Determinants of Willingness-to-Pay For Internal Carbon Pricing Programs

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Abstract

Non-governmental entities such as businesses and a small number of U.S. universities have adopted voluntary internal carbon pricing to reduce greenhouse gas emissions, to finance carbon reduction programs, to signal sustainability and to prepare for future mandatory carbon reductions. Little is known, however, about individual preferences for the introduction of these programs, or how preferences for these programs vary across potential program designs. We conduct a stated preference survey in the form of an advisory referendum on potential internal carbon-pricing programs at a large public university. Roughly 1,000 individuals each consider unique sets of several hypothetical programs which vary in their costs, emission reductions, types of fees charged, and uses of revenue. We use these data to estimate a structural random-utility model to explain program preferences. This model permits us to infer, for different constituencies within the campus community, willingness to pay for internal carbon pricing programs that vary in their attributes. Our model is flexible enough to allow for benefit transfer exercises to campuses with populations that differ in their political attitudes, income levels and other characteristics. Individual administrative data on both respondents and non-respondents, plus permanent-address neighborhood data at the zip code level, allow us to adjust our estimates for systematic differences in response rates that may be correlated with willingness to pay.

JEL classification: Q50, Q51, Q54, M14

Keywords: climate, carbon pricing, stated preferences, distributional effects, WTP

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1 Introduction

Given that the U.S. has stepped away from any plans to price carbon at a national level, either through a carbon tax or a carbon cap-and-trade program, policymakers, climate advocates and others have expressed hope that voluntary non-governmental programs can substitute, at least in part, for the federal government's lack of a coordinated climate change mitigation policy. More than 500 U.S. businesses have implemented voluntary internal carbon pricing (ICP) programs which charge internal company divisions and individual projects for the carbon emissions they generate. Firms institute internal carbon pricing for several reasons. Some firms see it as a way to signal their commitment to sustainability, while others view it as a way to raise revenue for green energy projects. Other firms view internal carbon pricing as a means to prepare for the adoption of potential mandatory carbon government pricing policies in the future, either by enacting their own fee, or using an estimate of future carbon prices to make long-term decisions about cost-effective combinations of fixed and variable inputs (i.e. capital equipment and fuel choices) that would be relatively more cost-effective under a future carbon price, even though they might not be today. These strategies could also be used by academic institutions, non-profit organizations, and the public sector, as argued by Barron and Parker (2018).

These internal carbon pricing programs have yet to receive much attention from the formal economics literature. The extent to which individuals are willing to pay to support these programs, or how preferences vary with program design, is relatively unknown. A better understanding of individual preferences for internal carbon-pricing would increase our sense of when and where private climate change mitigation programs may be acceptable to stakeholders. In addition, understanding preferences over the design of private carbon-pricing programs may also clarify some aspects of how people might react to alternative designs for eventual governmental carbon-pricing programs (at either the state or the national level).

A few universities have begun to experiment with internal carbon pricing. Most notably, Yale has recently introduced an internal carbon price in the form of a building energy fee, as described in Gillingham et al. (2017). Universities offer a rich setting to study individuals' preferences for carbon pricing programs, as they are large institutions consisting of several administrative divisions and many types of stakeholders who are likely to have varying preferences concerning alternative designs of internal carbon pricing programs. However, these programs are still rare, so existing evidence remains limited.

We conduct a stated-preference survey using an advisory referendum format, yielding a sample of ICP program preferences for approximately 1,000 respondents (including students, faculty and staff) at a large public university. In each choice scenario, respondents are asked to consider either one or two hypothetical carbon-pricing programs, along with a status quo alternative (with no program and no out-of-pocket costs). Programs vary in the emission reductions they achieve, and the unavoidable cost of the program to the respondent, as well as by the initial incidence of their costs across the university's population and how the collected revenues would be spent. These choices are then used to estimate a Random Utility Model (RUM) that is used to recover willingness to pay (WTP) for carbon reductions as a function of program attributes and respondent characteristics.

Increasing attention has been paid to equity issues in the implementation of carbon-pricing programs more generally. In this context, individuals may have different views of two programs that cost the same and deliver the same reductions in carbon emissions, depending on how the costs are borne across stakeholder groups, and how the revenues produced by carbon pricing are distributed across alternative uses. For example, uniform lump sum fees for everyone may be perceived as less "fair" than a fee schedule that reflects a "polluter pays" principle. In our choice scenarios, the funding for carbon emissions reduction projects can be raised, to varying extents, through simple lump-sum carbon fees on students, faculty and staff, through carbon fees on university-paid air travel, through charges on emissions generated through building energy use, or through state-government support funded by taxpayers. The revenue can be spent, to varying extents, for on-campus carbon reduction projects, for off-campus carbon "offsets," or it can be "recycled" back into academic programs.[1]

A natural concern is that the subset of stakeholders who respond to a survey about internal carbon pricing programs may differ systematically from the stakeholder population as a whole. Fortunately, we have access to conformable individual-level administrative data, for both respondents and non-respondents, which allow us to correct for systematic sample selection.[2] Having basic data on both respondents and non-respondents allows us to create a statistical model of survey response propensity. We construct a measure of each respondent's deviation from the average response propensity in our random sample from the university population who were invited to take the survey. This de-meaned response propensity is allowed to affect the estimated marginal utility of all program attributes, and we then simulate the WTP measures that would be expected, had everyone in the usable sample had a response propensity equal to the mean in the invited population.

Additionally, we strive to make our estimated WTP function useful for benefit transfer purposes. Other universities that might consider internal carbon pricing programs may have systematically different stakeholders from those at the university where our study was conducted. Our WTP function depends on the distribution of incomes, political attitudes, and other demographic and climate-related extreme-weather experience variables. It will thus ultimately be possible for us to simulate the demand for specific types of internal carbon-pricing programs within the range spanned by our randomized design, at other universities with mixes of stakeholders that differ from the mix at the university where we fielded our survey.

The paper is organized as follows. Section 2 reviews the context for internal carbon pricing and briefly discusses the prior literature. Section 3 lays out our empirical strategy. Section 4 presents the results of our estimated choice model. Section 5 concludes and discusses potential

[1]Of course, the case with 100% of the funding raised from state taxpayers and 100% of the spending devoted to academic programs would not be an internal carbon pricing program at all, just government-funded higher education. We do not include extreme mixes such as these in our program design.

[2]A protocol for identity-redaction protected campus subjects, and all data for this study are stored on a FERPA-compliant server.

future directions for research.

2 Institutional Setting And Prior Literature

Over 500 companies in the U.S., as of 2017, had established internal carbon pricing (ICP) programs, and at least another 700 planned to enact a program within the next two years CDP (2017). These ICP programs have taken several different different forms.[3] The most simple ICP program involves a carbon levy on individual divisions, which is then used to fund carbon reduction programs. ICPs can also be used to meet emission reduction goals for the institution or merely as a trial run for an anticipated future mandatory government carbon pricing program. Institutions may also consider adding accounting charges based on the anticipated lifetime emissions of new (or replacement) buildings, equipment or technologies under consideration.

Universities have similar goals in the use of internal carbon pricing, seeking to use these programs as a way, simultaneously, to reduce emissions and/or raise money for future carbon-reduction projects. Universities may also see internal carbon pricing as a way to develop a reputation for sustainability as a means to attract students, to advance the university's mission, or as a way to educate their students about sustainability and carbon pricing.

It is technologically cost-prohibitive to meter accurately all carbon emissions related to a university campus, so we choose instead to focus this study on two major source of emissions: air travel and building energy use. On most campuses, these tend to be some of the largest sources of carbon emissions, with building heating often being the largest. For the university surveyed in this study, building heat accounts for about 48 percent of total estimated carbon emissions, and university-sponsored air travel accounts for about 13 percent. Air travel and building energy use also tend to be the carbon sources for which universities have the most information about the origin and quantity of their carbon emissions. Yale University's program is perhaps the most well-known

[3]For a full discussion of ICP programs in the private sector see Ahluwalia (2017) and Camuzeaux and Medford

current example of a university internal carbon pricing program (see Gillingham et al., 2017). In the Yale program, campus building carbon emissions are "taxed" and the revenue is refunded, according to their relative performance, to occupants. Other programs are being explored at Swarthmore and Smith Colleges.

Little academic work has addressed individual preferences for internal carbon pricing. In contrast, there is an extensive literature that has used stated preference methodologies to examine the demand for climate change mitigation for national-scale climate mitigation policies.

For national-level climate policies, Lee and Cameron (2008), and Cai et al. (2010) explore preferences concerning the distribution of costs of climate-change mitigation programs across groups, and the perceived distribution across country groups of the benefits of these programs (i.e. avoided damages). Groh and Ziegler (2018) finds that individuals prefer a "polluter-pays approach" over a distribution following an "ability to pay" approach which in turn is preferred to a scenario that distributes costs equally across households. Brannlund and Persson (2012) find evidence for distributional preferences within a developing country. The literature clearly demonstrates that distributional consequences have a strong influence on people's willingness to bear the costs of climate change mitigation programs more broadly.

Prior work has established that individuals are skeptical of revenue recycling. Carattini et al. (2017) examine consumers' preferences for carbon pricing programs using voting data from a Swiss carbon-tax referendum. They find that an important determinant of opposition to carbon taxes is concern about negative distributional effects from the carbon tax. Voters are skeptical of alternative revenue recycling plans and prefer that revenues be spent directly on pro-environmental programs, such as green energy or R&D. These voters, however, can be influenced to support revenue recycling more enthusiastically if they are provided with more-comprehensive information about changes in carbon emission levels as a result of the tax. Brannlund and Persson (2012), Sonnenschein and Smedby (2019) and Rotaris and Danielis (2019) all find evidence that WTP for emission charges increases if revenues are specifically "earmarked" for emission-reduction projects. Baranzini and Carattini (2017) show that individuals tend to ignore the incentive effects of carbon taxation.

Also relevant to this paper is Baranzini et al. (2018). Through a choice experiment, these authors study preferences for international versus domestic forestry-based carbon offsets. Participants are more likely to choose international offsets after being reminded about their relative cost-effectiveness. Information treatments that remind participants about co-benefits or monitoring concerns seem to show no effect.

Our survey also contributes to our understanding of consumer demand for clean energy and energy financing. In the broader literature, several papers have examined green energy demand, including Ma et al. (2015), and Conte and Jacobsen (2016). These papers find that consumers express a positive WTP for green energy that tends to increase with education level, to be higher for women than for men, and that this demand often seems to include a "warm glow effect," where consumers wish to buy at least low levels of renewable-derived electricity, but are less willing to pay for higher levels.

3 Survey Design and Analytical Framework

3.1 Description of Survey

Our survey was administered electronically, using the Qualtrics survey platform, in two waves—one in the late Spring of 2018 and one in the Fall of 2018. Our respondents are randomly selected from the set of all students, employees, staff and administrators affiliated with the university.[4] The survey invitation states that the university is seeking input about whether, and how, to implement an internal price on carbon and that the responses to the survey will be used by university administrators as they decide whether such a program should be implemented. Respondents are offered

[4] In the spring wave, we excluded graduating seniors because their affiliation with the university was ending and their "votes" would have no consequences for them, personally.

a five-dollar incentive in the form of a digital gift certificate to the campus store. On average, the survey took about twenty minutes to complete, although some respondents chose to study the optional background information in considerably more detail. In total, we collected 1052 responses, of which 997 were fully usable, representing a 9.4% response rate.

A detailed description of the structure of the entire survey, and one instance of the randomized survey instrument, are provided in the Appendices to this paper.[5] We sought to incorporate current best practices for stated-preference survey design, as documented in Johnston et al. (2017). Here, we review just the key features. The core of our survey is a set of "program choice" tasks. Respondents are offered the opportunity to express their preferences (i.e. to "vote") on their most-preferred alternative from a choice set that includes either one or two specific internal carbon-pricing programs versus No Program. Each alternative is described in terms of a common set of attributes, with the No Program alternative representing the status quo. The key attributes of each internal carbon-pricing program are the percentage-point net reduction in carbon emissions that the program is projected to achieve, and the unavoidable annual cost to the respondent. But we also focus on the fact that internal carbon-pricing programs can be implemented in a wide variety of different ways. We direct our respondents' attention to the distributional consequences of the different programs, in terms of both (a) how the costs of the program would be borne, and (b) how the revenue raised by these programs might be spent.

We define the default program as one which would be funded by an across-the-board "average carbon fee" charged to all students and employees of the university. The revenue to be raised, in this default case, would also be spent entirely on internal carbon-reduction projects within the university. However, it is not yet clear how the other details of any prospective ICP program would be settled. Thus, we designed our survey to permit an assessment of how individual willingness to pay for carbon emissions reductions might vary systematically with differences in the way the costs are borne and differences in the way the revenues are used. We allow the cost of the program

[5] The survey instrument can be found online by clicking on this link

to be funded in four distinct ways. In addition to (a) a flat carbon fee on all students and employees, funds can be raised through (b) a fee on university-sponsored air travel, (c) a charge for the carbon emissions of campus buildings, or (d) by relying on funds raised from the state's taxpayers. Besides spending the revenue raised for (a) on-campus carbon-reduction projects, some of the revenue could go towards (b) off-campus "carbon offsets," or (c) some revenue could be recycled in the form of spending on academic programs. All choice sets offered to each respondent are randomly populated, in advance, with different mixes of program attributes, so every copy of the digital survey "instrument" is essentially unique. The only constraints are that programs offering higher carbon reductions generally cost more money, and the difference in cost between any pair of programs offered in the same choice set is constrained to be at least five dollars.[6]

The survey begins with an extensive tutorial. Respondents are given information about the university's current carbon emissions and about internal carbon pricing programs in general. Each respondent's degree of familiarity with existing governmental carbon pricing programs is elicited. The choice task and each program attribute are explained in detail. Throughout the tutorial we check the respondent's understanding through frequent questions. Misconceptions are corrected. After the choice tasks, we collect information on stated attention to attributes, perceptions of research bias, history of exposure to potentially climate-related disasters, responses to a four-question version of the so-called "Six Americas" classification of climate attitudes (as described in Maibach et al. (2011), as well as a series of questions to collect potentially relevant individual-level sociodemographic information not available in the administrative data provided by the university's

[6]Our randomizations are not D-efficient due to complexity that arises from the fact that the cost shares and revenue shares must both sum to one. Additionally we wish to explore non-linearities in functional forms which would be more difficult with traditional D-efficient designs that weight choices towards extremes in attribute space and thus may have trouble distinguishing functional forms. We note that consumer rationality is sometimes tested by offering pairs of programs where one program is both less costly and more effective. However, we elect to forgo such choice sets in favor of more cases where we force people to make tradeoffs. When one program strictly dominates another in terms of cost and effectiveness, one risks having the survey respondent wonder whether they are being tricked. Of course, sufficiently negative *distributional* consequences of a cheaper program that produces greater carbon reductions could overwhelm its cost advantage, but we will be able to infer the circumstances where this might happen from our parameter estimates.

Office of Institutional Research.

3.2 Empirical Strategy

We follow standard stated-preference choice modeling procedures and use our survey data to estimate a random utility model (RUM) of consumer preferences. We assume that U^i_{jt} is the unobserved utility level anticipated by respondent i from internal carbon-pricing program j on choice occasion t. We assume that this indirect utility consists of a systematic component, V^i_{jt}, which can be expressed as a function of the stated attributes of program j (and selected characteristics of respondent i) and estimated parameters, plus a random component that summarizes all other unmeasured factors that affect utility, ε^i_{jt}. This random component is assumed to be known to the respondent who is making the program choice, so that the respondent is fully able to discern the best alternative from their own perspective, but this random component is unobserved by the researcher and therefore contributes an error term to the model.

The systematic component of the level of anticipated indirect utility under any given ICP program is assumed to depend on the respondent's annual household income, Y^i, minus the unavoidable annual cost of the program to that person, C^i_{jt} The key program attribute, other than its cost, is the level of the carbon-reduction benefit expected from the program, B^i_{jt} (measured as a percentage-point reduction in university carbon emissions). However, programs also differ in the shares of their costs borne in ways other than as a fee charged to all students and university employees, denoted as the vector $CostShares^i_{jt}$. If all of these "other" shares are simultaneously zero, the cost of the program in question will be borne entirely as an annual fee charged to all students and employees.

Programs also differ in the shares of the revenue they raise that will be used for things other than internal carbon-emissions reduction programs, denoted as the vector $ExpShares^i_{jt}$. As with the cost shares, if all of these other expenditure shares for a particular program are simultaneously zero, all of the revenue raised by that program will be spent exclusively on internal carbon-reduction programs.

3.2.1 Homogeneous preferences

In our simplest specification, the anticipated indirect utility from a program depends only upon the respondent's income, the program's cost and benefits, and the two vectors of non-default shares of program costs and program revenues. The simplest version of the indirect utility function, for estimation using a standard conditional logit algorithm, is:

$$(1) \qquad U^i_{jt} = V^i_{jt} + \varepsilon^i_{jt} = \alpha(Y^i - C^i_{jt}) + \beta B^i_{jt} + CostShares^i_{jt}\gamma + ExpShares^i_{jt}\delta + \eta^i_{jt}$$

In logit-based binary or multiple discrete choice models suitable for analyzing people's responses to the choice questions posed in our survey, it is assumed that the *relative* anticipated indirect utility levels of the different alternatives drive the choices made by individuals. Every choice task in this study includes No Program as an alternative, indexed as $j = 0$. The No Program alternative involves no cost, no benefits, and thus no issue of the distribution of either the costs or the revenues. Thus $U^i_{0t} = \alpha(Y^i) + \eta^i_{0t}$. The difference in anticipated utility between alternative j and the No Program alternative can then be written as:

$$(2) \qquad (U^i_{jt} - U^i_{0t}) = \alpha(-C^i_{jt}) + \beta B^i_{jt} + CostShares^i_{jt}\gamma + ExpShares^i_{jt}\delta + \varepsilon^i_{jt}$$

where $\varepsilon^i_{jt} = \eta^i_{jt} - \eta^i_{0t}$. In this linear and additively separable specification for utility, individual household incomes conveniently drop out of the utility differences.[7]

The model in equation (2) involves several fixed but unknown preference parameters, including α, the marginal utility of net income, and β, the marginal utility of a percentage-point reduction in

[7]Given that it is always difficult to determine which fraction of household income represents disposable income that might be allocated to the object of choice, many researchers find it convenient to specify anticipated indirect utility as additively separable in income, so that the level of income drops out of the model. While utility is unlikely to be linear in income overall, researchers typically rely on a locally linear approximation when annual program costs can be considered to be relatively small compared to annual income.

carbon emissions, as well as *vectors* of fixed parameters: γ, which conveys the marginal utility (or disutility) of the shares of program costs borne in ways other than just a flat carbon fee imposed on all members of the university community, and δ, which conveys the marginal utility (or disutility) of the shares of revenues spent on things other than just on-campus carbon reduction projects.

If we assume that preferences are homogeneous, or that the estimated marginal utility parameters apply to a "representative consumer," it is possible to back out of the estimated preference function an expression for (a) the representative consumer's willingness to pay for a program with specified coefficients, as well as (b) this consumer's marginal willingness to pay for incremental amounts of each attribute. Maximum annual willingness to pay for a given carbon-pricing program is assumed to be that unavoidable yearly cost that would make this representative individual just indifferent between paying that amount and gaining the benefits from that program, or not paying and forgoing those benefits. Specifically, this yearly cost would make the utility-difference in equation (2) equal to zero. We can impose this equality and solve for the implied annual cost:

$$0 = \alpha(-C^i_{jt}) + \beta B^i_{jt} + CostShares^i_{jt}\gamma + ExpShares^i_{jt}\delta + \varepsilon^i_{jt} \tag{3}$$

$$WTP^i_{jt} = C^{*i}_{jt} = (1/\alpha)\left[\beta B^i_{jt} + CostShares^i_{jt}\gamma + ExpShares^i_{jt}\delta + \varepsilon^i_{jt}\right] \tag{4}$$

At the zero mean of the symmetrically distributed error term, this expression would be simple to calculate. However, it must be remembered that the estimated maximum likelihood parameters are random variables that are asymptotically jointly normally distributed. Given that α is not constrained to be strictly positive, zero is a potential value for this parameter and the analytical expected value is therefore undefined. Many researchers, however, elect to build up a sampling distribution for the value of the implied willingness-to-pay (WTP) function. Using the so-called Krinsky-Robb technique, we make 10,000 draws from the asymptotically joint normal distribution of the maximum likelihood parameters. We combine each independent draw for a set of parameter vectors with the specified levels of the attributes of a given program, namely its percentage-point carbon reduction, B^i_{jt}, along with its non-default shares of costs, $CostShares^i_{jt}$, and its non-default shares of expenditures, $ExpShares^i_{jt}$, to calculate one point estimate of WTP. Over the 10,000 different draws, we build up a sampling distribution for the 10,000 resulting WTP estimates, and report the mean and 5th and 95th percentiles of this distribution to convey a sense of the central tendency for total willingness to pay for such a program, as well as an approximate 90 percent confidence interval for this WTP estimate.

