible for approximately 40% of all carbon dioxide (CO₂) and 70% of all sulfur dioxide (SO₂) emitted domestically [1].

Historically, public support has played an important role in shaping electricity sector decisions. Public reaction to poor air quality helped push for more stringent emissions regulations, while opposition to proposed low-carbon energy projects such as Cape Wind and the Shoreham nuclear power plant helped to stymie those projects [2–4]. Other forms of public support might include paying a premium for low-emissions electricity, accepting new renewable generation and accompanying transmission, or supporting low-carbon portfolio standards.

Recent studies have explored public support for different clean energy technologies and policies. For example, a 2012 survey evaluated Americans' support for a clean energy standard, finding a willingness to pay

of 13% in higher electricity bills for a policy targeting 80% clean energy by 2035 [5]. Despite the rise in the study of attitudes toward clean energy, however, there has been less attention to the attributes or information most valued by individuals when evaluating these alternatives. Konisky and Ansolabehere (2014) find that preferences for clean energy technologies are typically based on the perceived attributes of these sources, such as lower cost of electricity or reduced environmental harm [6]. Other research has also shown that health information can be more salient than bill savings in motivating persistent reductions in energy consumption and garnering support for renewable portfolio standards [7, 8], that social co-benefits can increase support for climate mitigation [9], and that information on energy saving actions can crowd out support for climate change mitigation [10].

While studies of public opinion often rely on surveys or other direct elicitation methods, more recent work has explored the viability of using choice experiments to evaluate energy preferences. Discrete choice experiments can be used to replicate real choice scenarios in order to encourage respondents to engage with tradeoffs, and can serve as proxy for decision making

Table 1. Attribute levels (see SI section B for details on the mixes that comprise each portfolio level).

Attribute	Levels used in survey
Electricity portfolio	Current national mix (baseline)/natural gas/nuclear/renewables/energy efficiency
Monthly electricity bill	+20%/ +10%/ no change/ −10%/ −20%
Climate change related emissions (CO ₂)	+70%/ +30%/ no change/ −30%/ −70%
Health related emissions (SO ₂)	+70%/ +30%/ no change/ −30%/ −70%

when it is difficult to observe actual choices [11]. Recent energy-related discrete choice surveys have studied the effect of labeling on consumers' preferences for energy efficiency appliances [12], preferences for buying electricity from renewable sources [13], tradeoffs between electricity bills, reliability, emissions, and energy sector employment [14], and the effect of technology labels on support and willingness-to-pay [15, 16].

In this study, we explore how providing information on climate change and health-related air pollution affects individuals' consideration of electricity generation alternatives. We deploy a choice-based survey to US citizens ($N=822$) recruited using Amazon Mechanical Turk. Respondents are asked to compare alternatives with different sources of electricity, climate related emissions, emissions of air pollutants that affect respiratory health, and changes to electricity bills. Using a randomized control trial, we investigate how varying information on climate and health aspects of emissions reductions affects respondents' implicit support and willingness to pay for alternative energy portfolios.

Methods

Here we explain the design of the survey, the experimental design for the randomized control trial, the sampling method used to collect respondents, and the methods used to analyze the results.

Survey design: Respondents in the survey choose between different alternatives of electricity generation portfolios for their state. Each alternative is characterized by a combination of up to four possible attributes, described as follows:

1. The mix of electricity sources—referred to as the '**electricity portfolio**'—shown as a bar graph with the percentage of electricity generation coming from coal, natural gas, nuclear power, or renewable sources. Because demand-side energy efficiency interventions offer an important mitigation alternative, we also include the use of energy efficiency to offset the need for additional generation.
2. Economic cost to the consumer, conveyed as a percentage change to their '**monthly electricity bill**.'
3. Annual carbon-dioxide (CO₂) emissions relative to current levels in their state, which is described to respondents as '**climate change related emissions**.'

4. Annual sulfur dioxide (SO₂) emissions in their state, and which is described to respondents as '**health related air pollution**.' Both emissions changes are presented with a number line to facilitate understanding.

The levels for the attributes are shown in table 1. For the electricity portfolios, each level is a representative portfolio named for the fuel that is dominant in that portfolio. The current national mix portfolio corresponds to the 2014 electricity generation in the United States, in which coal supplied about 40% of total generation [17]. To construct the other portfolio levels, we decrease generation from coal and increase generation from the alternative sources (see SI section B for each portfolio level, available at stacks.iop.org/ERL/13/024026/mmedia).

