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 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. Over 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 types of consumers, 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 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:

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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. Roughly 500 U.S. businesses have voluntary internal carbon pricing (ICP) programs which charge internal company divisions and individual projects for the carbon emissions they generate. There are several reasons that firms give for using internal carbon pricing. 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. 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 with varying preferences concerning alternative designs of internal carbon pricing programs.

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. Respondents are asked to consider either one or two hypothetical carbon-pricing programs, where in each choice scenario, opt-out alternative is included (consisting of the status quo with no program and no out-of-pocket costs). Programs vary in the emission reductions they achieve, 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. Two programs with the same cost to the individual and the same carbon-reduction potential may be viewed differently depending on how the overall costs are distributed across different groups of stakeholders. Uniform lump sum fees may be perceived as less "fair" that a fee schedule that reflects a "polluter pays" principle. To model preferences over the distributional consequence of carbon-pricing programs, we allow revenue to be raised and spent in multiple different ways across the set of programs offered to each individual on each choice occasion. Here, 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. Having 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 randomly 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 who 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

[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.

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.

2 Institutional Setting And Prior Literature

Over 500 companies, as of 2017, had established internal carbon pricing programs in the U.S. with at least another 700 planning on enacting a program in the next two years [citeCDP2017]. Internal carbon pricing programs can take different forms. One alternative is a carbon levy on individual divisions, which is then used for green energy programs. Another is an accounting charge 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 projects. Universities also see internal carbon pricing as a way to develop a reputation for sustainability as a means to attract students, as well 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 instead we choose in this study to focus 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 typically being the largest. For the university surveyed in this study, building heat accounts for about 48 percent of estimated carbon emissions, and university-sponsored air travel accounts for about 13 percent. These two sources also tend to be the carbon sources about which universities have the most information about the origin and quantity of their carbon emissions. Yale University's ICP is perhaps the most well-known current example of university internal carbon pricing Carattini et al. (2017). Campus building carbon emissions are taxed and the revenue is refunded to occupants. Additional programs also exist at Swarthmore and Smith Colleges.

Limited prior empirical work has used stated preference methodologies to examine the demand for climate change mitigation. 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. 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). This work clearly demonstrates that distributional consequences have a strong influence on people's willingness to bear the costs of climate change mitigation programs more broadle.

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 unwilling to pay for higher levels.

3 Survey Design and Analytical Framework

3.1 Description of Survey

Our survey was administered electronically, through Qualtrics, 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. 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 a five dollar incentive in the form of a digital gift certificate to the campus store. On average, the survey takes about twenty minutes to complete, although some respondents opt to study the background information in considerably more detail. In total, we collect 1052 usable responses, representing a roughly 13% 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. 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 can be described in terms of a common set of attributes, with the No Program alternative constituting 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 acknowledge that internal carbon-pricing programs can be implemented in a wide variety of different ways. We choose to focus our respondents' attention on the distributional consequences of the program, both in terms of how the costs would be borne and how the revenue raised by these programs might be used.

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, 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 to be funded in four distinct ways. In addition to the average carbon fee, funds can be raised through a fee on university-sponsored air travel, a charge for the carbon emissions of campus buildings, or by relying on funds raised from the state's taxpayers. Besides spending the revenue raised for on-campus carbon-reduction projects, some of the revenue could go towards off-campus "carbon offsets," or some revenue could be recycled in the form of spending on academic programs. All choice sets offered to respondents are randomly populated, in advance, with different mixes of program attributes. The only constraints are that programs offering higher carbon reductions generally cost more money and that the difference in costs between any pair of programs offered should be at least five dollars.[2]

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. 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 respondents understanding through frequent questions. Misconceptions are corrected. After the choice

[2]Our randomizations are not D-efficient due to complications that arise from the fact that the cost and revenue shares must 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 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 cost/benefit 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, the negative distributional consequences of a cheaper program that produces greater carbon reductions overwhelm the cost difference, but we will be able to infer the circumstances where this might happen from our parameter estimates.

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 Anthony Leiserowitz's "Six Americas" classification of climate attitudes (as described in Maibach et al. (2011), as well as a series of questions to collect standard demographic information not available in the supplementary administrative data provided by the university's Office of Institutional Research. Many, but not all of the available variables are employed in the current analysis. Additional variables, after further processing, will be used in subsequent revisions.

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.[3] 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 able to discern the best alternative from their own perspective, but is unobserved by the researcher and therefore constitutes a random component in the model.

The systematic component of the level of anticipated indirect utility under any given program depends 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, $CostShares^i_{jt}$.

[3] For overviews of stated preference methodologies see [...]