For the marginal willingness to pay for different attributes, for example, a one percentage-point increase in the size of the carbon reduction, our homogeneous-preferences model implies that:

$$\frac{\partial WTP^{*i}_{jt}}{\partial B^i_{jt}} = \frac{\partial C^{*i}_{jt}}{\partial B^i_{jt}} = \frac{\beta}{\alpha} \tag{5}$$

Correspondingly, for share k of each of the three possible non-default cost shares and the two possible non-default expenditure shares, the elements of the two vectors of marginal WTP estimates take the form:

$$\begin{aligned} \frac{\partial WTP^{*i}_{jt}}{\partial CostShare^i_{kjt}} &= \frac{\gamma_k}{\alpha} \\ \frac{\partial WTP^{*i}_{jt}}{\partial ExpShare^i_{kjt}} &= \frac{\delta_k}{\alpha} \end{aligned} \tag{6}$$

The presence of α in each denominator likewise means that a sampling distribution of estimates for each marginal WTP should likewise be built up using draws from the joint distribution of the estimated parameters, and means and 5th and 95th percentiles reported to convey a sense of the precision with which these quantities are estimated.[8]

[8] We note that there exists a user-written program in Stata to calculate, by several methods, *marginal* willingness-to-pay point estimates and standard errors associated with a conventional conditional logit specification where the index is linear in variables. However, this Stata program does not seem to be able to calculate interval estimates for total WTP for programs consisting of specified levels of the full set of attributes. Just knowing the marginal WTP estimates for each attribute and their standard errors is insufficient, because non-zero correlations among the various marginal utility parameters are ignored. Total WTP is a linear combination of correlated random parameters, so the covariances among these parameters must be recognized.

3.2.2 Heterogeneous preferences

We can also generalize the model to allow preferences to vary systematically across individuals with different characteristics. We wish to allow our model to be useful for benefit transfer exercises to other universities that differ in the mix of people that make up their populations (provided that the distribution of people's characteristics has roughly the same support). This requires us to estimate models that explain preference heterogeneity as an explicit function of observable individual characteristics. One of the most popular alternatives for modeling heterogeneous preferences, random-parameters mixed logit models) allow heterogeneity to be unobserved. Mixed logit models estimate, instead, a small number of parameters that describe the specific distribution of specific preference parameters (across the population represented in the sample), among a family of distributions assumed by the researcher. When benefit-transfer exercises are anticipated, however, there is no basis upon which to forecast the possibly different locations and scales of these random preference parameters in the "policy population" to which the model is to be transferred. It is preferable to be able to capture observed heterogeneity to the fullest extent possible.

Let Z_{it} be a vector of individual characteristics. We can then introduce heterogeneity by interacting the individual characteristics with the program characteristics:

$$(7) \qquad \begin{aligned} U^i_{jt} - U^i_{0t} = &-(\alpha' Z_i) C^i_{jt} + (\beta' Z_i) B^i_{jt} \\ &+ (\gamma' Z_i) DistCosts^i_{jt} + (\delta' Z_i) DistSpend^i_{jt} + \varepsilon^i_{jt} \end{aligned}$$

In this more-general model, the marginal WTP for a one-percent-point reduction in carbon would be:

$$(8) \qquad MWTP^i_{jt} = \frac{\hat{\beta}' Z_i}{\hat{\alpha}' Z_i}$$

3.3 Response/Non-Response correction

It is always a concern, in surveys, that the unexplainable component of response rates (due to unobserved heterogeneity that affects response propensities) may be correlated with with the unexplained component of respondents' WTP, such that systematic sample selection bias may therefore distort the estimates. To correct at least partially for sample selection bias, we estimate a model of propensity to respond and use the de-meaned fitted response propensities as ad hoc controls in our model. Rigorous Heckman-style correction models require that the error term in the selection equation and the error term in the "outcome" model be distributed joint normal. This condition is not satisfied when the outcome equation is a conditional-logit choice model for multiple alternatives.

Through an agreement with the University's Office of Institutional Research, we have access to a wide variety of standard administrative data on all invited respondents to the survey. For students, this dataset includes the zip code for the respondent's high school, which we take as a proxy for the location of the neighborhood in which they came of age (and presumably formed some of their opinions about climate change). We treat this zip code as corresponding to each student's "permanent address." For each university employee, we use the zip code of their current residence, taking advantage of the fact that there are some very different communities within commuting distance of the university, where political ideologies differ systematically.

We convert to zip-code extents a wide variety of data on proportions of the population in different categories. These data are drawn from the American Community Survey (originally at the census tract level), from David Leip's Election Atlas for the 2016 Presidential election (originally at the county level), and from the League of Conservation Voters (originally at the congressional-district level). We use a very large selection of these variables to predict response propensities. This huge number of candidate regressors necessitates the use of variable selection techniques. The reported results use a linear probability model with stepwise selection for variable selection. The remaining variables are then used to estimate a probit model to explain response propensities and to calculate response probabilities. We have also estimated our selection equation using LASSO methods for variable selection. The results appear to be qualitatively similar, so we use the stepwise approach for the selection equation in this paper.[9]

4 Results

4.1 Estimated Sample Selection Model

Table 1 gives descriptive statistics for the set of regressors with estimated coefficients that appear to be robustly statistically significant after our variable-selection process. Given the huge number of candidate variables among all of the zip-code proportions in different groups, and the administrative data about individual members of the campus community, it was not possible to estimate a maximum likelihood probit model for the complete set. Ordinary least squares, applied to a linear probability model (LPM), however, can handle many more regressors. We winnowed the universe of potential regressors using LPM. We then employed the surviving variables in a binary probit specification to yield the fitted response propensities employed subsequently, in de-meaned form, as ad hoc "individual attributes" that are permitted to shift the marginal utility for each program attribute used in our main models.

Table 2 provides the parameter estimates for this model. The choice experiments presented in our survey were complex and participation was completely optional, and our monetary incentives were relatively meager, so our 9.4% response rate is not surprising. Invited respondents are *more* likely to complete our survey if their permanent-address zip code has:

- More housing lacking a complete kitchen
- More people commuting via public transit
- More people employed in retail

[9]LASSO results are available upon request.

Invited respondents are *less* likely to complete the survey if their permanent address zip code has:

- More households with no vehicle available
- More people commuting a long way to work (45 to 59 minutes)
- More people employed in arts, entertainment, recreation, accommodations or food industries

At the individual level, based on our person-specific administrative data, invited respondents are *more* likely to complete the survey if they are:

- Female
- A university employee, rather than a student
- A student in Environmental Studies, the Law School, or Music

Individuals are *less* likely to complete the survey if they are:

- Black or African American, or Hispanic or Latino
- A non-resident alien
- A student employee
- A university employee affiliated with Athletics, Architecture and Allied Arts, Education, Physical Education or Recreation, Music and Dance, or Housing
- A student in something other than one of the nine major Schools and Colleges in this university (but not "undeclared")
- A student in Journalism and Communications

4.2 Estimated Choice Model

If preferences were homogeneous, our model would have only eight parameters: the coefficient on the size of the carbon reduction, the coefficient on the cost of the program, the five coefficients capturing the distribution of costs/benefits, and a coefficient on a status-quo indicator. The distributional features of the program are captured by the four cost shares borne by different groups, and the three shares describing how the revenue would be used. Relative to the default cost share (for a common carbon fee charged to all members of the university community), there are coefficients on the three other shares of costs. Relative the default expenditure share (spent on carbon projects at the university) there are coefficients on the other two non-default shares of revenue. As is standard practice in the modeling of data from choice experiments, we also include a "status quo" indicator for all choice occasions.

It is, however, a maintained hypothesis that we need to allow for non-zero "nuisance" parameters associated with each person's deviation from the invited sample's mean response propensity. Thus we always interact each program attribute with this demeaned response propensity. When we simulate zero for all demeaned response propensities, then, we are implicitly simulating a situation where everybody in our estimating sample shares the same response propensity and this propensity is the mean in the entire invited sample, which represents the population of interest (up to some sampling weights that control for a higher proportion of employees than students in the spring sampling wave).

Given that the marginal utility of every feature in our offered ICP programs may vary systematically with respondent characteristics, the same characteristic may persist as being influential in more than one interaction with the program attributes. Thus Table 3 displays descriptive statistics for each of the dimensions of respondent heterogeneity that have a persistently significant effect and survive our winnowing process. These summary statistics are also displayed next to each parameter estimate in the next table, displaying the choice model, to emphasize the importance of individual heterogeneity for the total WTP for a given program.

Table 4, which spans two pages, reports our preferred specification for respondents' preferences among the wide range of randomly designed ICP programs proposed across the different (essentially unique) survey instruments used in our study. The first thing to note is that the fitted demeaned response propensities, from the model in Table 2, have a persistently statistically significant effect on the marginal utility of the unaviodable cost to respondents, the cost share borne by taxpayers, the share spent on academic and on the status quo indicator variable. (In cases where interaction variables have persistently statistically insignificant coefficients, we drop those interactions.)

The parameter estimates in Table 4 are an intermediate step on our way to exploring the model's implications for total and marginal WTP amounts for different programs and for different people. Thus we will not reiterate each of those parameter estimates. Instead, we note that the table is structured so that each of the eight basic program attributes is followed by that attribute's interactions with selected respondent characteristics (either for their permanent address zip code, or individually from administrative data). Any interaction term bearing a positive coefficient suggests that the marginal utility from the attribute in question increases when that zip-code proportion is larger, or when the individual indicator is "switched on."

For every program for which we will calculate WTP, the status-quo indicator will be set to zero. Given this, we will not discuss this parameter in the WTP simulations below, but will comment here on those respondent characteristics that affect their preference for the status quo, rather than any ICP program, regardless of the attributes of that program.

Specifically, a respondent is more likely to prefer NO program if:

- They are an administrator or staff member, instead of a student.
- They identify as somewhat or very conservative
- Their permanent address is in a low-income zip-code
- They have recently experienced any harm from an extreme weather event

In contrast, a respondent is more likely to prefer ANY program, regardless of its characteristics, if:

- They are affiliated with the college of design, the biology department or have not yet declared their major.
- They have recently experienced a heatwave
- They identify as somewhat or very liberal
- They are from a zip-code with a high share of people who have recently moved from a foreign country.

4.3 WTP Simulations for Specific Programs and Specific Individuals

We now discuss some specific willingness-to-pay results from the estimated choice model. The fitted WTP function depends both the attributes of the ICP program in question, and on numerous respondent characteristics (that may enter the model in more than one place). To illustrate how WTP (willingness to bear the costs of) ICP programs depends on specific program attributes or specific respondent characteristics, we will explore several notable cases.

Table 5 summarizes these illustrations of the scope of the influence of program attributes and respondent characteristics. As we discuss Table 5 we will consider one panel at a time.

4.3.1 Panel 1: Percentage-point carbon reduction

In this illustrative case, the program involves the default distributional shares—student/employee fees only, and revenues spent on campus carbon projects only. Respondent characteristics are set at the sample means and baseline categories for indicator variables. This panel illustrates that WTP responds to the scope of the program. Furthermore, the marginal WTP for an additional percentage-point carbon reduction declines over the range of the illustration, from about \$5 per year at a 10% reduction, down to just \$1.78 at a 50% reduction. There is diminishing marginal

WTP as the program becomes more aggressive, although MWTP does not become negative within the range of our choice set designs.

A natural question one may ask with this model is what is the implied WTP for a ton of carbon dioxide reduction? Since WTP varies by individual respondent characteristics, it is not accurate to speak of a single number which can be applied to every member of the university population. However, for illustrative purposes, suppose every member of the campus community was identical to the person described in Section 1 of Table 8. Consider the benchmark 40% carbon reduction, which corresponds to the university changing their physical plant from natural gas to green energy. The mean WTP for this type of person, \$167, can be multiplied by the roughly 28,100 people at the university and divided by the 24,000 metric tons (from the original 61,000 metric ton estimate of university emissions that was described to respondents). In this example, this would lead us with an average WTP, per ton of carbon dioxide reduced, of \$195. Importantly, however, this person is not the mean member of the university's population of stakeholders, but merely an illustration.

4.3.2 Panel 2: Baseline ICP Program; Proportion of the costs borne as air travel fees

Each of these next simulations corresponds to a 40% reduction in campus carbon emissions. Now we divert the costs increasingly away from the default category of student/employee fees, and increase the share of costs borne as air travel fees. This is still the same "person" with the same basic characteristics as panel 1. Total WTP for an ICP program increases with the share of the costs borne as air travel fees, but only up to the maximum 40% share used in the experimental design. Total WTP is diminishing in this feature over the range of programs used in this study, and the statistically significant coefficient on the quadratic term in the proportion of costs borne as air travel fees means that total WTP, for programs above the range included in our choice-sets, would be predicted to decrease as a result of additional increases in air-travel fees. However, this is merely an out-of-sample forecast. Within the range of our data, all we can say is that there is diminishing marginal utility from an increasing share via air-travel fees.

4.3.3 Panel 3: Baseline ICP Program; Proportion of costs borne as building energy fees

This is the dimension most similar to the program at Yale University. Ceteris paribus, our benchmark person is willing to bear higher personal costs for an ICP program if that program results in a greater share of costs borne via building energy fees. Our choice set designs included up to a 100% share of costs borne this way, to allow us to benchmark WTP in this campus population against the Yale example. For this arbitrary person, total WTP ranges from $167 per year for the default share scenario, up to $279 per year if all costs are borne via building energy fees. This is consistent with a preference for a "polluter pays" approach.

4.3.4 Panel 4: Baseline ICP Program; Proportion of costs borne by the state's taxpayers

We find additional evidence of distributional preferences in the estimates relating to the proportion of costs paid by taxpayers in the fitted WTP values shown in this panel. As the amount of funds provided by the state's taxpayers increases, the WTP increases from $167 to $174 when taxpayer contributions are raised from the program baseline to cover 30 percent of the program's costs. One may be concerned that the decreasing WTP reflects a false perception of respondents that programs with a higher share of taxpayer support may reflect reductions in the cost of the program to respondents. We find this explanation unlikely due to the small size of the change in WTP in response to increases in taxpayer support. An agent who thought they could avoid paying in programs with higher levels of taxpayer support should be willing to pay an amount for this taxpayer support equal to the savings. However each 10 percent step in Table 5 results in an increase in WTP far less than 10 percent suggesting that respondents incorrect perceptions of program costs are unlikely to be the only reason behind the sign of the estimates.

4.3.5 Panel 5: Baseline ICP Program; Proportion of revenues spent on academic programs

The estimates in this panel show how our benchmark individual responds to a portion of the revenue raised by the ICP being spent on academic programs, which we view as a form of revenue recycling. When spending on academic programs increases to 30 percent, from the program where all revenues are spent on on carbon reduction projects, the WTP falls to $151. This suggests that, all else equal, respondents would prefer the revenues to be spent on some form of carbon reduction.

4.3.6 Panel 6: Baseline ICP Program; Proportion of revenues spent on carbon offsets

Estimates in this panel show the tradeoff our benchmark individual is willing to make between off-campus carbon-reduction projects (in the form of offsets) and on-campus carbon reduction projects. WTP is increasing in the proportion of the revenue spent on offsets. Total WTP increases to $245 when half of the money is spent on offsets, from $167 when all of the money is spent on on-campus carbon projects. We find no evidence that respondents have a systematic preference for local reductions (i.e. on campus projects) instead of distant projects (i.e. offsets).[10]

4.3.7 Panel 7: ICP Program with mixed shares: Percentage-point carbon reductions

For our baseline program, with all costs borne as a flat fee on all students and employees, and with all revenues spent on carbon-reduction programs at the university, the only types of heterogeneity that can affect willingness to pay are those respondent characteristics that shift the marginal utility of a percentage-point carbon reductions. As is common in choice experiments, we constrain the marginal utility of net income to be constant across respondents. It is therefore necessary to select programs that have non-zero values for the non-default shares if we are to explore the sensitively of WTP for an ICP program to other respondent characteristics that shift only the marginal utilities of some of these non-default shares. For illustration, then, we now examine a program with 20%

[10]Our survey did not mention co-pollutants. If the survey had mentioned co-pollutants we might have seen a preference for local emission reductions. These results should therefore be interpreted as holding local air quality constant.

of costs borne as air travel fees, 30% of costs borne as building energy fees, and 20% of costs borne by the state's taxpayers (leaving 20% to be borne in the form of a flat fee on all students and employees). Analogously, this new benchmark ICP program will feature 30% of its revenues spent on academic programs, and 30% of its revenues spent on off-campus carbon offsets. This leaves just 40% being spent for on-campus carbon projects.

For this program, increases in the amount of carbon reductions can be compared directly to Panel 1. Total WTP for a 10% carbon reduction changes minimally, from \$53.54 to \$55.44, and Total WTP for a 50% carbon reduction goes from \$188 to \$190. The positive and negative effects of shifting the different shares more or less cancel out. The action, in this case, is going to stem from different respondent characteristics.

4.3.8 Panel 8: ICP Program with mixed shares: Respondent household income

Income is measured coarsely in our survey, and is treated as no more than an indicator for preferences that vary with socioeconomic status, rather than as an accurate measure of disposable income. In the estimated model, income enters as a shifter of marginal utilities in the form of deviations from the sample mean, so that a zero value for the interaction implies a model that applies for someone with mean household income. The estimated model suggests that ICP programs are a normal good. Willingness to pay increases with household income.

4.3.9 Panel 9: ICP Program with mixed shares: Respondent age

Given that we control for so many other respondent characteristics, any heterogeneity attributed solely to age has essentially disappeared.

4.3.10 Panel 10: ICP Program with mixed shares: Perceived researcher bias

It is difficult to field a survey about a topic and to succeed in leaving respondents with the perception that the research team is indifferent about the results. In the process of survey design, the goal is to have as many people as possible respond that the survey seemed "unbiased," but it is fairly typical to have an imbalance in the tails. For this survey, people who garnered the impression that the research team had a pro-ICP bias were willing to pay about $40 less per year for this benchmark ICP program than people who perceived that the survey was unbiased. Relatively few respondents felt that the survey was biased against ICP programs.

There is some question about the exogeneity of this variable, of course. People who take a dim view of the necessity for dealing with climate change might unsurprisingly be more inclined to feel that *any* survey that discusses climate change programs is biased in favor of these programs. We leave the observed values of this respondent characteristic this attribute in our specifications as we simulate predicted WTP amounts, therefore, rather than simulating (counterfactually) that everyone perceives no bias.

4.3.11 Panel 11: ICP Program with mixed shares: Extreme weather in last 12 months?

The salience of climate change mitigation policies can be expected to depend on recent experience with extreme weather events on the part of the respondent, since such events are increasingly attributed to climate change. This panel shows that respondents who have experienced extreme cold in the last year seem to be less willing to pay for carbon reductions through a campus ICP program. Less intuitive, however is the finding that respondents who have experience drought in the last year are also less willing to pay for carbon reductions. One possibility is that drought may be correlated with time spent in rural agricultural areas over the last year. We may be picking up "time spent in red counties" via the drought indicator, but this apparent anomaly may warrant further study.

4.3.12 Panel 12: ICP Program with mixed shares: Prior experience with extreme-weather harm

This respondent characteristic was intended to capture the individual's lifetime exposure to extreme-weather events, as well as the exposure of family and friends. However, it seems that extreme-weather harm over a longer time-span, or to other people known to the respondent, has no significant effect on WTP for this particular program.

4.4 Campuswide Distributions of WTP for Specific Programs

Our model can be used to compute the distribution of WTP across the entire campus community. We generate and display the entire distribution, as opposed to limiting our analysis to simple summary statistics such as the mean or median, and perhaps the variance in WTP. Knowledge of the entire distribution for a specifically configured ICP program, across the entire campus community, can be very useful to policymakers as they assess the level of support for that type of program. The ability to consider the entire distribution of fitted WTP amounts allows the policy-maker to understand, for a program with a given per-person cost, what fraction of the campus community is predicted to be accepting of such a program. Those individuals whose WTP exceeds the cost of the program would be predicted to vote "yes" for such a program, if it were put to a vote. Analyses that yield only the WTP of the "median voter" on campus may have difficulty separating programs that only achieve a narrow majority of support from those which are uncontroversial. Additionally, the WTP distribution can be used to assess equity concerns about the distribution of benefits from the program.

A key point to appreciate is that if we were to model preferences as homogeneous, there would be just one estimate of WTP for any given program, based solely on the attributes of that program. The *distribution* of WTP amounts for a given program stems entirely from all the heterogeneity, across the campus community, in respondent characteristics.

4.4.1 Campuswide distribution of WTP for our baseline ICP program

Figure 1 shows the distribution of fitted WTP values across the sample of all respondents, weighted to reflect, as well as possible, the demographic distribution of the university. This WTP corresponds to our baseline program that raises all revenue from lump-sum fees and spends it all for on-campus carbon-reduction projects that achieve a 40% reduction in university emissions. The distribution of total WTP amounts (which can be interpreted as "support" for the specified program) is unimodal with a long right tail.

For comparison, Figure 2 shows the same baseline program along with a program with identical revenue and spending shares but instead achieves half the emission reductions. The program with the smaller carbon reduction has a more compact distribution suggesting that preference heterogeneity becomes more important, the larger the scope of the ICP program.