The levels used for changes in emissions and electricity bills are based on either proposed or discussed policy objectives. For example, the EPA's Clean Power Plan targeted a national reduction in annual CO₂ emissions of 30% from a 2005 baseline and predicts a range of possible changes to retail electricity prices on the order of 3%–10% [18, 19]. We also include a level representing deeper emissions cuts of 70% reductions in annual emissions, which the Intergovernmental Panel on Climate Change (IPCC) suggests is necessary for stabilizing CO₂ levels by the end of the century [20]. With four attributes and five levels each, there are a total of 625 possible combinations, and each respondent sees a semi-random subset of these combinations generated using Sawtooth Software's complete enumeration algorithm.

Respondents entering the survey are first provided information on the survey objectives and structure, and are asked to sign a consent form to participate. After indicating their state of residence, respondents then see a visual guide to the structure of the survey. We also supply information on the attributes provided in the task, including on the effects associated with CO₂ and SO₂ emissions.

After this introduction, respondents answer a screening question to assess their comprehension of the introductory material on the attributes. Respondents proceed with the choice experiment and are faced with 16 screens that provide two alternatives from which to choose. The survey ends with follow-up and demographic questions.

The entire survey was designed and hosted using Sawtooth software. The survey is available online (see link in SI) and a full, printed example of the online survey shown to respondents in group 4 is given in SI section M. Except for some tasks that were fixed to test for comprehension and attention, the levels of the attributes and their combinations with other attributes were randomized for each respondent.

Experimental protocol: To test for the relative importance of emissions information to individuals' preferences, we include a between-subjects experimen-

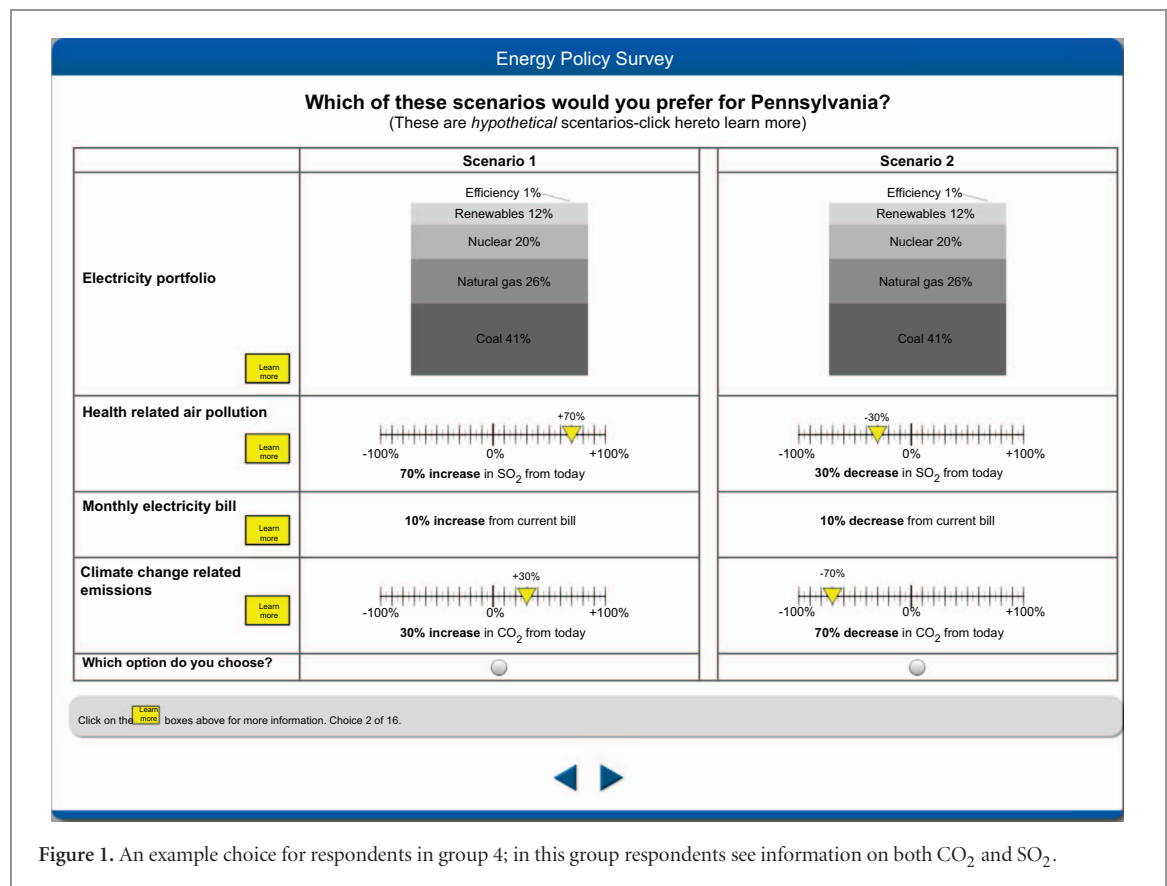


Figure 1. An example choice for respondents in group 4; in this group respondents see information on both CO₂ and SO₂.

tal design in which the number of attributes displayed in the task varies by respondent. Between-subjects designs have been used in several previous energy related stated preference contexts [12]. Specifically, we have four experimental groups that see alternatives that either include or omit the two emissions attributes. The groups are outlined as follows.