Figure 3 shows distributions of campus-wide WTP amounts for programs that vary from the baseline ICP program by changing either the non-default cost shares or the non-default revenue shares, one at a time. In general, the shape of the distribution does not noticeably change due to differences in program design. Instead changes in WTP due to changes in program attributes seems to be best described as a change in the mean of the WTP distribution.

Figure 4 shows the distribution of WTP for our second program that includes all sources of revenue and all shares of spending. This distribution of WTP tends to be more diffuse than the distribution fo the baseline program. This can be expected, given that different segments of the university population have different views about the means of raising and using revenues across the different programs.

4.5 Campuswide Distributions of WTP Within Distinct Stakeholder Groups

For any given program, instead of just showing the entire marginal distribution of WTP amounts across the whole university community, we can split our sample into specific groups of interest.

Figure 5 shows the distribution of WTP sorted according to respondents' self-reported political ideology. Figures 6 and 7 show the distribution sorted by self-reported income and by home zip-code income levels, respectively. Finally, Figure 8 shows the WTP distribution for students and non-students, and Figure 9 shows WTP distributions for two of the better -represented academic departments in our sample, business and environmental studies. The examples we use to illustrate the different distributions of total WTP for a given program across different groups have been arbitrarily selected, as they are intended to serve merely as an illustration of the results our model is capable of generating.

5 Conclusions and Directions for Further Research

In this paper, we describe the findings from a stated-preference survey, in the form of an advisory referendum, designed to explore preferences for internal carbon pricing programs at a university. Our estimates suggest that there exists substantial support for local climate action, with predicted individual WTP amounts exceeding or matching many estimates of the social cost of carbon. This suggests that support for non-governmental programs is substantial enough to justify significant emission reductions, at least for institutions whose stakeholder preferences can be adaquately captured by the same explanatory variables we use in this study.

We also find substantial evidence that program *design* influences demand for internal carbon pricing. Respondents have preferences over the initial incidence of the program's costs. They prefer programs where costs are linked to emissions. Even for programs with the same cost to the individual, we find that support is higher when taxpayers across the state are perceived as sharing the burden of the carbon reduction program. Additionally we find that revenue recycling lowers support for these programs. There is no evidence of a preference for carbon reduction projects to be local, instead of being achieved through offsets.

Our survey and choice model are designed to facilitate benefit transfer exercises across universities. The next chapter will use a variation on our estimated model to construct WTP estimates for another (stylized) university from publicly available data. These estimates, and the method more generally, would give university administrators and sustainability coordinators a means of assessing support without the expense of fielding a new survey and new analysis themselves.

Our model can estimate the entire WTP distribution across the campus community, allowing the amount and degree of support for a given program to be assessed. Future work could explore ways of further utilizing this information by perhaps formally ranking distributions using tools from the inequality literature. Future work could also explore the extent to which our results generalize to other types of institutions in both the private and public sector.

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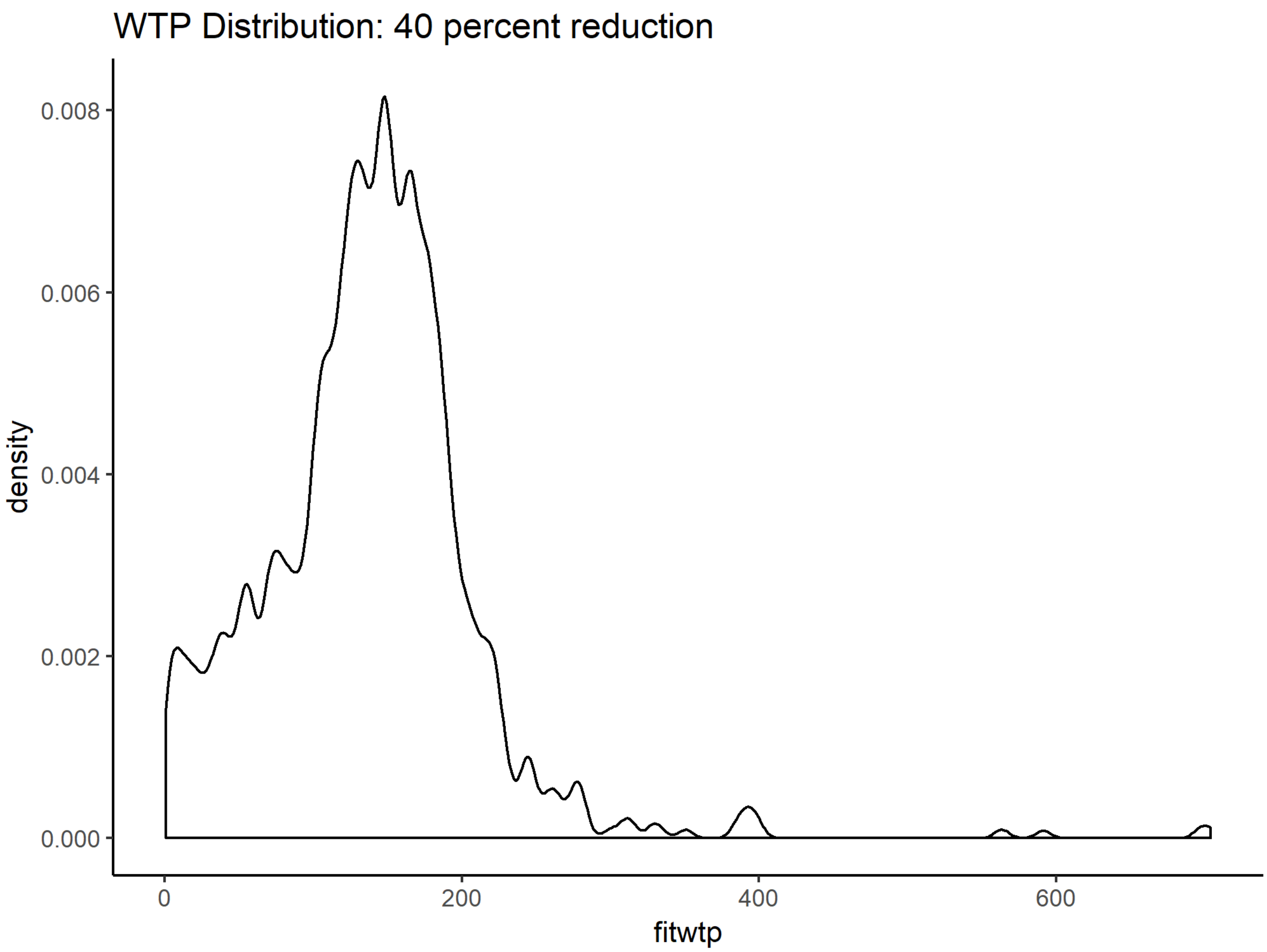


Figure 1: Distribution (weighted) across the university population of expected individual WTP amounts for a program that produces a 40% reduction in carbon emissions, where the costs are borne entirely as a flat fee on all students and employees, and where all of the revenues are spent on carbon-reduction projects

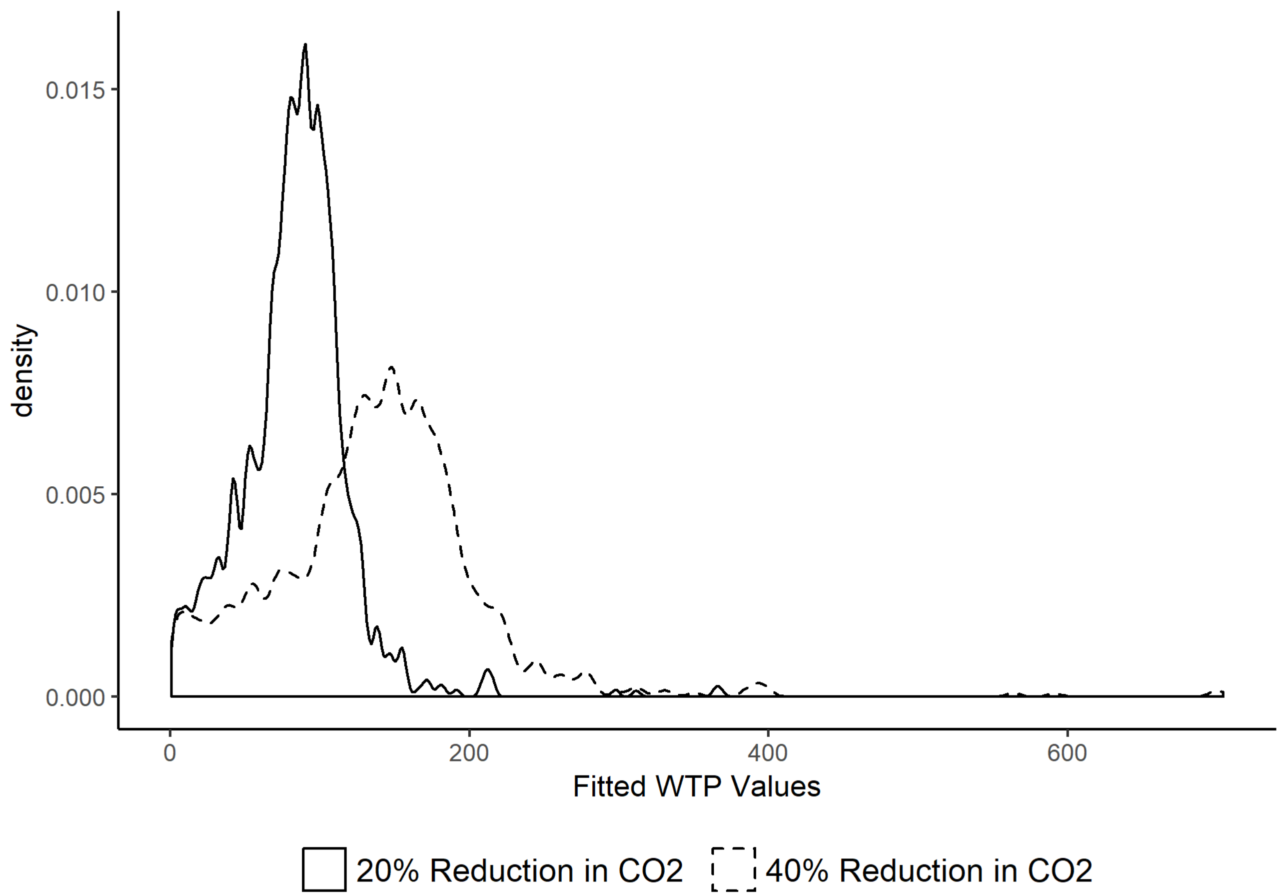
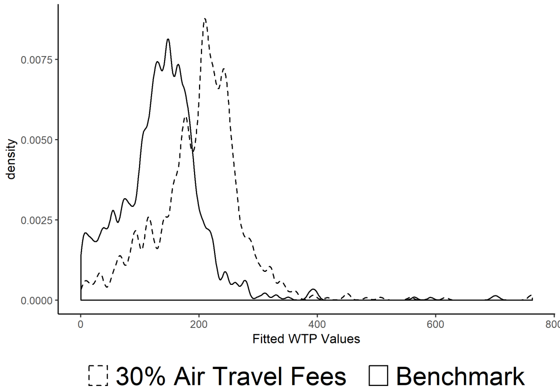
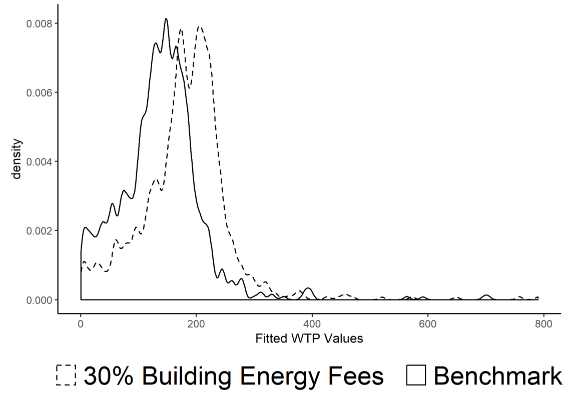


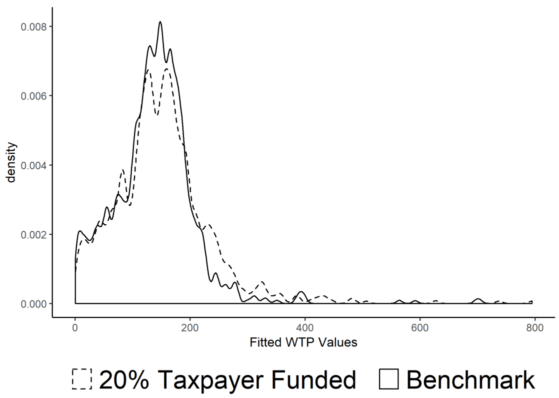
Figure 2: Distribution (weighted) across the university population of expected individual WTP amounts for programs that produce a 40% and a 20% reduction in CO_2. Both programs raise all of their money from lump-sum student/staff fees and spend all revenue on on-campus carbon reduction projects.



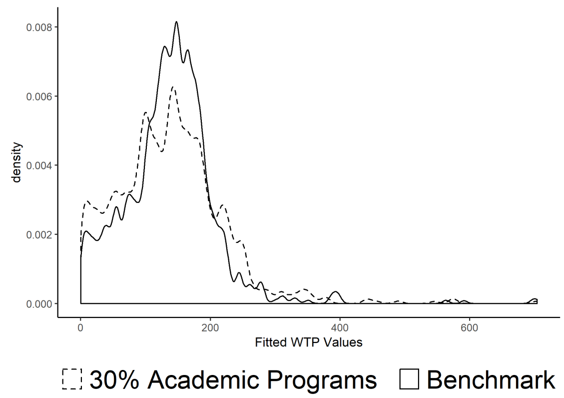
(a) 30% Air Travel Fees



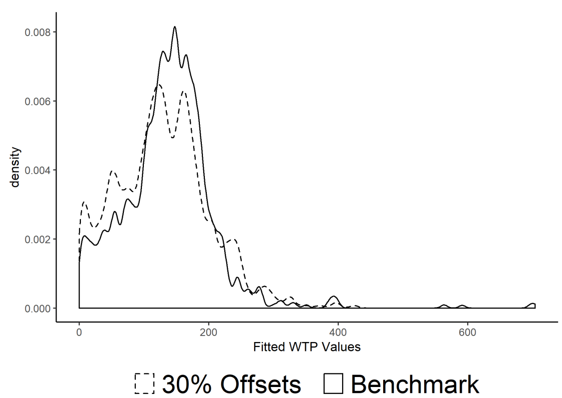
(b) 30% Building Energy Fees



(c) 20% Taxpayer Funding



(d) 30% to Academic Spending



(e) 30% Offsets

Figure 3: Distribution (weighted) across the university population of expected individual WTP amounts for programs with various spending and revenue shares.

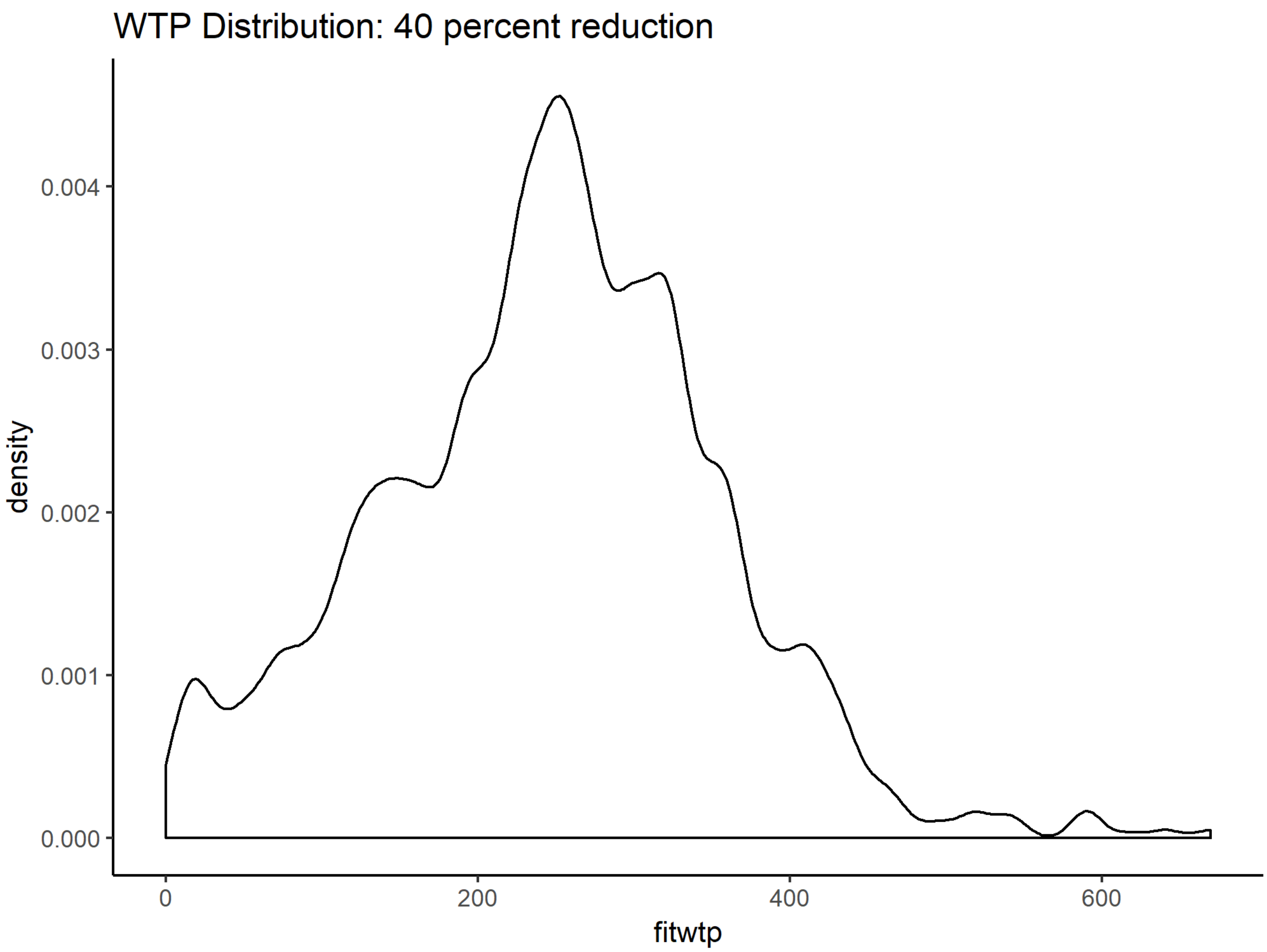
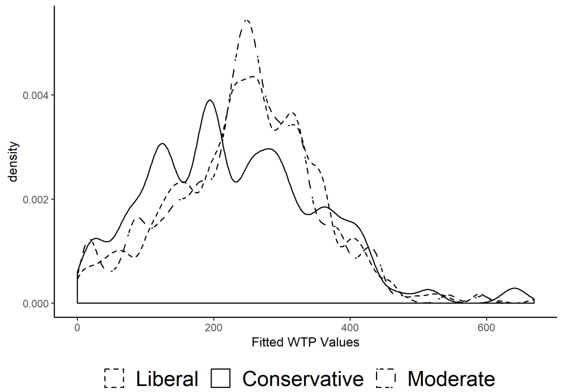
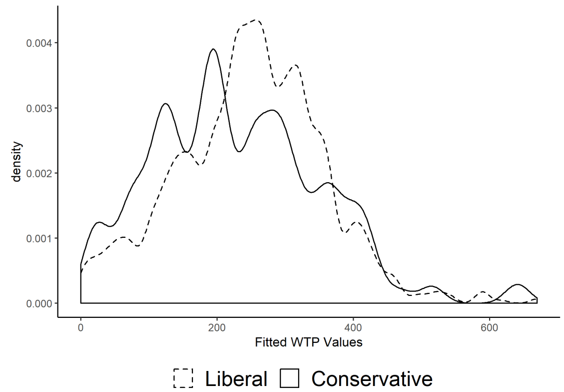


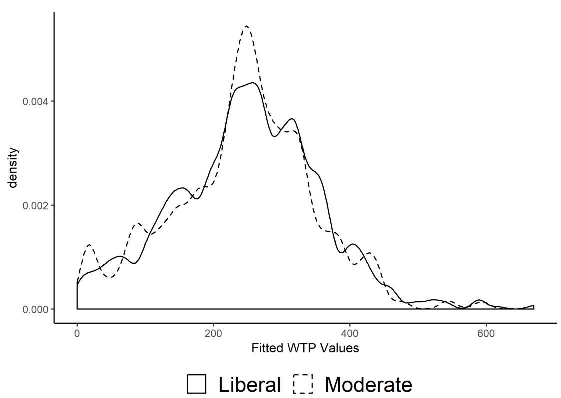
Figure 4: Distribution (weighted) across the university population of expected individual WTP amounts for a program that produces a 40% reduction in carbon emissions, where the costs are borne: 20% as a flat fee on everyone, 30% as air travel fees, 30% as building energy fees, and 20% by Oregon taxpayers, and revenues are spent 40% on carbon reduction projects, 30% on academic programs, and 30% on carbon offsets.



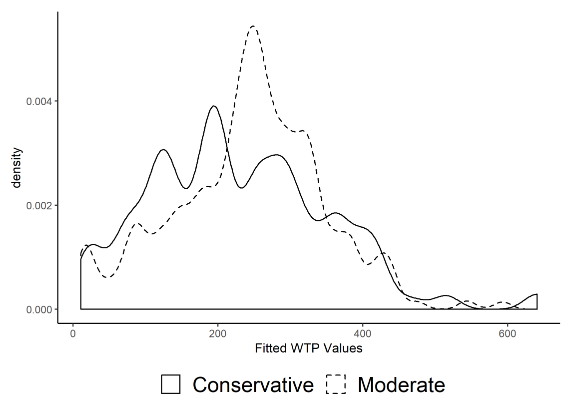
(a) All Political Alignments



(b) Liberal/Conservative



(c) Liberal/Moderate



(d) Conservative/Moderate

Figure 5: Distribution (weighted) across the university population of expected individual WTP amounts for self-identified conservative, moderates, and liberals.

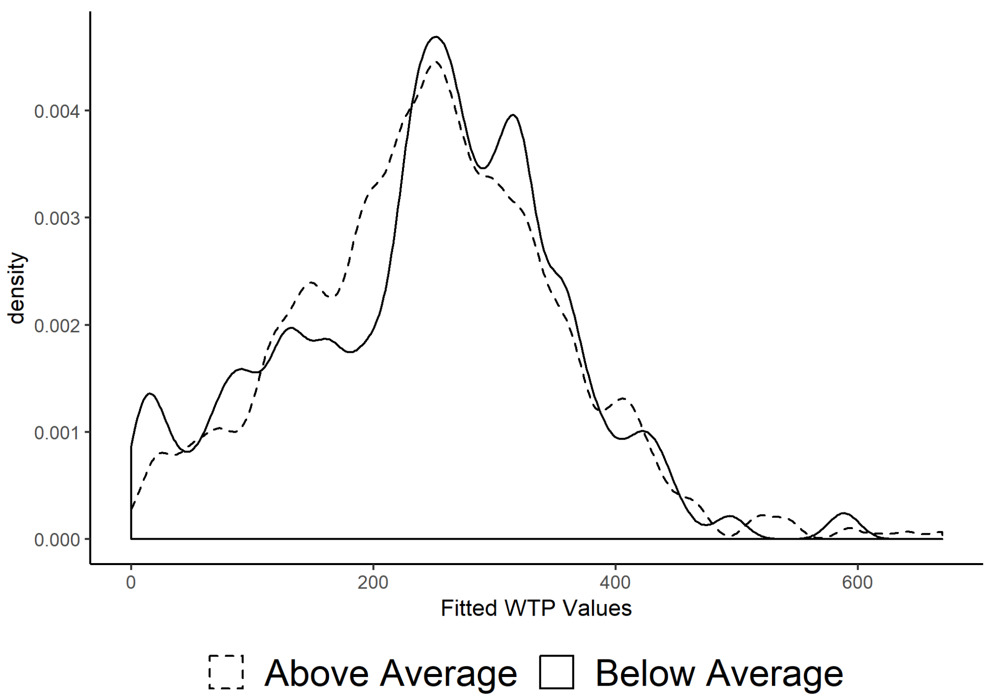
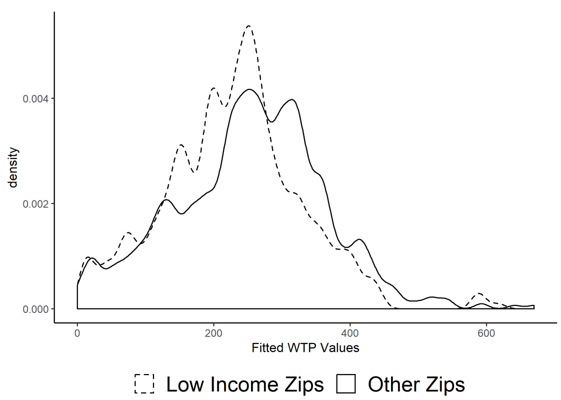


Figure 6: Distribution (weighted) across the university population of expected individual WTP amounts shown separately for respondents with above average and below average self-reported income.



(a) Low Income Zip-Codes

(b) High Income Zip-Codes

Figure 7: WTP Distributions by Origin Zipcode Household Income

Notes: Distribution (weighted) across the university population of expected individual WTP amounts shown separately for individuals from zip codes with above and below average shares of high and low income households respectively.

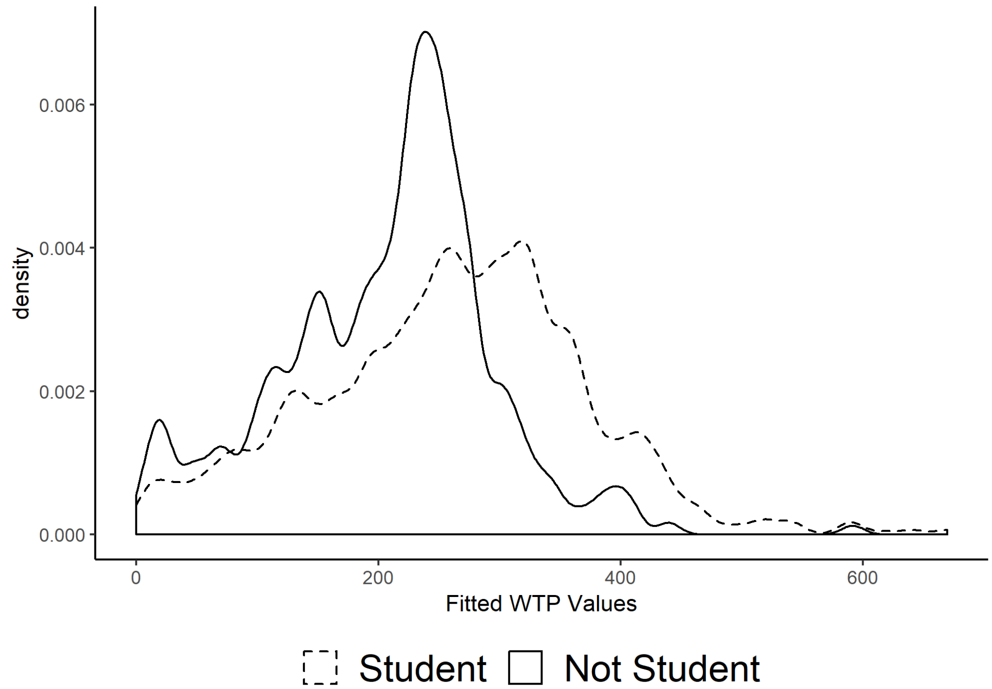
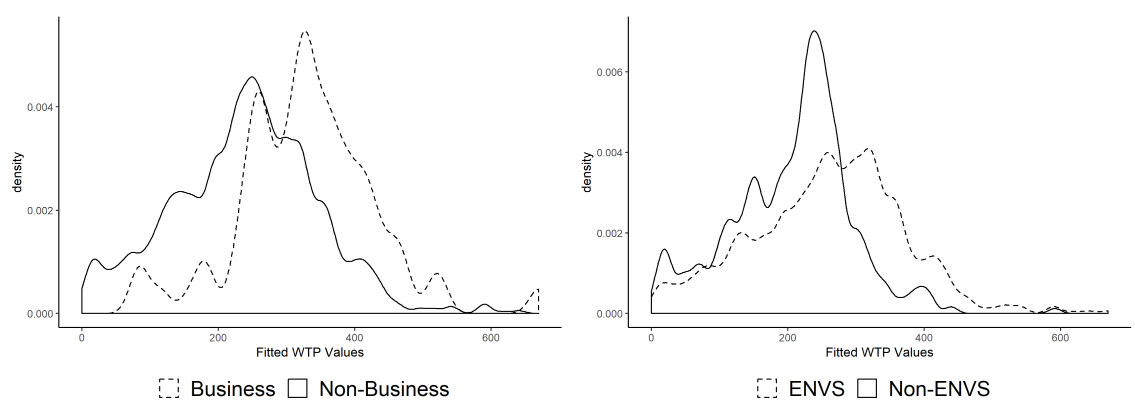


Figure 8: Distribution (weighted) across the university population of expected individual WTP amounts shown separately for individuals who are students versus those who are not



(a) Business Department

(b) ENVS Program

Figure 9: WTP Distributions by Selected University Department

Notes: Distribution (weighted) across the university population of expected individual WTP amounts shown separately for individuals for individuals in the business school and environmental studies program.

Table 1: Descriptive statistics: Response-nonresponse model

	mean	sd
1=respondent; 0=nonrespondent	0.094	
zip pr No vehicles available	0.049	0.034
zip pr Housing lacking complete kitchen	0.006	0.008
zip pr Commute any public transit	0.055	0.030
zip pr Commute 45 to 59 min	0.038	0.036
zip pr Industry retail trade	0.124	0.026
zip pr Industry arts/enter/recr/accom/food	0.100	0.023
1=female	0.534	
1=Black or African American	0.019	
1=Hispanic or Latino	0.089	
1=Nonresident alien	0.090	
1=employee: student employee	0.195	
1=have employee home organization	0.540	
1=organization: Athletics	0.027	
1=organization: Arch and Allied Arts	0.006	
1=organization: Education	0.030	
1=organization: PhysEd and Rec	0.015	
1=organization: Music and Dance	0.011	
1=organization: Housing	0.075	
1=student: Other	0.084	
1=department: environmental studies	0.015	
1=department: journalism and communications	0.074	
1=department: law	0.013	
1=department: music	0.016	
Observations	10520	

Table 2: Response-nonreponse model estimates; persistently significant explanatory variables (weighted estimates)

Explanatory variables	Estimate	Std. Err.
zip pr No vehicles available	-2.681***	(0.857)
zip pr Housing lacking complete kitchen	12.59***	(3.101)
zip pr Commute any public transit	2.183**	(0.858)
zip pr Commute 45 to 59 min	-2.418***	(0.669)
zip pr Industry retail trade	2.885***	(1.025)
zip pr Industry arts/enter/recr/accom/food	-2.611***	(0.907)
1=female	0.145***	(0.0357)
1=Black or African American	-0.521***	(0.183)
1=Hispanic or Latino	-0.143**	(0.0671)
1=Nonresident alien	-0.359***	(0.0785)
1=employee: student employee	-0.187***	(0.0533)
1=have employee home organization	0.483***	(0.0442)
1=organization: Athletics	-0.481***	(0.125)
1=organization: Arch and Allied Arts	-0.655**	(0.277)
1=organization: Education	-0.405***	(0.107)
1=organization: PhysEd and Rec	-0.295*	(0.157)
1=organization: Music and Dance	-0.473**	(0.187)
1=organization: Housing	-0.241***	(0.0738)
1=student: Other	-0.146**	(0.0647)
1=department: environmental studies	0.402***	(0.123)
1=department: journalism and communications	-0.185**	(0.0804)
1=department: law	0.269**	(0.135)
1=department: music	0.294**	(0.141)
Constant	-1.631***	(0.198)
No. Survey Invitations	10520	
Max. log-likelihood	-3113.14	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Descriptive statistics: Heterogeneity in choice model

	mean	sd
Permanent-address zip code proportions:		
zip pr Asian alone (.027)	0.027	0.031
zip pr Black alone (.009)	0.009	0.016
zip pr Cmt 15-19 min (.199)	0.199	0.028
zip pr Cmt 30-34 min (.092)	0.092	0.032
zip pr 25+, some coll, no degr (.285)	0.285	0.031
zip pr Heat fuel oil, kero (.009)	0.009	0.024
zip pr Inc 100K-150K (.11)	0.110	0.039
zip pr Inc 15K-25K (.141)	0.141	0.033
zip pr Inc 150K-200K (.037)	0.037	0.019
zip pr Inc lt 10K (.072)	0.072	0.020
zip pr Moved; from abroad (.004)	0.004	0.004
zip pr Moved; dif cty, sme st (.041)	0.041	0.015
zip pr Moved; same cty (.094)	0.094	0.028
zip pr No vehicle avail (.046)	0.046	0.026
zip pr Hous-multi-unit (.107)	0.107	0.098
zip pr Ind constr (.06)	0.060	0.010
zip pr Ind publ admin (.041)	0.041	0.011
zip pr Ind ret trade (.127)	0.127	0.023
zip pr Hsng incompl kitch (.006)	0.006	0.008
zip pr Hsng incompl plumb (.002)	0.002	0.003
zip pr No phone service (.023)	0.023	0.006
zip pr Green votes 2016 Pres elect.	0.031	0.005
Administrative data–individual characteristics		
1=individual's age known	0.751	0.433
demean indiv. age, if known	0.127	10.416
1=have gender	0.997	0.055
1=female (.601)	0.601	0.490
1=Non-white (.38)	0.380	0.486
1=stu: Design (.066)	0.066	0.249
1=stu: Other (.083)	0.083	0.276
1=stu: Undeclared (.044)	0.044	0.205
1=dept: Biology (.033)	0.033	0.179
1=dept: Bus admin (.063)	0.063	0.243
1=dept: Env studies (.025)	0.025	0.156
1=empl: Officer of admin (.143)	0.143	0.351
1=empl: Career non-tenure (.058)	0.058	0.234
1=empl: Athletics (.023)	0.023	0.126
1=empl: Business (.027)	0.027	0.137
1=empl: Facilities (.03)	0.03	0.144
1=empl: Design (.044)	0.044	0.174
1=empl: Classified staff (.144)	0.144	0.352
1=empl: Library (.041)	0.041	0.168
1=empl: Student employee (.186)	0.186	0.389
Survey Data - Individual Characteristics		
=1 if have hhld inc	0.876	0.330
hhld inc ('000) if known	47.025	60.268
1=perceive anti-ICP bias (.032)	0.032	0.176
1=perceive pro-ICP bias (.445)	0.445	0.497

Continued on next page

Table 3 – continued from previous page

1=somew/very conserv (.087)	0.087	0.282
1=somew/very liberal (.673)	0.673	0.469
1=12 mos: Severe winter (.138)	0.138	0.346
1=12 mos: Heat wave (.422)	0.422	0.494
1=extr weath: any harm (.615)	0.615	0.487
1=fall 2018 wave (.41)	0.410	0.492
Observations	997	

Table 4: Final specification, displayed in wide format (Omitted categories: those not included in the specification, by factor)

	Estimate	Std.Err.
Unavoid cost to resp. ($22 to $232)	-0.00946***	(0.00112)
× demeaned resp propensity	0.00122**	(0.000511)
Pct-point C reduction (10 to 50)	-0.0591*	(0.0350)
× Pct-point C reduction (10 to 50)	-0.000419**	(0.000178)
× zip pr Asian alone (.027)	0.176*	(0.0983)
× zip pr Moved; dif cty, sme st (.041)	-0.478***	(0.146)
× zip pr 25+, some coll, no degr (.285)	0.185*	(0.107)
× zip pr No vehicle avail (.046)	-0.167*	(0.0962)
× zip pr Hsng incompl plumb (.002)	-1.536**	(0.744)
× zip pr No phone service (.023)	0.458	(0.331)
× zip pr Green votes 2016 Pres elect.	-0.794*	(0.476)
× 1=have gender	0.0986***	(0.0185)
× 1=female (.601)	-0.00703*	(0.00392)
× 1=empl: Business (.027)	0.0247*	(0.0129)
× 1=empl: Library (.041)	-0.0306**	(0.0132)
× 1=12 mos: Severe winter (.138)	-0.0155***	(0.00566)
× 1=perceive pro-ICP bias (.445)	-0.0100**	(0.00450)
× =1 if have hhld inc (.889)	0.00490	(0.00595)
× hhld inc ('000) if known	0.0000531	(0.0000341)
Cost shr air trav fees (0 to .5)	-0.0647**	(0.0301)
× Cost shr air trav fees (0 to .5)	-0.000423***	(0.000102)
× zip pr Inc lt 10K (.072)	0.277***	(0.0993)
× zip pr Inc 15K-25K (.141)	-0.178**	(0.0739)
× zip pr Hsng incompl plumb (.002)	1.235**	(0.611)
× zip pr Hsng incompl kitch (.006)	-0.439	(0.269)
× zip pr Cmt 15-19 min (.199)	0.272***	(0.0781)
× 1=have gender	0.0491*	(0.0263)
× 1=empl: Athletics (.023)	-0.0173	(0.0111)
× 1=empl: Business (.027)	-0.0102	(0.00740)
× 1=empl: Facilities (.03)	-0.0267*	(0.0144)
× 1=12 mos: Severe winter (.138)	0.00807**	(0.00384)
Cost shr bldg en fees (0 to 1)	0.0148***	(0.00365)
× zip pr Cmt 30-34 min (.092)	-0.0929***	(0.0320)
× 1=empl: Athletics (.023)	-0.0124	(0.00830)
× 1=empl: Design (.044)	-0.0130***	(0.00390)
× 1=somew/very liberal (.673)	0.00614***	(0.00237)
Cost shr taxpayrs (0 to .2)	0.0322	(0.0228)
× zip pr Inc 100K-150K (.11)	-0.576***	(0.201)
× zip pr Inc 150K-200K (.037)	1.115***	(0.388)
× zip pr Hsng incompl plumb (.002)	2.469**	(0.979)
× zip pr Heat fuel oil, kero (.009)	-0.282*	(0.145)
× zip pr Ind constr (.06)	-0.613*	(0.328)
× zip pr Ind publ admin (.041)	0.812***	(0.282)
× 1=empl: Athletics (.023)	-0.0457*	(0.0266)
× 1=empl: Design (.044)	-0.0324*	(0.0179)

Continued on next page

Table 4 – continued from previous page

× 1=empl: UGS (.02)	0.0540***	(0.0198)
× 1=stu: Design (.066)	0.0239*	(0.0143)
× 1=stu: Other (.083)	0.0374***	(0.0129)
× 1=dept: Bus admin (.063)	-0.0377***	(0.0117)
× 1=dept: Env studies (.025)	0.0277*	(0.0163)
× demeaned resp propensity	-0.00384**	(0.00182)
Spend shr acad prog (0 to .3)	-0.0766***	(0.0263)
× zip pr Black alone (.009)	0.562***	(0.146)
× zip pr 25+, some coll, no degr (.	0.303***	(0.0818)
× zip pr Ind publ admin (.041)	-0.604***	(0.217)
× 1=Non-white (.38)	-0.0104*	(0.00554)
× 1=individual's age known (1)	0.00399	(0.00636)
× demean indiv. age, if known	-0.000547*	(0.000303)
× 1=empl: Career non-tenure (.058)	-0.0164	(0.0104)
× 1=empl: Athletics (.023)	0.0456**	(0.0186)
× 1=empl: Health, Counsel. (.021)	-0.0671***	(0.0181)
× 1=extr weath: any harm (.615)	0.0123***	(0.00471)
× 1=perceive anti-ICP bias (.032)	-0.0397***	(0.0149)
× demeaned resp propensity	0.00662**	(0.00272)
Spend shr offsets (0 to .5)	0.0123	(0.0172)
× zip pr Hous-multi-unit (.107)	-0.133***	(0.0395)
× zip pr No vehicle avail (.046)	0.332**	(0.133)
× zip pr Hsng incompl kitch (.006)	-0.596	(0.374)
× zip pr Heat fuel oil, kero (.009)	0.156*	(0.0908)
× zip pr Ind ret trade (.127)	-0.125	(0.114)
× 1=individual's age known (1)	0.00934*	(0.00522)
× 1=empl: Career non-tenure (.058)	-0.0263***	(0.00981)
× 1=empl: Health, Counsel. (.021)	0.0194	(0.0126)
× 1=dept: Bus admin (.063)	0.0122*	(0.00677)
× 1=fall 2018 wave (.41)	-0.00990***	(0.00383)
Status quo w/ no prog	-5.334***	(1.256)
× zip pr Moved; same cty (.094)	9.709***	(3.157)
× zip pr Moved; from abroad (.004)	-72.56***	(21.73)
× zip pr Inc 15K-25K (.141)	6.849**	(3.097)
× 1=have gender	4.466***	(1.099)
× 1=empl: Classified staff (.144)	0.851***	(0.239)
× 1=empl: Officer of admin (.143)	0.580**	(0.232)
× 1=empl: Student employee (.186)	-0.534***	(0.190)
× 1=empl: Design (.044)	-1.287***	(0.449)
× 1=stu: Undeclared (.044)	-0.373	(0.302)
× 1=dept: Biology (.033)	-0.555*	(0.325)
× 1=extr weath: any harm (.615)	0.283*	(0.155)
× 1=fall 2018 wave (.41)	-0.272*	(0.155)
× 1=12 mos: Heat wave (.422)	-0.387***	(0.143)
× 1=perceive pro-ICP bias (.445)	0.434**	(0.177)
× 1=somew/very liberal (.673)	-0.607***	(0.192)
× 1=somew/very conserv (.087)	0.768**	(0.302)
× demeaned resp propensity	0.125*	(0.0657)
No. alternatives	12466	
Max. log-likelihood	-6047.73	

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Table 4 – continued from previous page