1. **Group 1:** respondents see only information about the electricity portfolio and the electricity bill.
2. **Group 2:** respondents see only information about the electricity portfolio, the electricity bill, and CO₂ emissions.
3. **Group 3:** respondents see only information about the electricity portfolio, the electricity bill, and SO₂ emissions.
4. **Group 4:** respondents see information about the electricity portfolio, the electricity bill, CO₂ emissions, and SO₂ emissions.

We administer the survey by randomly assigning respondents to one of the four groups. Respondents are assigned to a group automatically by a computerized random number generator and have no ex ante or ex post knowledge that there are different experimental conditions. An example choice screen for the Group 4 experimental condition is provided in figure 1. Examples of choice screens for the other groups and a schematic of the experimental design can be found in SI section A.

Study respondents: Respondents were recruited through Amazon Mechanical Turk (MTurk) ($N=822$). MTurk provides a convenience sample, although previous research has found that MTurk samples are often comparable to other internet sampling methods [21, 22]. This sample size was selected based on the minimum size needed to produce standard errors to distinguish main effects, based on a statistical power analysis from an initial pilot test of 50 individuals (see SI section H for details). Respondents were recruited such that representation from different US states would be proportional to that state's share of the total US population.

The survey was posted online on MTurk from 28–29 November 2015. Respondents were compensated \$1.50 for participating in the survey, with an additional \$0.50 incentive for those who responded correctly to attention checks. The self-reported demographics of our sample are fairly similar to that of the US population, with the exception that our sample had more individuals with higher education levels and who self-identified as Democrats. Summary statistics can be found in SI section C.

Choice modeling and analysis: We analyze the responses to the discrete choice experiment using a random utility model in which utility U for individual i is a function of the attributes in choice j and an unobserved error component (ϵ_{ij}). The error component is modeled by random draws from a Type I Extreme Value distribution [23]. We assume an additively

Table 2. Representation of attribute levels in the mixed logit model.

Variable	Description
X_j^{GAS}	dummy variable for the natural gas portfolio [1: yes, 0: no] (baseline is coal)
X_j^{NUC}	dummy variable for the nuclear portfolio [1: yes, 0: no] (baseline is coal)
X_j^{REN}	dummy variable for the renewable portfolio [1: yes, 0: no] (baseline is coal)
X_j^{EE}	dummy variable for the energy efficiency portfolio [1: yes, 0: no] (baseline is coal)
$X_j^{\text{CO}_2}$	percentage change in annual CO ₂ from current emissions levels (1: 100%)
$X_j^{\text{SO}_2}$	percentage change in annual SO ₂ from current emissions levels (1: 100%)
X_j^{BILL}	percentage change in monthly electricity bill from current level (1: 100%)

separable model that is linear in parameters and has the basic form:

$$\begin{aligned}
 U_{ij}(X) = & \beta_{\text{GAS}} X_j^{\text{GAS}} + \beta_{\text{NUC}} X_j^{\text{NUC}} + \beta_{\text{REN}} X_j^{\text{REN}} \\
 & + \beta_{\text{EE}} X_j^{\text{EE}} + \beta_{\text{CO}_2, i} X_j^{\text{CO}_2} \\
 & + \beta_{\text{CO}_2, i}^2 (X_j^{\text{CO}_2})^2 \\
 & + \beta_{\text{SO}_2, i} X_j^{\text{SO}_2} \\
 & + \beta_{\text{SO}_2, i}^2 (X_j^{\text{SO}_2})^2 \\
 & + \beta_{\text{BILL}, i} X_j^{\text{BILL}} + \varepsilon_{ij}
 \end{aligned} \quad (1)$$

where each β represents the modeled coefficient for an attribute variable X , described in table 2. We include a semi-quadratic emissions term based on an initial analysis that suggested non-linearity in these terms (SI section I), preserving the sign after squaring the change in emissions. Each model is estimated separately for each experimental group, and groups that do not see emissions information are modeled without those regressors.