Clustering	caseid
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

Table 5: Heterogeneity in WTP by program attributes and respondent characteristics

1. By percentage-point carbon reduction
(40% carbon reduction, student/employee fees only, spend revenues on carbon projects only)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

10	53.54***	4.96***
	(35.69, 73.26)	(3.47, 6.57)
15	77.33***	4.56***
	(52.82, 104.19)	(3.35, 5.85)
20	99.14***	4.16***
	(69.35, 131.46)	(3.21, 5.17)
25	118.96***	3.77***
	(85.39, 155.45)	(3.02, 4.56)
30	136.80***	3.37***
	(100.61, 175.45)	(2.72, 4.06)
35	152.65***	2.97***
	(115.08, 192.61)	(2.21, 3.75)
40 (benchmark case)	166.53***	2.58***
	(128.58, 206.73)	(1.59, 3.55)
45	178.41***	2.18**
	(140.84, 218.48)	(0.91, 3.42)
50	188.32***	1.78*
	(150.93, 227.81)	(0.2, 3.32)

2. By proportion of costs borne as air travel fees (vs. student/employee fees)
(40% carbon reduction, spend revenues on carbon projects only)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

0 share	166.53***	2.58***
	(128.58, 206.73)	(1.59, 3.55)
0.10 share	195.96***	"
	(155.50, 239.90)	
0.20 share	216.36***	"
	(173.49, 263.20)	
0.30 share	227.70***	"
	(183.60, 276.29)	
0.40 share	229.99***	"
	(185.75, 279.17)	
0.50 share (out-of-sample)	223.24***	"
	(179.14, 271.95)	
0.60 share (out-of-sample)	207.44***	"
	(161.84, 258.20)	

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Table 5 – continued from previous page

3. By proportion of costs borne as building energy fees (vs. student/employee fees)		
(40% carbon reduction, spend revenues on carbon projects only)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
0 share	166.53***	2.58***
	(128.58, 206.73)	(1.59, 3.55)
0.20 share	198.43***	"
	(157.63, 242.51)	
0.30 share	212.62***	"
	(170.00, 258.94)	
0.40 share	225.64***	"
	(181.52, 274.33)	
0.60 share	248.15***	"
	(201.54, 299.97)	
0.80 share	265.97***	"
	(216.11, 321.47)	
1.00 share	279.08***	"
	(224.89, 340.26)	
4. By proportion of costs borne by state's taxpayers (vs. student/employee fees)		
(40% carbon reduction, spend revenues on carbon projects only)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
0 share	166.53***	2.58***
	(128.58, 206.73)	(1.59, 3.55)
0.10 share	169.03***	"
	(129.90, 210.49)	
0.20 share	171.53***	"
	(130.50, 215.07)	
0.30 share (out-of-sample)	174.03***	"
	(129.85, 221.67)	
5. By proportion of revenues spent on academic programs (vs. carbon-reduction programs)		
(40% carbon reduction, costs borne as student/employee fees only)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
0 share	166.53***	2.58***
	(128.58, 206.73)	(1.59, 3.55)
0.10 share	161.41***	"
	(122.62, 202.21)	
0.20 share	156.30***	"
	(115.06, 199.31)	
0.30 share (second benchmark)	151.18***	"
	(106.51, 197.54)	
0.40 share (out-of-sample)	146.07***	"
	(97.34, 196.43)	

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Table 5 – continued from previous page

6. By proportion of revenues spent on carbon offsets (vs. carbon-reduction programs) (40% carbon reduction, costs borne as student/employee fees only) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
0 share	166.53***	2.58***
	(128.58, 206.73)	(1.59, 3.55)
0.10 share	182.39***	"
	(139.41, 228.59)	
0.20 share	198.26***	"
	(140.58, 260.52)	
0.30 share (second benchmark)	214.12***	"
	(137.12, 296.91)	
0.40 share	229.99***	"
	(132.02, 334.91)	
0.50 share	245.86***	"
	(126.07, 373.79)	
0.60 share (out-of-sample)	261.72***	"
	(119.37, 413.41)	
7. By carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30 (40% carbon reduction, student/employee fees only, spend revenues on carbon projects only) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
10	55.44***	4.96***
	(37.47, 75.16)	(3.47, 6.57)
15	79.23***	4.56***
	(54.62, 106.18)	(3.35, 5.85)
20	101.04***	4.16***
	(71.26, 133.39)	(3.21, 5.17)
25	120.86***	3.77***
	(87.16, 157.45)	(3.02, 4.56)
30	138.70***	3.37***
	(102.56, 177.62)	(2.72, 4.06)
35	154.55***	2.97***
	(116.94, 194.59)	(2.21, 3.75)
40 (initial benchmark case)	168.43***	2.58***
	(130.33, 208.83)	(1.59, 3.55)
45	180.31***	2.18**
	(142.67, 220.53)	(0.91, 3.42)
50	190.22***	1.78*
	(152.93, 229.93)	(0.2, 3.32)

Continued on next page

8. By deviations from sample mean household income (40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
-64.818 (min = 15)	144.59***	1.98**
	(100.83, 190.55)	(.81, 3.13)
-57.318 (20th %ile = 22.5)	147.35***	2.05***
	(104.57, 192.60)	(0.91, 3.17)
-17.31 (40th %ile = 62.5)	162.06***	2.42***
	(123.04, 203.58)	(1.39, 3.43)
0 (at mean = 79.8)	168.43***	2.58***
	(130.33, 208.83)	(1.59, 3.55)
7.68 (60th %ile = 87.5)	171.25***	2.65***
	(133.52, 211.31)	(1.68, 3.61)
32.68 (80th %ile = 112.5)	180.44***	2.88***
	(143.42, 220.14)	(1.95, 3.81)
145.18 (max = 225)	221.82***	3.91***
	(178.36, 270.75)	(2.85, 4.99)
9. By deviations from sample mean age (40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
-3.33 (min = 18)	168.48***	2.58***
	(130.38, 208.88)	(1.59, 3.55)
-1.33 (20th %ile = 20)	168.43***	"
	(130.34, 208.84)	
-.331 (40th %ile = 21)	168.41***	"
	(130.32, 208.82)	
0 (mean = 21.33)	168.41***	"
	(130.32, 208.81)	
3.668 (60th %ile = 25)	168.33***	"
	(130.27, 208.75)	
15.6685 (80th %ile = 37)	168.07***	"
	(130.06, 208.52)	
51.6685 (max = 73)	167.29***	"
	(129.31, 207.56)	

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Table 5 – continued from previous page

10. By perceived bias of researchers		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
No perceived bias	168.43***	2.58***
	(130.33, 208.83)	(1.59, 3.55)
Perceived pro-ICP bias	128.71***	1.58**
	(88.88, 169.37)	(0.48, 2.62)
Perceived anti-ICP bias	70.60	0.13
	(-24.26, 163.78)	(-2.44, 2.51)
11. By respondent's experience with extreme weather in last 12 months		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
No extreme weather events	168.43***	2.58***
	(130.33, 208.83)	(1.59, 3.55)
Drought	111.11***	1.14
	(48.50, 173.20)	(-.57, 2.77)
Extreme cold	121.85***	1.40
	(72.88, 171.83)	(-0.05, 2.75)
12. Any prior experience with extreme-weather harm?		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
No prior harm	168.43***	2.58***
	(130.33, 208.83)	(1.59, 3.55)
Some prior harm	168.88***	"
	(130.72, 209.30)	

t footnote1
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A Appendix 1: Survey Design

A.1 Basic components of the survey

Oath-taking. The survey begins with an "oath-taking" page, where the respondent is asked to confirm that they will "thoughtfully provide" their best answers to each question in the survey.

Social priorities. Respondents are asked to check their three highest personal priorities from a randomly ordered list that includes "Conserve natural resources," "Improve education,", "Improve public health," "Prevent climate change," "Prevent violence, crime," and "Reduce poverty, hunger."

Background information. Respondents are reminded about fossil fuels and greenhouse gases of human origin, that almost all climate scientists agree that emissions from human activities are causing Earth's climate to change, but that some people remain unconvinced. They are then quizzed about the geographic scope of carbon impacts from a university (and incorrect perceptions are corrected). Carbon pricing is introduced as an incentive to reduce carbon emissions that will simultaneously create a revenue stream. Existing government-run carbon-pricing schemes are reviewed, and respondents are quizzed about their awareness of discussions in Washington and Oregon about possible carbon-pricing programs (including state-wide cap-and-trade). Internal carbon-pricing programs by roughly 500 individual U.S. businesses are outlined, along with the reasons firms give for embarking on these programs (followed by a quiz about which of these reasons were included on the previous page). Respondents are reminded that the benefits of carbon emissions reductions are global, but a number of ways in which a university might benefit from instituting such a program are suggested. It is noted that these effects are not guaranteed, but are possibilities.

A university carbon-pricing program. The survey reviews how it would be difficult to price all carbon emissions from a university, so the focus would be on energy use in buildings and on university-sponsored air travel. It is noted that no specific program is currently being proposed, so that the survey will describe a range of different possible programs, each described in terms of the overall reduction in net carbon emissions, how the costs would be shared, how the money raised by the program would be spent, and what would be the unavoidable cost to the individual. We emphasize that the programs are designed so that some programs are small, others are moderate, and some may seem like just too much. We then use the individual's own specific variant of "Program A" as a training example, as we explain in detail how to interpret the program summaries that are used in each choice set the individual will consider. First, however, respondents are reminded that they will always have the option to vote for "No Program." Reasons are suggested why reasonable people may choose that alternative in some or all cases. The programs are also described as remaining in effect indefinitely. However, if the federal government or the state implement a mandatory carbon-pricing program, the university's program would be re-evaluated.

Review of the specific university's circumstances. Before the choice tutorial section begins, respondents are reminded about the basic facts of their university's carbon footprint, including the number of students and the number of faculty and staff. The most recent estimate of the university's carbon footprint (not counting the carbon content of other purchased products) is estimated in metric tons of carbon dioxide equivalent emissions. Building energy use and air travel are noted explicitly, in terms of the total annual emissions and the percent of total university-related carbon emissions.

Choice set tutorial. Due to randomization at the individual level, every respondent has a unique set of programs making up their choice sets. We use the first alternative in the first choice set to illustrate how the respondent is asked to interpret the information in each choice set "summary table." The benefit information appears first, by itself.

The second feature of every internal carbon-pricing program concerns information about how costs are shared. For public universities, these costs are shared four ways, and this information is displayed as an additional set of four rows in the table. Each share, as it is discussed on its own page, is highlighted in yellow in the table. Option additional information is provided in pop-up "modals" that appear superimposed on the main screen, so that respondents do not have to change browser windows.[11] Pre-testing of the survey identified a couple of points of potential confusion on the part of respondents. For example, some thought that air travel fees would also be paid by foreign students when they went home to visit their families. A quiz question checked for this mis-perception and corrected it if necessary. Other pre-test subjects were confused about whether they could avoid the cost of the carbon-pricing program if the share borne via student/employee fees was zero. If they believe this, they are reminded that everyone affiliated with the university would bear costs via building energy use fees, even if they were not charged directly.

The third feature of each program is a summary of how the revenues raised by the program are to be spent. The dominant form of spending is on internal carbon-reduction projects, and several possible examples are outlined. Another use would be for a variety of academic programs, for undergraduates, graduate students and/or faculty, for teaching or research. The third potential use of the revenues is described as "to pay for offsets." Offsets are explained, and respondents are asked to assume that there are "no legal or political considerations that would prevent your institution from spending money on high-quality verifiable carbon offsets."

The final program feature is the cost per year, "all told, after you have done what you can to adapt to the program." Respondents are asked to assume that they will pay these costs for as long as they remain with the university, and are reminded that these may be direct fees or indirect costs that filter down to everyone who benefits from the use of campus buildings, including residence halls, or via higher air-travel costs for other programs that end up affecting you if they are covered by higher fees and/or reductions in other services.

The final pages of the tutorial section caution people that they should fully consider their future expenses, and should think very carefully about what they would have to give up, if the program in question were to be put in place at their institution. This is the "cheap talk" component of the preparation for program choices. They are also reminded that the university plans to use the results of the study to help decide whether to implement a carbon-pricing program and, if so, what type. This is the "consequentiality" component of the preparation for program choices. Finally, respondents are reminded that they should consider each policy choice independently, as though the options in each choice scenario are the ONLY ones being offered. They should vote as they would if these were real and secret ballots, and they should feel free to vote "no" if the program(s) in question would be just too costly.

[11]The survey was designed to be feasible on the screen of a mobile device, as well as on a computer or tablet.

Choice tasks. The first choice task consists of just Program A versus No Program (replicating the attributes for Program A used in this respondent's tutorial section. The second task consists of just Program B versus No Program (with Program B's new set of attributes).

The third choice is a three-way choice between new Program C, new Program D, and No Program. If they choose either of Programs C or D, their next choice branches to a choice between the non-chosen Program alternative and No Program. Then each respondents is offered another three-way choice between new Program E, new Program F, and No Program, again with a followup question (if either of Programs E or F is chosen) between the non-chosen Program alternative and No Program.

If No Program is chosen in any of these choice sets, the respondent is asked for reasons why they preferred the No Program alternative. Some of these reasons are "economic" reasons why they preferred No Program (for example: "Program C would cost me more than I would want to pay," "I did not approve of the way the costs of Program C would be shared," "I did not approve of the ways the money from program C would be spent," "I did not believe that the benefit to the university of Program C justified its cost to me," "I did not believe that the global benefits of Program C justified its cost to me.". But one of the offered reasons suggests some form of scenario rejection: "The mix of features described for Program C did not seem believable." Respondents were given the opportunity to specify other reasons as well. Choices where an individual gave a reason for choosing No Program that suggested scenario rejection will cause those choices to be omitted from the analysis.

We made a conscious effort to reduce the burden of the survey for people who strongly object to carbon-pricing programs. Respondents who chose No Program in the first choice set were asked a follow-up question if they indicated that their reasons for choosing No Program included that the benefits to the university (or the global benefits) did not justify the cost. If they checked a box indicating that they "did not like Program A, but there might be some type of program, at some cost low enough for me, for which I could possibly vote "Yes," they were allowed to continue with the rest of the choice sets. But they were also given an opportunity to check instead that "Carbon-pricing programs are a BAD idea. It would not matter how the program is set up. I would not vote "Yes" for ANY carbon-pricing program!" These respondents were then skipped to the end of the choice tasks, and we will mark them as preferring "No Program" in all of the subsequent choice tasks. This strategy is designed to limit the attrition of anti-carbon-pricing respondents prior to the end of the survey.

Debriefing. After making their program choices, respondents were asked to think back and check those program attributes that were especially important to them. This information will help us assess attribute non-attendance. If a respondent voted for No Program in every choice set, they were given a list of reasons to consider why they might have chosen that way, including "These choice tasks were just too difficult for me to process." and "I am not convinced that climate change is actually happening." and "Even if climate change is actually happening, I don't believe that anything we do (or don't do) will make any real difference." Also offered were "I don't think universities produce enough carbon emissions to matter. Instead, heavy industries should be required to cut back," "I would be hurt by the effect of the program on my livelihood or the cost of my education," "I would be hurt by the effect of the program on the cost of university-paid air travel that is important to me."

Personal exposure to climate change impacts. Respondents are invited to indicate whether they have ever lived, for more than a few month in total, in places that are exposed to specific different types of climate-related risks (including "in a developing country with limited preparedness for natural disasters," where they are then subsequently asked whether this experience was a result of a study-abroad program). Respondents are then asked if they, or any close family members or friends, have been personally harmed to different degrees by weather-related hazards. They are then asked about their experience, if any, with specific extreme weather events over the last 12 months (to check for any "recency" effects).

Perceived researcher bias. Respondents were asked "Overall, the wording of this survey made it seem that the researchers conducting this study really wanted me to choose..." The options included "some carbon-pricing program, rather than No Program," "No Program, rather than some carbon-pricing program," "The best alternative for me, personally, based on all of the features of the programs," and "Not sure/couldn't tell." The goal in survey design is to have the majority of people choose one of the last two options.

Climate change attitudes. We included, at this point in the survey, a set of five questions about "global warming" developed by researchers at Yale University, for which there is existing evidence about the relative frequency of these climate attitudes in the general population of the U.S.

Sociodemographics. The survey collects information about gender, the respondents main role at the university (and any secondary roles), age, race, ethnicity, educational attainment, and employment status. Finally, we inquire about the respondent's political views (including an explicit "prefer not to say" option) and their household's income bracket.

A.2 Randomizations

The survey template is populated according to a set of "parameters" specific to the university. These parameters include strings to identify the university and its state, the total number of students, total number of faculty and staff, the year of the last carbon inventory (or approximate inventory), the estimated total emissions due to the operation of the university (not including carbon embodied in purchased inputs other than the fuel for the physical plant and transportation), the type of heating fuel, the carbon emissions related to district heating, the percent of emissions attributed to district heating, the carbon emissions due to air travel and the percentage of emissions due to air travel, and the nature of the incentive for survey participation.

Most universities will have basic demographic data on file for everyone affiliated with the university. If key variables are available from administrative data, and therefore do not need to be elicited from survey respondents, some respondent effort can be saved. Thus the parameters for the survey include indicators for whether there is available administrative data for gender, age, race, ethnicity and educational attainment.

Given that the shares of total percentage points of carbon emissions reduction must sum to one, and that the shares in which the proceeds of an internal carbon-pricing scheme might be spent must also sum to one, it was more difficult than usual to pursue a d-optimal design for the mix of attributes among the choice sets. We elected instead to randomize the portfolio of shares for each potential carbon-pricing program, and then to follow up by pairing these portfolios to eliminate pairs of programs where one program dominates the other by having both greater carbon-reduction benefits and lower cost. We wished to force respondents to trade off between basic benefits and costs. While it is possible that one program might dominate the other on these two dimensions, yet be less preferred because of its distributional consequences, we did not wish to risk too many of these likely easier choices.

The design options for the choice sets where as follows:

- Percentage point reductions in carbon emissions: 10, 15, 20, 25, 30, 35, 40, 45, 50
- Distribution of program costs:
  - Percent of program cost borne as student/employee fees: 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100
  - Percent of program cost borne as air travel fees: 0, 10, 20, 30, 40, 50
  - Percent of program cost borne as building energy fees: 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100
  - Percent of program cost borne by the state's taxpayers: 0, 10, 20
- Distribution of program revenues (Spring 2018 Survey Wave):
  - Percent of revenues spent on internal carbon-reduction projects: 50, 60, 70, 80, 90, 90, 100, 100
  - Percent of revenues spent on academic programs: 0, 10, 20, 30
  - Percent of revenues spent on carbon offsets: 0, 10, 20, 30
- Distribution of program revenues (Fall 2018 Survey Wave):
  - Percent of revenues spent on internal carbon-reduction projects: 20, 30, 40, 50, 60, 70, 80, 90, 90, 100, 100
  - Percent of revenues spent on academic programs: 0, 10, 20, 30
  - Percent of revenues spent on carbon offsets: 0, 10, 20, 30, 40 50

For the overall benefits of the program (percentage-point carbon reduction), one value is drawn randomly from the list. For the distribution of program costs, and also for the distribution of program benefits, the design algorithm draws one value randomly from each list in the set and calculates whether the total sums to 1.0. If yes, that mix of shares is accepted as viable; if no, another set of shares is randomly drawn and their total is calculated. The process continues until a valid set of shares is produced.[12]

[12] In the Spring 2018 design, we specifically limited the possible shares to that range of values most likely to be relevant in any prospective real program for the university in question. In the Fall 2018 design, we extended the range

For complete orthogonality among program attributes, it might seem preferable to draw the cost of each program independently from that program's attributes. However, we wished to avoid scenario rejection due to implausible combinations of program benefits and program costs. Thus we constructed program costs that would be systematically related to program benefits, but also incorporate a uniformly distributed random component. The random component for costs is drawn from the distribution: -3, -2, -1, 0, 1, 2, 3. Unavoidable program costs per year (to the individual) are then constructed from a formula that includes an intercept (set at 40 for students and 20 for employees), a cost per percentage-point reduction in carbon emissions (set at 3.0), and a scale factor that multiplies the random component for costs (set at 14). After randomization, any cost per year less than 10 is set to 10, and any cost greater than 250 is set at 250.

The number of programs to generate is based on the number of email addresses in the sample in question. While only three pairs of programs are eventually used in each person's survey, we build ten two-policy choice sets per person and utilize the first three pairs of programs that do not fail the inclusion criteria. These criteria include the "no dominance in terms of both higher carbon emissions and lower costs for one of the alternatives in a pair" and "the difference in costs between the two alternatives should be at least $5 per year." (Costs are rounded to the nearest whole dollar.)

used for the distribution of program revenues, to see if these more-extreme values induced a measurable reaction among respondents who received these designs. In the Spring 2018 design, people were not particularly responsive to expenditure on carbon offsets, and only students appeared to respond systematically to expenditure on academic programs.