We use a mixed logit model that allows for heterogeneous preferences across individuals as well as groups of observations, correlated errors, and unrestricted substitution patterns [23]. We allow for a distribution of coefficients for the emissions terms (i.e. changes in CO₂ and SO₂), assuming multivariate normal distributions. No random effects were estimated in Group 1 (where no emissions were shown).

Although we can compare the modeled coefficients for each attribute to evaluate individuals' tradeoff preferences, comparing the logit coefficients directly provides little insight into respondents' behavior. To make these coefficients interpretable, we translate them to probabilities that the average respondent supports an alternative with a specified attribute combination. These probabilities are derived from the modeled utility function using the following relationship:

$$P_j(X) = \frac{1}{1 + e^{-V_j(x)}} \quad (2)$$

where $V_j(x) = \bar{\beta} \cdot \bar{X}_j$ is the observed utility function for an average respondent, or $U(X)$ from equation (1) above, less the unobserved error term ε_{ij} . These conditional probabilities represent the probability that an average respondent will favor an alternative given a specified change in an attribute level, with all other attributes held at baseline levels. Thus, the utility function models differences in attribute levels between the two alternatives. We compare the estimated probabilities for different combinations of attribute levels to

assess the relative influence of different attributes. The probability results reported here represent results for individuals at the mean of the sample.

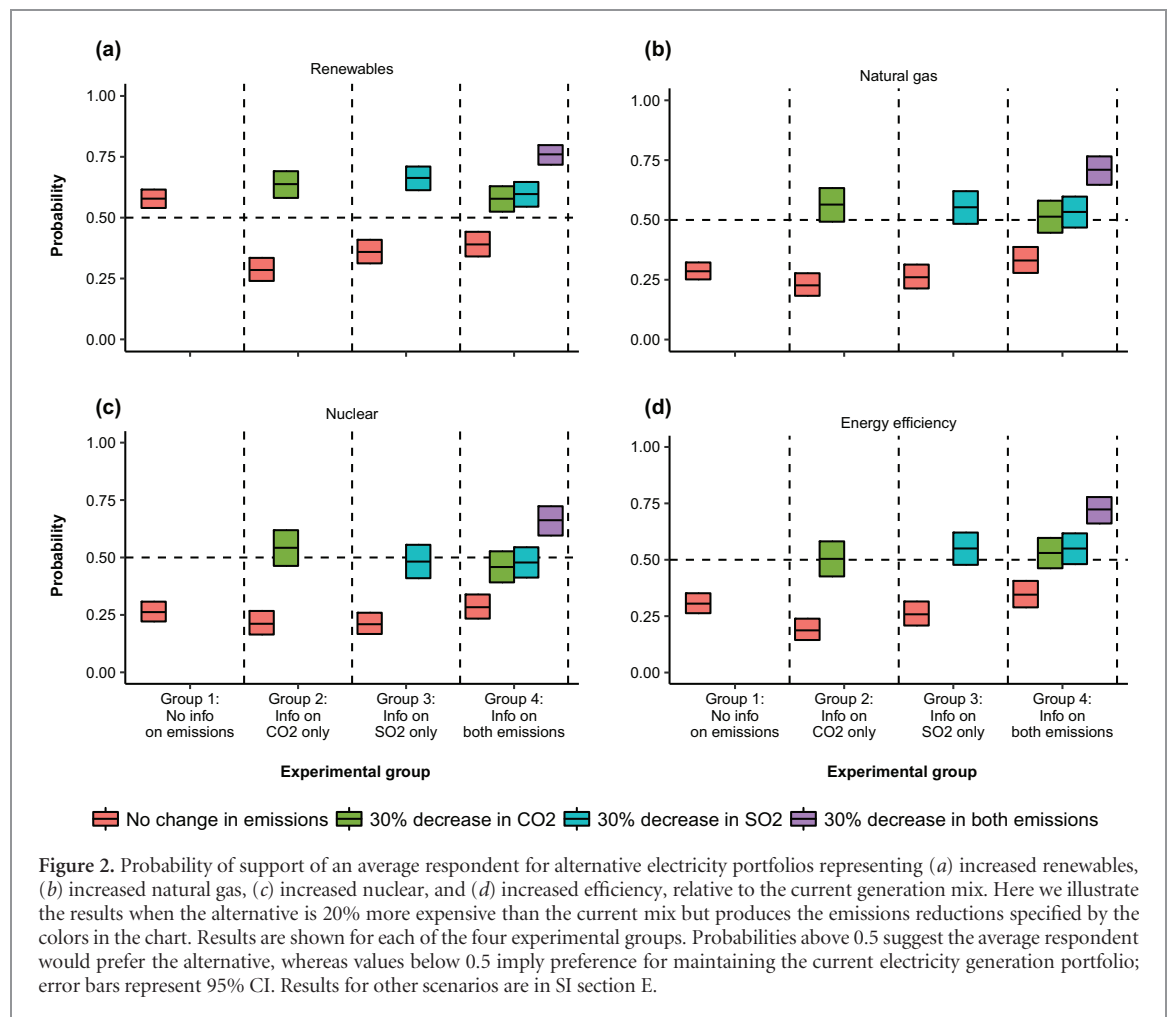
Likewise, we can use the regression results to compute willingness-to-pay (WTP), which represents how much an average individual is willing to pay in economic cost for an additional unit of another attribute [24]. WTP for a one-unit change in an attribute can be calculated using the ratio of coefficients from the estimated mixed logit model:

$$\text{WTP}^{\text{ATTRIBUTE}} = -\frac{\beta^{\text{ATTRIBUTE}}}{\beta^{\text{BILL}}} \quad (3)$$

WTP for any combination of attributes can be found by substituting the attribute levels into the utility function in equation 1 and then solving for the level of bill such that utility is zero. At this level of bill increase, the respondent is indifferent between the new alternative and the current scenario, so this value represents the WTP for that attribute combination. As with the probability results, the WTP values reported are those representative of individuals at the mean of the sample. While we refer to this estimate as the 'average WTP', it is the WTP of the average respondent and is distinct from the average of WTP values estimated for each respondent. Using respondents' self-reported average electricity bills and emissions estimates, we can also estimate the implicit WTP per ton of pollutant reduced from respondents' choices (see SI section J for details).

Results

Effect of emissions information: Figure 2 shows the probability of support for different electricity generation portfolios relative to the current electricity portfolio in the US. For illustration purposes, we present scenarios in which the alternatives have a 20% higher monthly electricity bill than the baseline, along with different combinations of 30% reductions relative to the baseline in either CO₂, SO₂, or both. We choose these levels in part because our linear model approximation seems most appropriate within this range, while larger changes to emissions seem to exhibit increasing non-linear effects (see SI section I). Overall, our results hold independently of the level of emissions and electricity bills changes in the range considered, and results for other levels of monthly electricity bills and emissions levels are explored in SI section E.



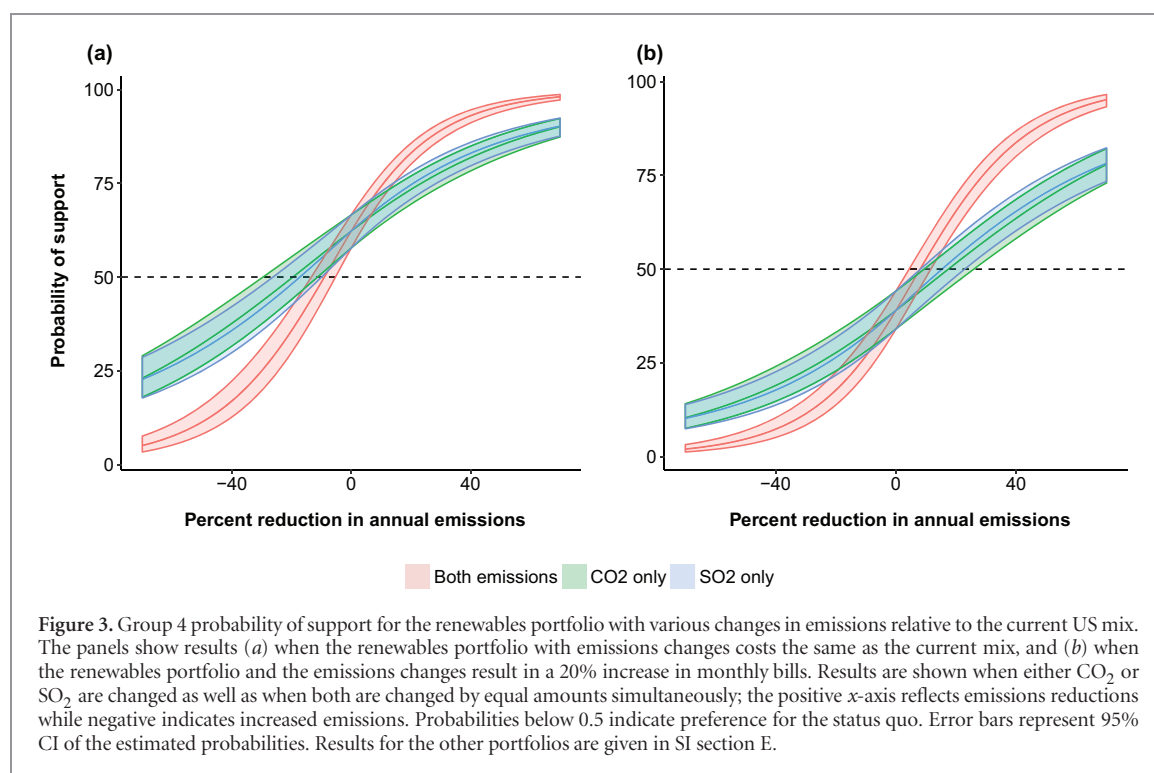
The figure shows that without any emissions information (Group 1), the average respondent supports paying 20% more for the renewables portfolio, but tends to prefer to keep the current electricity generation mix over the nuclear, natural gas, and efficiency portfolios. Respondents that are explicitly provided with information on either CO₂, SO₂, or both (Groups 2–4) place less importance on the portfolio itself and more on emission reductions, preferring the current mix to the more expensive alternative if emissions are the same.