B Appendix: Response-nonresponse Modeling

When respondents can choose whether or not to begin or complete a survey when they are invited to participate (i.e. in almost every voluntary survey context), it is important to question whether the sample of responses that is sufficiently complete to be included in estimation can be argued to be representative of the population of interest. Any given invitee's propensity to show up in the final estimating sample may be correlated with the value of the outcome variable of interest for that person—in this case, willingness-to-pay for carbon reductions via an internal carbon pricing program. It is vitally important to assess whether observable individual characteristics, including proxies for the environment within which the individual's preferences for carbon-pricing programs may have evolved, appear to have any bearing on the individual's decision about whether to participate fully in the survey.

The set of invitees was randomly drawn from the student sample and from the employee sample, albeit at slightly different rates from each group. In this study, due in part to the survey's launch just before the end of the Spring quarter, response rates were only on the order of 10 percent. This may be due in part to the modest incentive payment for each response (a five-dollar electronic gift card for the campus shop). A response rate this low does not necessarily imply that the sample will be non-representative. But nothing can be assumed, ex ante.

To model response/nonresponse propensities, it is necessary to have common explanatory variables available for both respondents and non-respondents. By prior arrangement with the university's Office of Institutional Research, we designed an elaborate procedure to connect all invited respondents to administrative data held by the university and to zip-code level information associated with employees via their current zip-code and with students via the zip-code of the high-school they attended prior to their admission to the university. Our goal with these zip-code level variables is to proxy for the "neighborhood" in which the individual may have developed their preferences with respect to climate change policies and carbon program. By zip code, we connect each individual to Census data from the American Community Survey (using the census-tract-to-zip-code crosswalk from Department of Housing and Urban Development). We also connect each zip code to David Leip's US Election Atlas, with its election results at the county level for every county in the U.S., for the 2012 and 2016 Presidential elections. Finally, we connect the centroid of each zip code to its corresponding Congressional District and merge in data from the League of Conservation Voters to capture the voting record of that district's representative on environmental legislation.

Our goal in response/nonresponse modeling is to capture systematic heterogeneity in each invited respondent's propensity to provide a completed survey for our use in estimation. To this end, we specify an ordinary probit model, with the binary outcome defined as 1 = completed survey and 0 = nonresponse or incomplete survey. We have explored two strategies for determining a parsimonious specification for the response/nonresponse model: (1) a conventional binary probit, subjected to backwards stepwise deletion of explanatory variables that are not statistically significant, and (2) LASSO models that employ a penalty function that help to zero-out the coefficient on explanatory variables that are both statistically insignificant and which contribute little to explaining variation in the outcome.

B.1 Binary probit with stepwise deletion

It would be ideal to be able to estimate the response propensity model simultaneously with the program choice models described in the body of this paper. As yet, there is no available full-information maximum likelihood estimator that can accomplish this task, either for conventional conditional logit specifications or when random-parameters mixed-logit or latent-class models are in play. Instead, we take a crude approach to assessment and correction of potential nonresponse bias in our estimated preference parameters.

We estimate an ad hoc probit specification that uses all available variables to explain systematic differences in response/nonresponse propensities. These propensities are interpreted to be the fitted "index" for the probit model. We then calculate the average of these fitted index values across all invited respondents (using exogenous weights to control for the different proportions of students and employees that were invited). For each person, we then calculate the deviation of their individual response propensity from this overall average in the target population (from which the invited sample was drawn at random). Then we estimate our choice models using only the sample of respondents. However, we allow each basic preference parameter in these models to vary systematically with the deviation of that individual's response propensity from the population mean response propensity. By including these controls, it is possible, subsequently, to simulate what would have been the basic preference parameters had everyone in the estimating sample had a response propensity exactly equal to the mean among the invited respondents drawn as a stratified random sample from the university's overall population. This "counterfactual" holds when everyone's "deviation from the mean response propensity" is exactly zero. As a practical matter, we can just ignore the coefficients on these deviations and pay attention to the "base" coefficients, which hold when all of the deviations are set to zero.

B.2 LASSO models

In the presence of a large number of variables, there is a danger of finding statistical relationships between variables that exist merely due to chance and do not reflect the actual data generating process. One approach to limit over-fitting is to use regularization, a technique where a penalty is assigned to the inclusion of variables. This penalty decreases the model variance due to variable selection and thus will produce lower levels of prediction error than simpler methods of mode selection.

For the response/non-response model we use a form of regularization known as Lasso.[13] The probability of response is modeled by estimating a logit with a penalty term in the likelihood function equal to the sum of the absolute value of each coefficient. We therefore want to find a vector of β's that maximize the following log-likelihood function

$$\sum_{i=1}^{N}\left[y_i(\beta x_i) - log(1+e^{\beta x_i})\right] - \lambda \sum_{j=1} K|\beta_j|$$

[13] Lasso is an abbreviation for Least Absolute Shrinkage and Selection Operator

where y_i is equal to one if the individual responded to the survey and is zero otherwise and λ is a tuning parameter that determines the level of penalty imposed on coefficient size.

The use of an absolute value specification of the penalty function has the advantage of making corner solutions likely, which means that in practice estimated coefficients are zero and variables are dropped from the model. Thus lasso selects the variables which are most predictive of response status and drops those with limited predictive power.

We select the value of λ using cross-validation techniques.[14]. A candidate grid of λ values is specified and the sample is divided into several subsets. Each subset is "held-out" of the sample and the model is estimated on the remaining data for each value of λ. A measure of model fit[15] is then computed using each holdout sample. The value of λ we use for the estimates in paper is the one with the best average score across the various holdout samples.

[14]We estimate all lasso models using the R package glmet

[15]In this case the deviance, equal to two times the negative of the log-likelihood function

C Appendix 2: Sample Selection Model Parameter Estimates

Table 6: Response/nonresponse model, fitted using probit (includes sampling weights for Spring wave

	LPM Selected subsets	LPM Remaining parsim.	Probit Remaining
main			
zip pr Black or African American alone	-0.0590		
	(0.0971)		
zip pr American Indian, Alaska Native alone	-0.00890		
	(0.209)		
zip pr Asian alone	-0.00224		
	(0.110)		
zip pr Native Hawaiian, Other Pac. Islander alone	0.386		
	(0.534)		
zip pr U.S. citizen, born abroad, American parent(s)	0.0529		
	(1.044)		
zip pr U.S. citizen by naturalization	0.108		
	(0.188)		
zip pr Renter occupied	0.0877*		
	(0.0470)		
1=have zip prop. by age bracket	0.0405	0.0348*	
	(0.186)	(0.0179)	
zip pr Aged 20 to 24 years	0.394*	0.217*	1.835*
	(0.228)	(0.132)	(1.025)
zip pr Aged 25 to 29 years	-0.646		
	(0.450)		
zip pr Aged 35 to 39 years	0.346		
	(0.612)		
zip pr Aged 45 to 49 years	0.314		
	(0.620)		
zip pr Aged 55 to 59 years	-0.264		
	(0.642)		
zip pr Aged 65 to 69 years	0.207		
	(0.822)		

Continued on next page

Table 6 – continued from previous page

zip pr Aged 70 to 74 years	0.636		
	(1.053)		
zip pr Aged 75 to 79 years	-1.802	-1.337*	-12.80**
	(1.346)	(0.687)	(5.807)
zip pr Aged 80 to 84 years	1.513	2.519***	20.29***
	(1.320)	(0.870)	(6.808)
zip pr Moved; within same county	0.220		
	(0.146)		
zip pr Moved; from different county, same state	0.118		
	(0.237)		
zip pr Moved; from different state	0.101		
	(0.309)		
zip pr Moved; from abroad	-0.844		
	(0.797)		
1=have zip prop. by houshold structure	0.148		
	(0.267)		
zip pr Nonfamily household	-0.0241		
	(0.0691)		
zip pr 25 yrs+, Less than 9th grade	0.105		
	(0.219)		
zip pr 25 yrs+, High school grad. (incl. equiv.)	0.0717		
	(0.113)		
zip pr Limited English, Spanish	-0.0987		
	(0.263)		
zip pr Limited English, Other Indo-European lang.	0.0915		
	(0.514)		
zip pr Limited English, Asian and Pacific Island lang.	-0.0564		
	(0.421)		
zip pr Limited English, Other languages	0.396		
	(1.360)		
zip pr Income less than 10,000	0.000395		
	(0.207)		
zip pr Income 15,000 to 24,999	-0.125	-0.193*	-2.902***
	(0.226)	(0.101)	(0.979)
zip pr Income 35,000 to 49,999	-0.0992		

Continued on next page

	(0.232)		
zip pr Income 150,000 to 199,999	0.0579 (0.302)		
zip pr Income 200,000 or more	0.0909 (0.154)		
zip pr Housing units - 2 units	-0.0251 (0.233)		
zip pr Housing units - 5 to 9 units	-0.0896 (0.192)		
zip pr Housing units - 20 or more units	-0.0248 (0.112)		
zip pr Housing units - Mobile home	-0.0452 (0.125)		
zip pr Housing units - Boat, RV, van, etc.	0.195 (1.226)		
zip pr Housing built 2010 to 2013	-0.0362 (0.916)		
zip pr Housing built 2000 to 2009	0.128 (0.806)		
zip pr Housing built 1990 to 1999	-0.0271 (0.776)		
zip pr Housing built 1980 to 1989	0.0742 (0.800)		
zip pr Housing built 1970 to 1979	0.138 (0.787)		
zip pr Housing built 1960 to 1969	0.0277 (0.798)		
zip pr Housing built 1950 to 1959	0.121 (0.794)		
zip pr Housing built 1940 to 1949	0.111 (0.798)		
zip pr Housing built 1939 or earlier	0.102 (0.798)		
zip pr Housing with 1 room	0.433 (0.323)	0.556** (0.220)	4.460** (1.919)

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Table 6 – continued from previous page

zip pr Housing with 3 rooms	-0.108		
	(0.210)		
zip pr Housing with 8 rooms	0.119		
	(0.247)		
zip pr Housing with 9 rooms or more	-0.0641		
	(0.120)		
zip pr Moved-in 2000 to 2009	-0.0505		
	(0.157)		
zip pr Moved-in 1990 to 1999	0.136		
	(0.194)		
zip pr Moved-in 1980 to 1989	-0.422		
	(0.312)		
zip pr Moved-in 1979 and earlier	0.0535		
	(0.262)		
zip pr No vehicles available	-0.250	-0.357***	-3.315***
	(0.174)	(0.111)	(1.118)
1=have zip prop. by substandard housing	-0.271		
	(0.796)		
zip pr Housing lacking complete kitchen	0.288		
	(0.512)		
zip pr No telephone service available	0.00189		
	(0.528)		
zip pr House value 50,000 to 99,999	-0.0531		
	(0.123)		
zip pr House value 300,000 to 499,999	0.0266		
	(0.0545)		
zip pr House value 500,000 to 999,999	0.00602		
	(0.0464)		
zip pr House value 1,000,000 or more	-0.0171		
	(0.0710)		
zip pr Rent 2,000 to 2,499	-0.0439		
	(0.110)		
1=have zip prop. by commut. travel mode	-0.0306		
	(0.263)		
zip pr Commute any carpool	0.0166		

Continued on next page

Table 6 – continued from previous page

	(0.152)		
zip pr Commute any public transit	0.123	0.0911*	
	(0.0931)	(0.0541)	
zip pr Commute by taxi	-0.177		
	(1.991)		
zip pr Commute by motorcycle	-0.713		
	(1.419)		
zip pr Commute by bicycle	0.00303		
	(0.256)		
zip pr Commute by other	0.226		
	(0.505)		
zip pr no commute, work at home	0.307		
	(0.193)		
zip pr Commute 10 to 14 min	0.0329		
	(0.112)		
zip pr Commute 15 to 19 min	-0.0195		
	(0.120)		
zip pr Commute 40 to 44 min	0.000138		
	(0.327)		
zip pr Commute 45 to 59 min	-0.175	-0.235***	-3.405***
	(0.163)	(0.0802)	(0.945)
zip pr Commute more than 90 min	-0.0878		
	(0.295)		
1=have zip prop. by heating fuel	0.0325		
	(0.201)		
zip pr Heat with electricity	0.00669		
	(0.0312)		
zip pr Heat with solar	-1.284		
	(1.325)		
1=have zip prop. by industry	-0.0214		
	(0.338)		
zip pr Industry manufacturing	0.101		
	(0.129)		
zip pr Industry retail trade	0.230	0.274**	2.540**

Continued on next page

	(0.175)	(0.117)	(1.054)
zip pr Industry transp/warehs/util	-0.0262		
	(0.289)		
zip pr Industry information	-0.0758		
	(0.312)		
zip pr Industry finan/insur/real estate	0.0464		
	(0.198)		
zip pr Industry professl/scientif/mgt	-0.0970		
	(0.160)		
zip pr Industry arts/enter/recr/accom/food	-0.235*	-0.310***	-3.247***
	(0.141)	(0.0985)	(1.012)
zip pr Industry other services	-0.110		
	(0.282)		
zip pr Industry public admin	-0.0385		
	(0.192)		
1=have zip prop. by urban/rural	-0.0000299		
	(0.0447)		
1=have zip prop. by 2016 votes	0.0847*	0.0683***	
	(0.0509)	(0.00943)	
zip pr Democratic votes 2016 Pres elect.	-0.000281		
	(0.0919)		
zip pr Green Party votes 2016 Pres elect.	-0.612		
	(1.243)		
zip avg legislator 2017 LCV score	-0.000529		
	(0.00151)		
zip avg legislator lifetime LCV score	-0.000219		
	(0.00161)		
1=have zip prop. congress. rep. party	-0.00331		
	(0.0982)		
zip pr Democratic representative	0.0616		
	(0.0605)		
nogiftcard	0.722***	0.719***	
	(0.117)	(0.116)	
1=have student's LDC continent	0.00418		

Continued on next page

	(0.186)		
1=have individual's gender	-0.0529		
	(0.0418)		
1=female	0.0192***	0.0178***	0.145***
	(0.00481)	(0.00470)	(0.0362)
1=Black or African American	-0.0434**	-0.0434**	-0.521***
	(0.0173)	(0.0170)	(0.185)
1=Hispanic or Latino	-0.0190**	-0.0178**	-0.149**
	(0.00837)	(0.00814)	(0.0678)
1=Native Hawaiian	-0.0663		
	(0.0427)		
1=Nonresident alien	-0.0294	-0.0486***	-0.534***
	(0.0248)	(0.00876)	(0.0892)
1=Race and ethnicity unknown	0.0109		
	(0.0101)		
1=Two or more races	-0.0149		
	(0.0105)		
1=individual's age is known	-0.0413	-0.0448*	-1.326**
	(0.0269)	(0.0239)	(0.662)
Individual's age squared, if known	0.00000232		
	(0.00000487)		
1=have individual's citizenship status	0.0451**	0.0419*	1.343**
	(0.0224)	(0.0222)	(0.661)
1=non-US citizen	-0.0202		
	(0.0250)		
1=employee: career non-tenure-track	-0.0178		
	(0.0137)		
1=employee: classified staff	0.0158	0.0232**	
	(0.0111)	(0.0101)	
1=employee: graduate employee	-0.00403		
	(0.0151)		
1=employee: student employee	-0.0234*	-0.0260***	-0.169***
	(0.0132)	(0.00910)	(0.0610)
1=have employee home organization	0.0706***	0.0697***	0.466***

Continued on next page

Table 6 – continued from previous page

	(0.0124)	(0.00766)	(0.0529)
1=organization: Athletics	-0.0690***	-0.0699***	-0.458***
	(0.0154)	(0.0151)	(0.125)
1=organization: Arch and Allied Arts	-0.0891***	-0.0881***	-0.616**
	(0.0326)	(0.0324)	(0.277)
1=organization: Business	-0.0368**	-0.0373**	
	(0.0184)	(0.0180)	
1=organization: Education	-0.0622***	-0.0667***	-0.395***
	(0.0155)	(0.0147)	(0.109)
1=organization: Journalism	-0.0412*	-0.0404*	
	(0.0228)	(0.0227)	
1=organization: PhysEd and Rec	-0.0462**	-0.0478**	-0.293*
	(0.0200)	(0.0197)	(0.157)
1=organization: Music and Dance	-0.0776***	-0.0763***	-0.442**
	(0.0260)	(0.0259)	(0.187)
1=organization: UGS	-0.0297		
	(0.0214)		
1=organization: Housing	-0.0445***	-0.0426***	-0.224***
	(0.0107)	(0.0105)	(0.0745)
1=student: Humanities	-0.0132		
	(0.0129)		
1=student: Natural Sciences	-0.00362		
	(0.00862)		
1=student: Education	-0.0271*		
	(0.0143)		
1=student: Journalism	-0.0164	-0.0159*	-0.203**
	(0.0107)	(0.00887)	(0.0823)
1=student: Business	-0.000695		
	(0.00975)		
1=student: Other	-0.0474	-0.0176*	-0.131*
	(0.0605)	(0.00928)	(0.0695)
1=student: Undeclared	0.00483		
	(0.0118)		
1=department: architecture	0.0183		

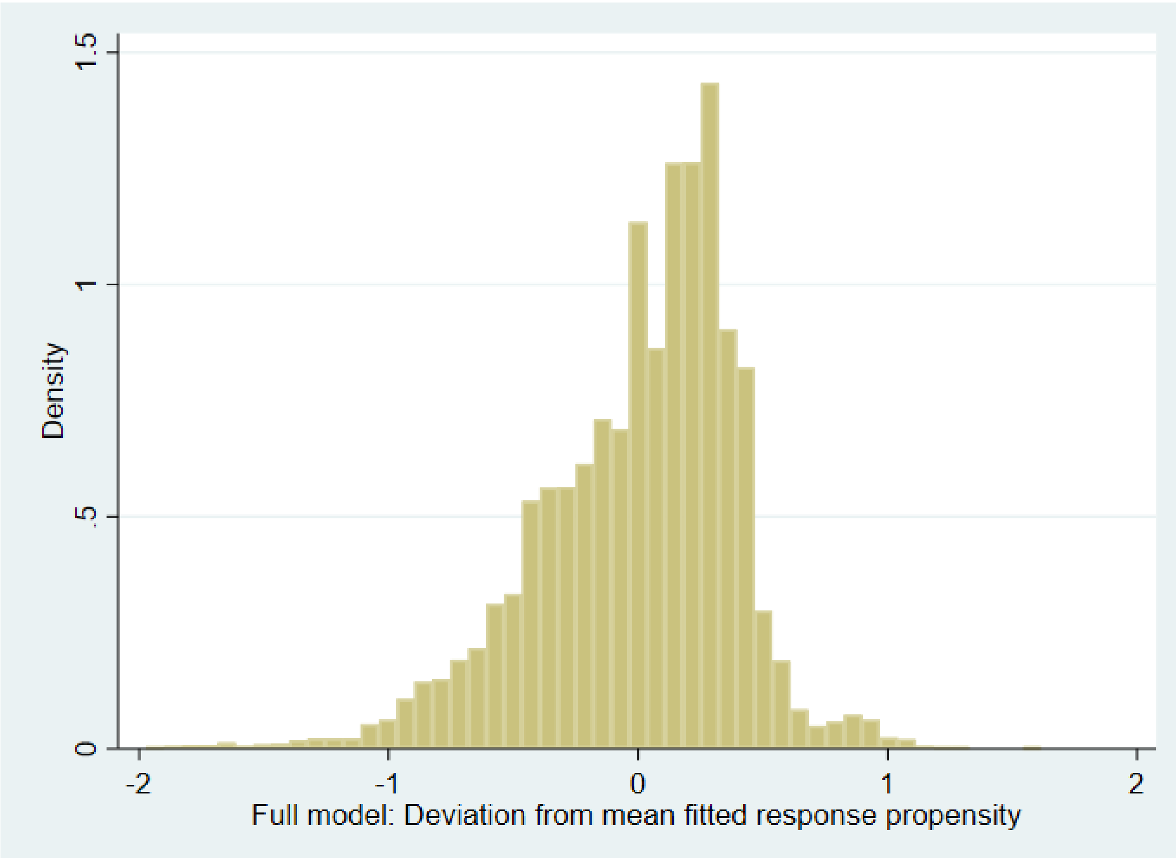
Continued on next page

Table 6 – continued from previous page

	(0.0187)		
1=department: biology	0.0221		
	(0.0152)		
1=department: chemistry	0.0231		
	(0.0209)		
1=department: community education	0.0277		
	(0.0613)		
1=department: environmental studies	0.0511***	0.0521***	0.383***
	(0.0195)	(0.0184)	(0.125)
1=department: law	0.0414**	0.0449**	0.277**
	(0.0210)	(0.0199)	(0.136)
1=department: music	0.0456**	0.0460**	0.293**
	(0.0219)	(0.0209)	(0.143)
1=department: special education	0.0330		
	(0.0223)		
1=department: smaller departments	0.00110		
	(0.00872)		
1=employee: fixed short-term faculty	-0.0249		
	(0.0177)		
Constant	0.0229	-0.0213	-1.114***
	(0.0439)	(0.0189)	(0.230)
Observations	12568	12568	10520

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 10: Distribution of fitted propensity to take and finish survey (six negative outliers omitted)