When a 30% reduction in either CO₂ or SO₂ accompanies the alternative portfolio, most respondents still prefer renewables but switch to preferring natural gas relative to the current mix. If the alternative reduces both emissions simultaneously, the average respondent prefers it regardless of its composition. When shown information that displays a 30% reduction in both pollutants, respondents show an even larger increase in support. Average support for renewables increases from 58% in Group 1 with no emissions information to 77% with a joint reduction in emissions of 30%, an increase of 19 percentage points (95% CI: 10%–25%).

While this increase is particularly evident for renewables, the average respondent would support any of the portfolios if they provide simultaneous 30% reductions in both pollutants. Although the findings for

30% emissions cuts are shown here, this pattern of support holds for other emissions changes as well (SI section E).

Respondents in groups which are only shown one emissions type tend to value reductions in that specific pollutant more highly than those who are shown both types of emissions. For example, a renewable alternative with a 30% reduction in SO₂ emissions elicits support from 66% of respondents in Group 3, but that same alternative attracts only 58% of respondents in Group 4, a decrease of about 8% (95% CI: 16% decrease to 4% increase for both CO₂ and SO₂). This pattern suggests that respondents value each emissions attribute more highly when presented individually relative to when it is presented as one of two types of emissions. One plausible explanation for this is that respondents are conflating the benefits of the two types of emissions when only one is shown; for example, respondents seeing SO₂ reductions in Group 3 may assume that reducing those emissions would also provide climate benefits. This process parallels a similar bias known as the embedding effect by which respondents tend to overvalue a good when presented alone if they perceive it to be part of a more inclusive set [25]. As Mitchell and Carson (1989) describe, respondents may treat one attribute or policy as ‘symbolic’ of another, inadvertently causing them to ‘assign to



the proposed policy some of the values they have for related policies' [26]. Accordingly, respondents seeing SO₂ reductions in Group 3 may associate that with additional action on climate change, inflating their valuation of those emissions reductions. When both health and climate emissions are shown explicitly in Group 4, respondents can more easily separate their values for those two benefits across the two types of emissions, causing them to value each attribute less. The value respondents assign to emissions reductions thus seems to depend on how explicitly defined the benefits of those reductions are, a finding which is also consistent with support theory [27].

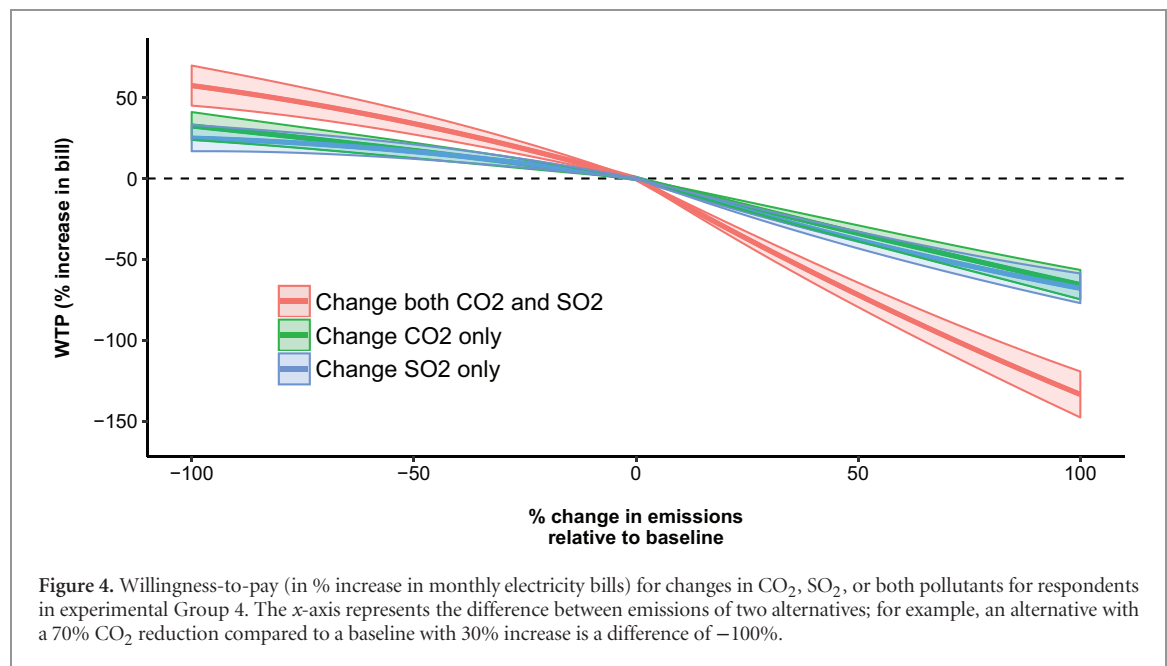
We can also focus on the tradeoffs respondents are willing to make when given complete information on both the emissions of CO₂ and SO₂. As an example, figure 3 shows the probability that an average respondent in Group 4 would choose a renewables portfolio over the current mix given various combinations of emissions reductions, assuming either no change in bills (left panel) or an increase of 20% (right panel). Results for the other portfolios are given in SI section E.

Absent any changes in emissions or electricity bills, respondents tend to prefer having a portfolio with higher renewables rather than the current portfolio, with respondents choosing the renewable portfolio 62% of the time (95% CI: 57%–66%). If renewables are expected to result in a 20% increase in electricity bills relative to the current mix (right panel), the probability of support drops to 35% (95% CI: 31%–41%) and respondents prefer to keep the current electricity generation portfolio. If the renewables option also yields a 30% reduction in either CO₂ or SO₂ emissions, however, respondents revert to preferring renewables even

with increased bills, with support around 57% when reducing CO₂ (95% CI: 51%–62%) and 58% when reducing SO₂ (95% CI: 53%–64%). This suggests a 30% reduction in emissions of either SO₂ or CO₂ alone was typically not enough to offset the bill increase and regain the same probability of support for renewables under the alternative with no increase in cost.

On the other hand, if 30% reductions in both emissions are achieved simultaneously, the probability of support is close to 77% (95% CI: 72%–81%) even with the 20% increase in monthly electricity bills. Thus, if both CO₂ and SO₂ emissions are reduced, respondents' choices suggest they overwhelmingly prefer renewables even with an increase in electricity bills. For a renewables alternative that is 20% more expensive, the average respondent required a 15% reduction in SO₂, an 18% reduction in CO₂, or an 8% reduction in both to be indifferent between that and the current mix (breakeven values for the other portfolios are reported in SI Section E). We also note similar probabilities for 30% reductions in CO₂ and SO₂, suggesting that despite heterogeneous preferences for these two types of emissions, the effect of reductions in emissions related to climate change and health effects is relatively similar on average. Support levels are also similarly high for the other portfolios if they can be expected to produce simultaneous reductions in both pollutants.

Willingness-to-pay for emissions reductions: Figure 4 illustrates respondents' implicit WTP for different levels of CO₂ and SO₂ reductions, independent of the electricity portfolio. The results show that the average respondent has a higher total WTP in electricity bills for addressing both climate change and air pollution simultaneously. As an example, a typical respondent in



experimental groups with only one type of emissions (Group 2 or 3) has a WTP around 22%–24% more in monthly bills for a 30% reduction in annual CO₂ or SO₂ (95% CI: 19%–27%). In the case where both CO₂ and SO₂ are shown (Group 4) and are simultaneously reduced by 30%, the average respondent's WTP is close to 34% (95% CI: 29%–39%).