D Appendix 3: Choice Model Parameter Estimates

Table 7: How surviving interaction terms affect utility parameter estimates (weighted, sw probit selection model); base case=zero value for nuisance interactions; persons= 965, choices= 5084 (Omitted categories: those not included in the specification, by factor)

	Base (homog.)	+Base × selected (Minimal)	pruned
1=chosen alt			
Unavoid cost to resp. (22 to 232)	-0.0126*	-0.00869***	-0.00876***
	(0.00664)	(0.00112)	(0.00112)
× demeaned resp propensity	0.00105		
	(0.00106)		
Pct-point C reduction (10 to 50)	0.0335	0.0640***	0.0568***
	(0.0253)	(0.0165)	(0.0170)
× Pct-point C reduction (10 to 50)		-0.000347*	-0.000340*
		(0.000182)	(0.000181)
× zip pr Asian alone (.034)		0.378***	0.381***
		(0.0969)	(0.0970)
× zip pr Native HI, etc., alone (.002)		-1.080**	-1.027*
		(0.514)	(0.526)
× zip pr Moved; dif cty, sme st (.041)		-0.326**	-0.299**
		(0.153)	(0.152)
× zip pr 25+, grad/prof degr (.114)		-0.199***	-0.191***
		(0.0719)	(0.0720)
× zip pr Hsng incompl plumb (.002)		-1.094*	-1.197*
		(0.634)	(0.635)
× zip pr Cmt 60-89 min (.042)		0.330*	0.340*
		(0.180)	(0.179)
× 1=empl: Arch, Allied Arts (.004)		0.135***	
		(0.0325)	
× 1=empl: Business (.026)		0.0222	0.0219
		(0.0141)	(0.0142)
× 1=empl: Library (.037)		-0.0316**	-0.0310**
		(0.0133)	(0.0132)
× 1=dept: Gen soc sci (.012)		-0.0341*	

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		(0.0177)	
× 1=dept: Jour/Comm (.045)		-0.0206* (0.0124)	-0.0203 (0.0125)
× 1=12 mos: Severe winter (.136)		-0.0149*** (0.00565)	-0.0141** (0.00569)
× 1=perceive pro-ICP bias (.443)		-0.0100** (0.00457)	-0.00986** (0.00457)
× 1=perceive anti-ICP bias (.028)		-0.0207* (0.0119)	-0.0213* (0.0119)
× demeaned hhld inc ('000) if known		0.0000763** (0.0000300)	0.0000647* (0.0000341)
× demeaned resp propensity	-0.00318 (0.00400)		
Cost shr air trav fees (0 to .5)	-0.00190 (0.00910)	-0.0853*** (0.0306)	-0.0816*** (0.0302)
× Cost shr air trav fees (0 to .5)		-0.000444*** (0.000105)	-0.000433*** (0.000104)
× zip pr Inc lt 10K (.07)		0.284*** (0.104)	0.287*** (0.104)
× zip pr Inc 75K-100K (.113)		0.393*** (0.125)	0.375*** (0.122)
× zip pr Hsng incompl plumb (.002)		0.737 (0.480)	0.754 (0.483)
× zip pr Cmt 15-19 min (.195)		0.266*** (0.0787)	0.257*** (0.0780)
× 1=empl: Athletics (.022)		-0.0223* (0.0129)	-0.0210* (0.0127)
× 1=empl: Arch, Allied Arts (.004)		-0.279*** (0.0586)	
× 1=empl: Business (.026)		-0.0133 (0.00867)	-0.0127 (0.00862)
× 1=empl: Facilities (.029)		-0.0268* (0.0140)	-0.0262* (0.0141)
× 1=empl: Health, Counsel. (.019)		0.0226	

Continued on next page

		(0.0154)	
× 1=12 mos: Tornado (.035)		-0.0142* (0.00809)	-0.0143* (0.00823)
× 1=12 mos: Severe winter (.136)		0.0113*** (0.00422)	0.0105** (0.00424)
× demeaned resp propensity	0.00229 (0.00144)		
Cost shr bldg en fees (0 to 1)	0.0106 (0.00669)	0.0137*** (0.00399)	0.0140*** (0.00398)
× zip pr Cmt 30-34 min (.096)		-0.0715** (0.0364)	-0.0731** (0.0363)
× zip pr Heat solar (.001)		1.273** (0.625)	1.315** (0.634)
× 1=empl: Courtesy appt (.01)		-0.0194*** (0.00682)	
× 1=empl: Arch, Allied Arts (.004)		-0.228*** (0.0438)	
× 1=empl: Design (.047)		-0.0134*** (0.00442)	-0.0133*** (0.00446)
× 1=empl: Music and Dance (.017)		0.0326*** (0.00978)	
× 1=empl: Health, Counsel. (.019)		0.0171* (0.00916)	
× 1=dept: Jour/Comm (.045)		-0.0108** (0.00545)	-0.0105* (0.00546)
× 1=somew/very liberal (.683)		0.00470* (0.00246)	0.00459* (0.00243)
× demeaned resp propensity	-0.000248 (0.00105)		
Cost shr taxpayrs (0 to .2)	0.0228 (0.0166)	0.273*** (0.0770)	0.262*** (0.0756)
× zip pr Nonfamily hhld (.45)		-0.0875* (0.0521)	-0.0748 (0.0516)
× zip pr Inc 100K-150K (.114)		-0.578***	-0.543**

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Table 7 – continued from previous page

		(0.215)	(0.212)
× zip pr Inc 150K-200K (.041)		1.056**	1.013**
		(0.440)	(0.438)
× zip pr Cmt 5-9 min (.149)		-0.270*	-0.262*
		(0.154)	(0.152)
× zip pr Cmt 15-19 min (.195)		-0.547***	-0.530***
		(0.198)	(0.195)
× zip pr Cmt 40-44 min (.022)		-1.311**	-1.312**
		(0.556)	(0.551)
× zip pr Cmt 60-89 min (.042)		-0.778**	-0.767**
		(0.314)	(0.309)
× 1=empl: Athletics (.022)		-0.0663**	-0.0565*
		(0.0321)	(0.0291)
× 1=empl: Arch, Allied Arts (.004)		-1.027***	
		(0.203)	
× 1=empl: Design (.047)		-0.0385**	-0.0392**
		(0.0190)	(0.0191)
× 1=empl: Music and Dance (.017)		0.0400	
		(0.0252)	
× 1=empl: UGS (.022)		0.0628***	0.0561***
		(0.0182)	(0.0186)
× 1=stu: Design (.067)		0.0305**	0.0278*
		(0.0153)	(0.0153)
× 1=stu: Other (.083)		0.120***	0.123***
		(0.0429)	(0.0425)
× 1=dept: Comm educ (.082)		-0.0722*	-0.0796*
		(0.0436)	(0.0433)
× 1=dept: Couns psych (.009)		0.0667***	
		(0.0226)	
× 1=dept: Educ studies (.012)		0.0998***	
		(0.0169)	
× 1=dept: Env studies (.025)		0.0362**	0.0314*
		(0.0162)	(0.0164)
× demeaned resp propensity	-0.00267		

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Table 7 – continued from previous page

	(0.00265)		
Spend shr acad prog (0 to .3)	0.00916	-0.000698	-0.00793
	(0.0160)	(0.0226)	(0.0238)
× zip pr Nonfamily hhld (.45)		0.0645*	0.0614*
		(0.0369)	(0.0369)
× zip pr Cmt 5-9 min (.149)		0.113**	0.106*
		(0.0561)	(0.0563)
× zip pr Heat solar (.001)		-4.083***	-4.139***
		(1.231)	(1.237)
× 1=Non-white (.365)		-0.0136**	-0.0122**
		(0.00541)	(0.00553)
× 1=individual's age known (1)			0.00690
			(0.00638)
× demean indiv. age, if known		-0.000601*	-0.000655**
		(0.000316)	(0.000311)
× 1=empl: Athletics (.022)		0.0355	0.0323
		(0.0219)	(0.0219)
× 1=empl: Arch, Allied Arts (.004)		-0.662***	
		(0.111)	
× 1=empl: Music and Dance (.017)		-0.0437***	
		(0.0146)	
× 1=empl: Health, Counsel. (.019)		-0.0495***	
		(0.0158)	
× 1=dept: Gen soc sci (.012)		0.0279	
		(0.0190)	
× 1=dept: Sociol (.01)		0.102***	
		(0.0283)	
× 1=extr weath: any harm (.607)		0.0116**	0.0125***
		(0.00484)	(0.00479)
× demeaned resp propensity	-0.00138	-0.00750***	-0.00707***
	(0.00251)	(0.00214)	(0.00219)
Spend shr offsets (0 to .5)	-0.0108	-0.106***	-0.108***
	(0.0120)	(0.0327)	(0.0326)
× zip pr Asian alone (.034)		-0.244**	-0.252**

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	(0.100)	(0.0998)
× zip pr Moved; same cty (.093)	0.196**	0.223***
	(0.0771)	(0.0760)
× zip pr Hous-multi-unit (.119)	-0.0469	-0.0473
	(0.0293)	(0.0291)
× zip pr Hsng incompl kitch (.006)	-0.743**	-0.673*
	(0.350)	(0.345)
× zip pr No phone service (.022)	1.401***	1.244***
	(0.360)	(0.347)
× zip pr Heat electr (.591)	0.0501*	0.0440
	(0.0287)	(0.0287)
× zip pr Heat fuel oil, kero (.011)	0.226**	0.210**
	(0.102)	(0.0983)
× zip pr Ind manuf (.089)	0.153*	0.149*
	(0.0831)	(0.0825)
× zip pr Dem votes 2016 Pres elect.	0.0797*	0.0889**
	(0.0451)	(0.0451)
× Avg 2017 LCV score, pop wtd	-0.000222*	-0.000192
	(0.000133)	(0.000132)
× 1=empl: Career non-tenure (.052)	-0.0266***	-0.0220**
	(0.00996)	(0.00996)
× 1=empl: Officer of admin (.134)	-0.0159**	-0.0151**
	(0.00637)	(0.00632)
× 1=empl: Arch, Allied Arts (.004)	0.173***	
	(0.0370)	
× 1=empl: Health, Counsel. (.019)	0.0284**	
	(0.0122)	
× 1=empl: VPFA, VPSL (.01)	0.0783**	
	(0.0338)	
× 1=dept: Bus admin (.068)	0.0238***	0.0236***
	(0.00672)	(0.00669)
× 1=dept: Music (.02)	0.0424***	0.0426***
	(0.0163)	(0.0155)
× 1=dept: Sociol (.01)	-0.0307**	

Continued on next page

Table 7 – continued from previous page

		(0.0146)	
× demeaned resp propensity	0.00144		
	(0.00191)		
status quo w/ no prog	-0.218	0.734	0.569
	(0.741)	(1.057)	(1.051)
× zip pr Moved; same cty (.093)		11.33***	11.61***
		(4.028)	(4.022)
× zip pr Moved; from abroad (.004)		-75.93***	-72.54***
		(22.27)	(22.34)
× zip pr Inc 25K-35K (.098)		9.879	10.38
		(6.323)	(6.387)
× zip pr Hous-mobile (.066)		-5.577**	-5.708**
		(2.625)	(2.607)
× zip pr Cmt 15-19 min (.195)		-7.565**	-7.743**
		(3.693)	(3.691)
× zip pr Cmt 25-29 min (.055)		-11.45*	-10.52*
		(6.297)	(6.296)
× zip pr Ind oth serv (.062)		13.19*	13.33*
		(6.829)	(6.825)
× 1=empl: Classified staff (.136)		0.568**	0.661***
		(0.239)	(0.233)
× 1=empl: Courtesy appt (.01)		-2.475***	
		(0.585)	
× 1=empl: Graduate employee (.084)		-0.563**	-0.495*
		(0.276)	(0.277)
× 1=empl: Student employee (.186)		-0.656***	-0.634***
		(0.182)	(0.185)
× 1=empl: Arch, Allied Arts (.004)		-34.24***	
		(5.759)	
× 1=empl: Design (.047)		-1.321***	-1.294***
		(0.465)	(0.461)
× 1=empl: Education (.036)		0.932*	0.953*
		(0.509)	(0.518)
× 1=empl: Health, Counsel. (.019)		1.682**	

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		(0.720)	
× 1=empl: VPFA, VPSL (.01)		2.575**	
		(1.119)	
× 1=stu: Business (.068)		0.778**	0.824***
		(0.314)	(0.312)
× 1=stu: Undeclared (.042)		-0.554*	-0.466
		(0.296)	(0.296)
× 1=dept: Biology (.033)		-0.720**	-0.669**
		(0.338)	(0.338)
× 1=dept: Jour/Comm (.045)		-1.268***	-1.189***
		(0.414)	(0.415)
× 1=extr weath: any harm (.607)		0.289*	0.303*
		(0.156)	(0.156)
× 1=12 mos: Heat wave (.432)		-0.390***	-0.392***
		(0.144)	(0.144)
× 1=perceive pro-ICP bias (.443)		0.465**	0.473***
		(0.181)	(0.180)
× 1=somew/very liberal (.683)		-0.607***	-0.611***
		(0.197)	(0.196)
× 1=somew/very conserv (.086)		0.680**	0.700**
		(0.293)	(0.295)
× demeaned resp propensity	0.0516		
	(0.117)		
× =1 if have hhld inc (.882)			0.00517
			(0.00591)
No. alternatives	12069	12069	12069
Max. log-likelihood	-6355.36	-5772.24	-5827.61
Clustering	caseid	none	caseid
Base case WTP (40% C red)	106.29	294.66	259.36
Implied lower CI	22.72	140.72	105.12
Implied upper CI	189.87	448.60	413.60

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Appendix 4: Additional WTP Simulations

Table 8: Heterogeneity in WTP by program attributes and respondent characteristics

13. Zip code proportions, interquartile heterogeneity: pc15to19min		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pc15to19min	168.24***	2.58***
	(130.16, 208.62)	(1.59, 3.55)
Upper quartile: pc15to19min	168.64***	"
	(130.56, 209.08)	
14. Zip code proportions, interquartile heterogeneity: pinc_150_199		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pinc_150_199	168.20***	"
	(130.11, 208.59)	
Upper quartile: pinc_150_199	168.30***	"
	(130.22, 208.68)	
15. Zip code proportions, interquartile heterogeneity: pinc_75_99		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pinc_75_99	152.05***	2.17***
	(112.79, 193.88)	(1.12, 3.21)
Upper quartile: pinc_75_99	171.35***	2.65***
	(133.13, 211.93)	(1.66, 3.63)
16. Zip code proportions, interquartile heterogeneity: pinc_lt_10		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pinc_lt_10	168.39***	2.58***
	(130.30, 208.80)	(1.59, 3.55)
Upper quartile: pinc_lt_10	168.58***	"
	(130.48, 209.05)	
17. Zip code proportions, interquartile heterogeneity: psub_kitchen		
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)		
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: psub_kitchen	168.60***	"
	(130.51, 209.01)	

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Upper quartile: psub_kitchen	168.34***	"
	(130.26, 208.72)	

18. Zip code proportions, interquartile heterogeneity: psub_plumbing
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: psub_plumbing	185.35***	3.00***
	(145.71, 227.50)	(2.00, 4.02)
Upper quartile: psub_plumbing	170.68***	2.63***
	(132.60, 211.10)	(1.65, 3.61)

19. Zip code proportions, interquartile heterogeneity: pasian
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pasian	150.35***	2.12***
	(111.47, 191.65)	(1.06, 3.15)
Upper quartile: pasian	165.43***	2.50***
	(127.62, 205.47)	(1.50, 3.47)

20. Zip code proportions, interquartile heterogeneity: pc20to24min
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pc20to24min	153.73***	2.21***
	(114.36, 194.61)	(1.15, 3.23)
Upper quartile: pc20to24min	190.57***	3.13***
	(145.21, 238.97)	(2.00, 4.27)

21. Zip code proportions, interquartile heterogeneity: pc60to89min
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pc60to89min	144.36***	1.97***
	(103.62, 186.69)	(0.9, 3.01)
Upper quartile: pc60to89min	176.24***	2.77***
	(136.46, 218.42)	(1.75, 3.79)

22. Zip code proportions, interquartile heterogeneity: ped_bachelor
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: ped_bachelor	192.08***	3.17***
	(150.43, 237.41)	(2.15, 4.22)

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Table 8 – continued from previous page

Upper quartile: ped_bachelor	170.20***	2.62***
	(132.11, 210.60)	(1.63, 3.60)
23. Zip code proportions, interquartile heterogeneity: pc30to34min (40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pc30to34min	168.48***	2.58***
	(130.37, 208.90)	(1.59, 3.55)
Upper quartile: pc30to34min	168.42***	"
	(130.32, 208.82)	
24. Zip code proportions, interquartile heterogeneity: pmvabroad (40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pmvabroad	168.34***	"
	(130.27, 208.72)	
Upper quartile: pmvabroad	168.53***	"
	(130.42, 208.92)	
25. Zip code proportions, interquartile heterogeneity: pmvsameco (40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pmvsameco	168.53***	"
	(130.41, 208.98)	
Upper quartile: pmvsameco	168.36***	"
	(130.32, 208.74)	
26. Zip code proportions, interquartile heterogeneity: pblack (40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pblack	168.22***	"
	(130.15, 208.60)	
Upper quartile: pblack	168.41***	"
	(130.31, 208.81)	
27. Zip code proportions, interquartile heterogeneity: pinform (40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30) Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables		
Lower quartile: pinform	168.16***	"
	(130.09, 208.50)	

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Upper quartile: pinform	168.54***	"
	(130.43, 208.97)	

28. Zip code proportions, interquartile heterogeneity: pnonfamily_hhlds
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pnonfamily_hhlds	168.29***	"
	(130.23, 208.68)	
Upper quartile: pnonfamily_hhlds	168.61***	"
	(130.47, 209.09)	

29. Zip code proportions, interquartile heterogeneity: pprofsnl
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pprofsnl	168.52***	"
	(130.42, 208.94)	
Upper quartile: pprofsnl	168.46***	"
	(130.37, 208.89)	

30. Zip code proportions, interquartile heterogeneity: pc45to59min
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pc45to59min	168.61***	"
	(130.47, 209.09)	
Upper quartile: pc45to59min	168.42***	"
	(130.32, 208.81)	

31. Zip code proportions, interquartile heterogeneity: pmanuf
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pmanuf	168.35***	"
	(130.28, 208.77)	
Upper quartile: pmanuf	168.46***	"
	(130.39, 208.90)	

32. Zip code proportions, interquartile heterogeneity: psub_telephone
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: psub_telephone	168.36***	"
	(130.27, 208.75)	

Continued on next page

Upper quartile: psub_telephone	168.45***	"
	(130.34, 208.85)	

33. Zip code proportions, interquartile heterogeneity: pinc_15_24
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pinc_15_24	168.43***	"
	(130.33, 208.83)	
Upper quartile: pinc_15_24	168.43***	"
	(130.33, 208.83)	

34. Zip code proportions, interquartile heterogeneity: pc40to44min
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pc40to44min	168.64***	"
	(130.53, 209.04)	
Upper quartile: pc40to44min	168.28***	"
	(130.21, 208.68)	

35. Zip code proportions, interquartile heterogeneity: pconst
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pconst	168.50***	"
	(130.40, 208.94)	
Upper quartile: pconst	168.38***	"
	(130.29, 208.75)	

36. Zip code proportions, interquartile heterogeneity: ppubadmin
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: ppubadmin	168.27***	"
	(130.22, 208.68)	
Upper quartile: ppubadmin	168.53***	"
	(130.41, 208.93)	

37. Zip code proportions, interquartile heterogeneity: pwhlsale
(40% carbon reduction, revenue shares = 20,30,30,20, spending shares = 40,30,30)
Characteristics: mean response propensity, means of other continuous variables, baseline categories for other indicator variables

Lower quartile: pwhlsale	168.11***	"
	(130.03, 208.46)	

Continued on next page

Table 8 – continued from previous page

Upper quartile: pwhlsale	168.84***	"
	(130.76, 209.30)	

t footnote1
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F Appendix 5: Construct Validity Assessment

F.1 Systematic differences in preferences according to elicited climate change attitudes

Our survey elicited responses to a number of questions designed to assess various dimensions of the respondent's attitudes towards the problem of climate change. These attitudinal questions tend to be multiple choice. We rely on ordinary stepwise regression methods to narrow down a complete set of interaction terms for all of the non-cost program attributes, reporting here only those factors that remain statistically significant at the 10% level. The program attributes are completely orthogonal, except for a logical correlation between the percentage-point carbon reduction and the program cost. Likewise, the answers to the attitudinal questions are categorical and mutually exclusive, ensuring that they are also orthogonal. There may, of course be other omitted variables that may distort the apparent relationship between of any attitudinal factor on marginal utilities, but our goal in this section is merely to explore whether the marginal utilities implied by our program choices are consistent with the attitudes that people express when asked directly about aspects of climate change.

Tables 9–12 duplicate the questions developed by Anthony Leiserowitz and his collaborators in their "Six Nations" of climate change attitudes. These questions mirror their shortest format.

Table 9 reveals that respondents exhibit a higher marginal utility from each percentage-point of carbon reduction if they feel that global warming is "extremely important." In addition, at the bottom of the table, the negative effect of this attitude on the individual's preference for the status-quo alternative means that the utility derived from any carbon reduction program, regardless of its scope, increases monotonically with the perceived importance of global warming. People who feel that global warming is extremely important are less enthusiastic about programs that charge air-travel fees or building energy fees, so they prefer programs that impose a uniform fee on everyone in the organization. In terms of spending shares, anyone who feels that climate change is somewhat important, very important, or extremely important would prefer to have all of the revenues spent on carbon reduction projects, rather than on academic programs or even on carbon offsets. These findings are all intuitively plausible.

Analogously, Table 10 explores the relationship between the respondents degree of worry about global warming and the marginal utilities implied by their program preferences. The results for this attitude are very similar. Being very worried about the problem increases the marginal utility from each percentage-point of carbon reduction and also increases the utility from any carbon-reduction program, regardless of its attributes, again in a monotonic fashion.

The results in Table 11, concerning the respondent's expectation of future harm to be experienced personally from climate change, suggest that those people who expect either a great deal of personal harm or modest personal harm are less likely to prefer the status quo alternative (no program), and thus more likely to prefer any carbon-reduction program, regardless of its attributes. The omitted category in this case is "Don't know," so there is a category for the expectation of "no personal harm," and this expectation increases preferences for the status quo (no program) alternative by a very large amount relative to the "Don't know" category.

Other-regarding preferences are elicited directly with the question about expected harm to future generations of people as a result of global warming. The omitted category is again "Don't know." Expecting a great deal of harm to future generations increases the marginal utility from each percentage-point carbon reduction in a program. This attitude, as well as an expectation of moderate harm to future generations, also corresponds to a higher utility from any program (as opposed to the status quo with no program). Respondents who expect that future generations will not be harmed at all have lower marginal utilities from carbon reductions.

We include an additional question from some of the earlier “Six Nations" work concerning the respondent's climate attitudes relative to their friends. This potential shifter of climate change preferences is summarized in Table 13. Compared to a respondent whose global warming views are shared by all of their friends, people whose global warming views are shared by fewer and fewer of their friends seem to derive less and less marginal utility from carbon reductions. For individuals having no friends that share their views, the marginal utility from an additional unit of carbon reduction become negative. However, this group consitiutes only about 1% of our sample (or about ten people), so this finding might not be robust in a larger sample.

In Table 14, we explore the relationship between a respondent's perception of a pro-ICP or anti-ICP on the part of the research team. Ideally, the wording of the survey would leave the impression that the research team is neutral, and we worked hard to have the survey instrument appear agnostic. However, given the political controversy in the U.S. about climate change, simply explaining the majority views of climate scientists can be perceive by some types of respondents as a bias in favor of carbon pricing. After all, if the research team did not care about climate change, why would they be doing this survey? It is likely that perceptions of research bias reflect as much the respondent's own attitudes about the importance or unimportance of dealing with climate change.

A slight majority of respondents perceived the survey to be unbiased or they couldn't tell. Only about 3% felt the research team wanted them to vote against the carbon pricing program, but 45% of respondents felt the research team wanted them to vote in favor of some carbon pricing program, rather than none at all. As expected, respondents who thought the research team wanted them to vote for some carbon-pricing program appear to derive less marginal utility from each percentage point reduction in carbon emissions, and they are markedly more likely to prefer the status quo over any program. Somewhat surprisingly, those thirty or-so-people who perceived that the researchers wanted them to choose no program make choices that imply that they derive essentially zero marginal utility per percentage point carbon reduction. However, they share with those perceiving no bias the baseline negative marginal utility from the status quo. Like everyone else, this group derives some positive utility from a carbon pricing program. Their preferred alternative just doesn't depend on the size of the carbon reduction.

F.2 Systematic differences in preferences as a function of initial misconceptions

Table 15 assesses how preferences appear to differ according to a respondent's errors in the tests of comprehension that we included during the tutorial portion of the survey. These questions were:

- Over how wide a geographic area will any negative effects of these carbon emissions eventually be felt? ["C global effects"]
- For what reasons might a private company (or an institution like a university) consider setting up an internal carbon-pricing program? ["Reasons for ICPs"]
- Many out-of-state and foreign students are far away from their families while they are at university. If the university's carbon-pricing program involves an airtravel carbon fee, will these students have to pay a carbon fee when they fly home to visit their families? ["C fees stud. trav"]
- Suppose a specific carbon-pricing program does not involve any direct student/employee "fees" for carbon. Consider a student who is not part of a team or group for which the university typically pays for air travel. Will that student be able to completely avoid the cost of that carbon-pricing program? ["unavoid. of fees"]

Anyone who answered any of these questions incorrectly was treated with a second and more detailed explanation, in an effort to correct these misperceptions before they began the choice tasks.

People who were unaware that carbon was a global pollutant have lower marginal utilities for each percentage-point carbon reduction. Those who were unaware that privately paid travel by students would not be subject to any air-travel fees were less in favor of programs that involved greater percentages of the cost borne via air travel fees, but they were more likely to approve of the revenues being spent on carbon offsets, and more likely to prefer any program relative to the status quo.

Those who did not pay sufficient attention to the list of reasons why private companies institute ICP programs to recognize that every reason on the offered list had been cited on the previous screen felt differently about how the revenues would be spent. They were less in favor of programs that spend more of the revenues on academic programs and more in favor of programs that allow greater spending on carbon offsets.

Finally, about 25% of respondents who did not initially understand that even without a flat fee on everyone at the institution, they could still bear the costs of carbon pricing through building energy fees and/or as state taxpayers. These respondents were less inclined to favor costs being borne as building energy fees and derived lower utility for increases in the proportion of revenues spent on academic programs.

F.3 Systematic differences in preferences with highest-priority social goals

At the beginning of the survey, respondents were asked to identify their three highest-priority social goals from a list that was randomized for each respondent. This list included:

- Prevent climate change
- Improve education

- Prevent violence, crime
- Conserve natural resources
- Improve public health
- Reduce poverty, hunger

Respondents who identified the prevention of violence and crime as one of their three highest priorities derive a lower marginal utility from additional percentage-points of carbon reduction. Those who indicated improvements to education as one of their three highest priorities did not share the disutility that others derived from the proportion of revenues spent on educational programs. Prioritizing climate change prevention, the conservation of natural resources, and the reduction of poverty and hunger were each associated with greater utility derived from any ICP program, regardless of its attributes.

F.4 Systematic differences in preferences by Spring and Fall survey waves

We oversampled employees in the Spring 2018 wave of the survey because the term was nearing an end and we did not want final exams to impinge on students' attention to the survey. In the fall, we oversampled students and invited relatively fewer employees to take the survey. As a result, it is entirely possible that the average preferences of the group with relatively more employees (Spring) would be different than the average preferences of the group with relatively more students (Fall). The differences reported in Table 17 tend to disappear when we control for other attributes that differentiate these two survey waves, but we provide these results for completeness. The Fall sample with its higher proportion of students disapproves of greater shares of program revenues being spent on carbon offsets, and is more inclined to prefer any program over the status quo.

Table 9: Persistently statistically significant parameter estimates for interactions with answers to “How important is the issue of global warming to you personally?” sw, pr(.10) (Omitted category: Not at all important)

1=Preferred program	Estimate	Std. Err.
Program’s cost to household (22 to 232)	-0.00850***	(0.00120)
× demeaned resp propensity	0.00309***	(0.00116)
Percentage-point C reduction (10 to 50)	0.0119**	(0.00463)
× 1=GW extremely important (.439)	0.0205***	(0.00408)
× demeaned resp propensity	-0.00877**	(0.00354)
Cost share: air-travel fees (0 to .5)	0.0145***	(0.00226)
× 1=GW extremely important (.439)	-0.00525*	(0.00316)
× demeaned resp propensity	0.00176*	(0.000973)
Cost share: building energy fees (0 to 1)	0.0114***	(0.00154)
× 1=GW extremely important (.439)	-0.00353*	(0.00214)
Cost share: taxpayers (0 to .2)	0.00877***	(0.00306)
Spend share: academic programs (0 to .3)	0.0234*	(0.0125)
× 1=GW extremely important (.439)	-0.0309**	(0.0128)
× 1=GW very important (.327)	-0.0270**	(0.0131)
× 1=GW somewhat important (.179)	-0.0238*	(0.0137)
× demeaned resp propensity	0.00627**	(0.00250)
Spend share: carbon offsets (0 to .5)	0.0226**	(0.0107)
× 1=GW extremely important (.439)	-0.0261**	(0.0110)
× 1=GW very important (.327)	-0.0246**	(0.0110)
× 1=GW somewhat important (.179)	-0.0206*	(0.0118)
× demeaned resp propensity	-0.00414*	(0.00214)
Status quo, no program	3.181***	(0.556)
× 1=GW extremely important (.439)	-3.922***	(0.574)
× 1=GW very important (.327)	-3.271***	(0.537)
× 1=GW somewhat important (.179)	-1.994***	(0.554)
× demeaned resp propensity	0.277***	(0.0933)
Max. log-likelihood	-6591.27	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Persistently statistically significant parameter estimates for interaction terms with answers to "How worried are you about global warming?" sw, pr(.10) (Omitted category: Not at all worried)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00854***	(0.00119)
× demeaned resp propensity	0.00280**	(0.00118)
Percentage-point C reduction (10 to 50)	0.0101**	(0.00510)
× 1=GW very worried (.587)	0.0181***	(0.00440)
× demeaned resp propensity	-0.00729**	(0.00356)
Cost share: air-travel fees (0 to .5)	0.0156***	(0.00259)
× 1=GW very worried (.587)	-0.00597*	(0.00305)
× demeaned resp propensity	0.00176*	(0.000959)
Cost share: building energy fees (0 to 1)	0.00930***	(0.00109)
Cost share: taxpayers (0 to .2)	0.00866***	(0.00316)
× 1=GW not very worried (.057)	-0.0312*	(0.0174)
Spend share: academic programs (0 to .3)	0.0482***	(0.0159)
× 1=GW very worried (.587)	-0.0527***	(0.0160)
× 1=GW somewhat worried (.325)	-0.0520***	(0.0163)
× 1=GW not very worried (.057)	-0.0644***	(0.0197)
× demeaned resp propensity	0.00549**	(0.00256)
Spend share: carbon offsets (0 to .5)	0.00303	(0.00304)
× 1=GW very worried (.587)	-0.00710*	(0.00365)
× demeaned resp propensity	-0.00343*	(0.00185)
Status quo, no program	3.655***	(0.689)
× 1=GW very worried (.587)	-4.198***	(0.695)
× 1=GW somewhat worried (.325)	-3.329***	(0.690)
× 1=GW not very worried (.057)	-1.718**	(0.806)
× demeaned resp propensity	0.235***	(0.0871)
Max. log-likelihood	-6614.00	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Persistently statistically significant parameter estimates for interaction terms with answers to "How much do you think global warming will harm you personally?" sw, pr(.10) (Omitted category: Don't know)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00792***	(0.00117)
× demeaned resp propensity	0.00293**	(0.00114)
Percentage-point C reduction (10 to 50)	0.0192***	(0.00405)
× demeaned resp propensity	-0.00753**	(0.00366)
Cost share: air-travel fees (0 to .5)	0.0110***	(0.00162)
× demeaned resp propensity	0.00180*	(0.000934)
Cost share: building energy fees (0 to 1)	0.00904***	(0.00107)
Cost share: taxpayers (0 to .2)	0.00799***	(0.00305)
Spend share: academic programs (0 to .3)	-0.00374	(0.00249)
× demeaned resp propensity	0.00597**	(0.00255)
Spend share: carbon offsets (0 to .5)	-0.00137	(0.00180)
× demeaned resp propensity	-0.00317*	(0.00176)
Status quo, no program	0.427**	(0.191)
× 1=GW personal harm-great deal (.258)	-1.053***	(0.205)
× 1=GW personal harm-mod. amount (.475)	-0.552***	(0.180)
× 1=GW personal harm-not at all (.033)	2.674***	(0.613)
× demeaned resp propensity	0.231***	(0.0863)
Max. log-likelihood	-6796.08	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Persistently statistically significant parameter estimates for interaction terms with answers to "How much do you think global warming will harm future generations of people?" sw, pr(.10) (Omitted category: Don't know)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00848***	(0.00118)
× demeaned resp propensity	0.00302***	(0.00111)
Percentage-point C reduction (10 to 50)	-0.0000452	(0.00659)
× 1=GW future harm-great deal (.830)	0.0239***	(0.00615)
× 1=GW future harm-not at all (.012)	-0.0991**	(0.0436)
× demeaned resp propensity	-0.00775**	(0.00359)
Cost share: air-travel fees (0 to .5)	0.0112***	(0.00163)
× demeaned resp propensity	0.00209**	(0.000944)
Cost share: building energy fees (0 to 1)	0.00918***	(0.00108)
Cost share: taxpayers (0 to .2)	0.00790**	(0.00308)
Spend share: academic programs (0 to .3)	-0.00318	(0.00252)
× demeaned resp propensity	0.00568**	(0.00253)
Spend share: carbon offsets (0 to .5)	-0.00145	(0.00184)
× demeaned resp propensity	-0.00340*	(0.00186)
Status quo, no program	1.459***	(0.396)
× 1=GW future harm-great deal (.830)	-1.727***	(0.395)
× 1=GW future harm-mod. amount (.096)	-0.780*	(0.449)
× demeaned resp propensity	0.245***	(0.0870)
Max. log-likelihood	-6710.84	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Persistently statistically significant parameter estimates for interaction terms with answers to "How many of your friends share your views on global warming?" sw, pr(.10) (Omitted category: All friends share views)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00766***	(0.00115)
× demeaned resp propensity	0.00302***	(0.00108)
Percentage-point C reduction (10 to 50)	0.0227***	(0.00425)
× 1=friends share GW view-none (.01)	-0.0750***	(0.0253)
× 1=friends share GW view-a few (.1)	-0.0154***	(0.00592)
× 1=friends share GW view-some (.211)	-0.0107**	(0.00450)
× demeaned resp propensity	-0.00850**	(0.00344)
Cost share: air-travel fees (0 to .5)	0.0126***	(0.00170)
× 1=friends share GW view-some (.211)	-0.00750**	(0.00310)
× demeaned resp propensity	0.00151*	(0.000890)
Cost share: building energy fees (0 to 1)	0.0102***	(0.00117)
× 1=friends share GW view-some (.211)	-0.00497**	(0.00219)
Cost share: taxpayers (0 to .2)	0.00741**	(0.00304)
Spend share: academic programs (0 to .3)	-0.00342	(0.00242)
× demeaned resp propensity	0.00613**	(0.00245)
Spend share: carbon offsets (0 to .5)	-0.000287	(0.00183)
× demeaned resp propensity	-0.00379**	(0.00192)
Status quo, no program	-0.0382	(0.131)
× demeaned resp propensity	0.223***	(0.0837)
Max. log-likelihood	-6888.06	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Persistently statistically significant parameter estimates for perceived researcher bias, based on responses to "Overall, the wording of this survey made it seem that the researchers conducting this study really wanted me to choose: some carbon-pricing program, no program, the best alternative for me personally, not sure/count't tell", sw, pr(.10) (Omitted category: No perceived bias on the part of the researchers)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00758***	(0.00115)
× demeaned resp propensity	0.00304***	(0.00112)
Percentage-point C reduction (10 to 50)	0.0227***	(0.00442)
× 1=Perceive pro-ICP bias (.452)	-0.00866**	(0.00408)
× 1=Perceive anti-ICP bias (.034)	-0.0225**	(0.0105)
× demeaned resp propensity	-0.00810**	(0.00353)
Cost share: air-travel fees (0 to .5)	0.0106***	(0.00161)
× demeaned resp propensity	0.00207**	(0.000951)
Cost share: building energy fees (0 to 1)	0.00894***	(0.00107)
Cost share: taxpayers (0 to .2)	0.00742**	(0.00299)
Spend share: academic programs (0 to .3)	-0.00345	(0.00245)
× demeaned resp propensity	0.00594**	(0.00254)
Spend share: carbon offsets (0 to .5)	-0.00103	(0.00184)
× demeaned resp propensity	-0.00352*	(0.00188)
Status quo, no program	-0.302**	(0.142)
× 1=Perceive pro-ICP bias (.452)	0.563***	(0.166)
× demeaned resp propensity	0.233***	(0.0822)
Max. log-likelihood	-6875.96	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Persistently statistically significant parameter estimates for interaction terms with incorrect answers to knowledge/comprehension questions during the tutorial section of the survey; sw, pr(.10) (Omitted category: Gave correct response to knowledge/comprehension question)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00755***	(0.00113)
× demeaned resp propensity	0.00287***	(0.000984)
Percentage-point C reduction (10 to 50)	0.0211***	(0.00400)
× 1=dnk: C global effects (.134)	-0.0252***	(0.00565)
× demeaned resp propensity	-0.00838***	(0.00319)
Cost share: air-travel fees (0 to .5)	0.0124***	(0.00169)
× 1=dnk: C fees stud. trav (.148)	-0.00924**	(0.00411)
× demeaned resp propensity	0.00178**	(0.000890)
Cost share: building energy fees (0 to 1)	0.00978***	(0.00121)
× 1=dnk: unavoid. of fees (.253)	-0.00384*	(0.00230)
Cost share: taxpayers (0 to .2)	0.00665**	(0.00303)
Spend share: academic programs (0 to .3)	0.00494	(0.00321)
× 1=dnk: Reasons for ICPs (.333)	-0.0150***	(0.00458)
× 1=dnk: unavoid. of fees (.253)	-0.0124**	(0.00499)
× demeaned resp propensity	0.00527**	(0.00257)
Spend share: carbon offsets (0 to .5)	-0.00613***	(0.00215)
× 1=dnk: Reasons for ICPs (.333)	0.00746**	(0.00366)
× 1=dnk: C fees stud. trav (.148)	0.00793*	(0.00473)
Status quo, no program	0.00550	(0.132)
× 1=dnk: C fees stud. trav (.148)	-0.527**	(0.221)
× demeaned resp propensity	0.235***	(0.0733)
Max. log-likelihood	-6882.85	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Persistently statistically significant parameter estimates for interactions with indicators for respondent's choices of three highest-priority social goals, among randomly ordered options of: prevent climate change, improve education, prevent violence/crime, conserve natural resources, improve public health, reduce poverty/hunger; sw, pr(.10) (omitted category: no priority on any category of problem)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00825***	(0.00117)
× demeaned resp propensity	0.00314***	(0.00115)
Percentage-point C reduction (10 to 50)	0.0237***	(0.00426)
× 1=Prioritize crime (.291)	-0.0130***	(0.00437)
× demeaned resp propensity	-0.00837**	(0.00348)
Cost share: air-travel fees (0 to .5)	0.0115***	(0.00162)
× demeaned resp propensity	0.00178*	(0.000966)
Cost share: building energy fees (0 to 1)	0.00916***	(0.00107)
Cost share: taxpayers (0 to .2)	0.00786***	(0.00304)
Spend share: academic programs (0 to .3)	-0.00877**	(0.00399)
× 1=Prioritize education (.606)	0.00878*	(0.00497)
× demeaned resp propensity	0.00660***	(0.00251)
Spend share: carbon offsets (0 to .5)	-0.000832	(0.00190)
× demeaned resp propensity	-0.00445**	(0.00220)
Status quo, no program	1.031***	(0.214)
× 1=Prioritize nat resour (.477)	-0.359**	(0.147)
× 1=Prioritize climate chng (.594)	-1.157***	(0.150)
× 1=Prioritize poverty (.571)	-0.394***	(0.147)
× demeaned resp propensity	0.280***	(0.0937)
Max. log-likelihood	-6761.60	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Persistently statistically significant parameter estimates for membership in the Fall 2018 wave of the survey (with proportionately more students than faculty, compared to the Spring 2018 wave); sw, pr(.10) (Omitted category: respondent belongs to Spring 2018 sample)

1=Preferred program	Estimate	Std. Err.
Program's cost to household (22 to 232)	-0.00765***	(0.00114)
× demeaned resp propensity	0.00286***	(0.00108)
Percentage-point C reduction (10 to 50)	0.0180***	(0.00398)
× demeaned resp propensity	-0.00730**	(0.00351)
Cost share: air-travel fees (0 to .5)	0.0109***	(0.00159)
× demeaned resp propensity	0.00181*	(0.000927)
Cost share: building energy fees (0 to 1)	0.00891***	(0.00106)
Cost share: taxpayers (0 to .2)	0.00708**	(0.00301)
Spend share: academic programs (0 to .3)	-0.00351	(0.00244)
× demeaned resp propensity	0.00619**	(0.00244)
Spend share: carbon offsets (0 to .5)	0.00303	(0.00312)
× 1=Fall 2018 survey wave (.432)	-0.00722**	(0.00351)
× demeaned resp propensity	-0.00358*	(0.00187)
Status quo, no program	0.114	(0.145)
× 1=Fall 2018 survey wave (.432)	-0.372**	(0.149)
× demeaned resp propensity	0.212***	(0.0814)
Max. log-likelihood	-6937.00	
No. respondents	1052	
No. choices	5547	
No. alternatives	13165	

t standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$