Interestingly, WTP for a joint reduction of both emissions by 30% in Group 4 is less than the sum of the WTP for CO₂ in Group 2 (22%) and SO₂ in Group 3 (24%). As discussed above, this suggests that even when respondents are not provided with information about one of the pollutants, they are still making assumptions about changes that are occurring with that omitted pollutant. WTP for changes to SO₂ for respondents in Group 4 is reduced by 16% relative to its value for respondents in Group 3, while WTP for changes to CO₂ in Group 4 falls by 30% compared to Group 2. This suggests that respondents without more complete information are more likely to presume air quality benefits from reducing CO₂ emissions. Respondents' choices also suggest that their WTP for emissions reductions is lower than the amount of money they would need to compensate for an increase in emissions of the same magnitude. This finding, reflected by the kink in the graph in figure 4, is consistent with the literature on prospect theory relative to gains (i.e. emissions reductions) and losses (i.e. increased emissions) (see SI section F for more details).

Using our model's WTP estimates along with respondents' self-reported monthly electricity bills, emissions of CO₂ and SO₂ from electricity generation in 2014, and the total number of US households, we also calculate the implicit WTP per ton of emissions reduced (see SI section J for details on the method used). On average, respondents in experimental group 4 made choices consistent with an implicit WTP of

\$30–50 per ton CO₂ and \$27 000–40 000 per ton SO₂ avoided in \$2015. For comparison, recent estimates of the marginal damages caused by each of these pollutants are approximately \$40 per ton for CO₂ and a national average of close to \$38 000 per ton for SO₂ [28, 29]. We note that these dollar per ton estimates require more assumptions, and that respondents may have made different choices if they had been given monetary values instead of percentages. Nevertheless, we think these implicit estimates serve as a useful benchmark and a test of how to connect this type of value elicitation to the social costs relevant for policy.

Finally, we explore heterogeneity in responses by demographic characteristics such as gender, race, income, education, and political party. Although there is substantial heterogeneity in responses, support for emissions reductions, and tolerance of bill increases, in general we find that there was little evidence that the demographic characteristics were significantly related to these preferences in our sample. One effect that we do observe is that respondents who self-identify as Republicans tend to place more importance on lower bills and less importance on changes to CO₂. The results from our demographic and heterogeneity analyses can be found in SI section D.

A concern when using discrete choice methods is whether respondents are providing responses that reflect true preferences, and whether the assumptions of the models used to assess these preferences apply. We assess the consistency of individuals' responses by: (i) including attention checks, (ii) testing for consistent responses with transitive preferences, and (iii) evaluating whether respondents have linear preferences. We find that 95% of the respondents correctly answer our two attention check tests, while 97% of respondents have transitive preferences. Fewer individuals—but still a majority (80%)—

demonstrate linear preferences for moderate changes in the attributes, although respondents tend to have diminishing sensitivity to larger emissions changes. Details on these checks are discussed further in SI section G.

Discussion and policy implications

Our results indicate that respondents are generally supportive of electricity generation portfolios that are associated with lower emissions, even if these options result in an increase in their electricity bills. This willingness to sacrifice monetary benefits for reducing emissions is consistent with other research on altruistic behavior in energy decisions [30, 31].

Our results also suggest that the attributes of electricity generation are an important determinant of support, a finding consistent with previous work [6]. If alternative energy portfolios will lead to large increases in electricity bills without corresponding emissions reductions (perhaps because of intermittency and the use of fossil fuel backup), support from the public may be lower than anticipated. However, if proposed new energy mixes do yield emissions reductions, communicating those outcomes in terms of both climate and health benefits is likely to increase people's willingness to support those mixes, even with increased monthly electricity bills. In addition, when more benefits of a policy are communicated (i.e. when information on CO₂ emissions is provided in addition to information on SO₂ emissions, or vice versa), respondents are increasingly willing to pay more for clean energy options.

Proposed climate mitigation policies have traditionally focused on the importance and benefits of reducing CO₂ emissions. The US Environmental Protection Agency (EPA) and other entities have in recent years worked to emphasize the 'co-benefits' of reducing other air pollutants such as SO₂. This research suggests that this focus is indeed likely to bolster support for climate mitigation efforts. Of course, actual support for mitigation policies will depend on how the policy options are presented and framed to people. If the proposed policy is a cap-and-trade market or carbon tax, support levels may be quite different. However, we note that a carbon tax or cap and trade program would likely result in changes to electricity prices and electricity generation portfolios such as the ones we present in our study. Thus, we do think there are important insights our research could contribute to evaluating support for these policies.

Social science research has shown that stated preference and choice experiments may have limitations in terms of predicting real choice behavior [31, 32], but in the absence of policy experimentation, they provide useful insight to guide policy design. Our work suggests that there is support for alternative electricity generation portfolios and emissions reductions

strategies, and that communicating information regarding both climate and health benefits is likely to increase public support and willingness to pay for efforts to reduce emissions.

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ORCID iDs

Inês Azevedo  <https://orcid.org/0000-0002-4755-8656>

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