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. Furthermore, programs also differ in the shares of the revenues they raise that will be used for things other than internal carbon-emissions reduction programs, $ExpShares^i_{jt}$. Similarly, 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. 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 these 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 such as those posed to survey respondents in this study, 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 thus 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.[4]

[4]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

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 carbon emissions, as well as *vectors* of fixed parameters γ and δ, which convey 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 the shares of revenues spent on things other than just on-campus carbon reduction projects.

If preferences are assumed to be 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 the representative consumer's willingness to pay for a program with specified coefficients, as well as 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:

$$0 = \alpha(-C_{jt}^{i}) + \beta B_{jt}^{i} + CostShares_{jt}^{i}\gamma + ExpShares_{jt}^{i}\delta + \varepsilon_{jt}^{i} \tag{3}$$

$$WTP_{jt}^{i} = C_{jt}^{*i} = (1/\alpha)\left[\beta B_{jt}^{i} + CostShares_{jt}^{i}\gamma + ExpShares_{jt}^{i}\delta + \varepsilon_{jt}^{i}\right] \tag{4}$$

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 asymptotically jointly normally distributed random variables. Given that α is not constrained to be strictly positive, zero is a potential value for this function 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,

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.

we make 10,000 draws from the joint distribution of the parameters. We use each independent draw in combination with the specified levels of the attributes of the specified program, namely its percentage-point carbon reduction, B^i_{jt}, and its non-default shares of costs, $CostShares^i_{jt}$, and 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 resulting WTP estimates, and report the mean and 5th and 95th percentiles of this distribution to convey a sense of the expected 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 must likewise be built up from 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.[5]

[5] 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

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 universities that differ from the one we have surveyed. This requires us to estimate models that explain heterogeneity as a function of observable individual characteristics, as opposed to models (such as random-parameters mixed logits) that allow heterogeneity in preferences to be unexplained, and instead merely estimate the dispersion of preferences in the sampled population (as opposed to their distribution in any other, systematically different population).

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 case the marginal WTP for a one-percent-point reduction in carbon would be

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

Note that in the current draft, we restrict $\alpha' Z_i = \alpha$, to simplify the calculation of our WTP estimates. Later revisions will explore systematically varying marginal utilities of net income (i.e. other consumption).

3.3 Response/Non-Response correction

It is always a concern in surveys that response rates may be correlated with respondents' WTP and that sample selection bias may distort the estimates. To correct at least partially for sample

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 must be recognized.

selection bias, we estimate a model of propensity to respond and use the de-meaned fitted response propensities as controls in our model. 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 of 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 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, using a simple probit specification as well as LASSO estimators. [NOTE: In the current draft, we employ only the probit response/nonresponse model. We will need to re-estimate the LASSO model with the newly acquired administrative data as well as the ACS data, the election data, and the LCV data.[6]

4 Results

[NOTE: The results in this version of the paper do not yet reflect all of the individual respondent characteristics that we will be able to include in the next revision.]

4.1 Descriptive Statistics

Descriptive statistics for selected individual characteristics that are persistently statistically significant determinants of at least one of the heterogeneous marginal utility parameters in the model are summarized in Table 1. The distributions from which we drew the attributes of the hypothetical internal carbon pricing scenarios in our study design are described in the appendix. Here, we note

[6]Further details about our response/nonresponse modeling efforts can be found in the appendix materials.

only that for all attributes other than program cost, attribute levels are drawn randomly from a set of admissible values for each attribute. For the sets of share values, independent draws are made for each share, but are "accepted" only if the set of shares sums to unity. Benefit levels are drawn randomly, but costs are constrained to be correlated with benefits to a certain degree (i.e. a linear function), but are randomized substantially away from perfect correlation to produce enough independent variation to permit their separate marginal utilities to be estimated with sufficient precision. At the extremes of the additive noise in the cost attribute, the distribution is truncated to prevent implausibly high or low costs.

A few features of Table 1 deserve note. First, about 45% of the sample has a perception that the research team would like them to vote in favor of some internal carbon pricing program. Less than 3% perceive that the team is trying to persuade them to vote against internal carbon pricing. However, a slight majority of respondents (about 52%) believe either that the research team was not biased either way, or that they did not know or could not tell. It is fairly typical for respondents to think that the researchers are interested in some program of the type being explored. Otherwise, why would they be asking about it? Ideally, everyone would perceive an absence of any bias. Thus we control for deviations from perceived neutrality in the process of estimation, and then simulate a perception of neutrality when calculating WTP estimates.

Preferences for carbon emissions reductions can be affected by a respondent's recent experiences with events that may be related to climate change. Substantial shares of respondents report having experienced wildfire smoke, and heat waves or inland or coastal flooding over the previous 12 months, any of which would make climate change a more salient problem. However, about 14% experienced severe winter weather, which might suggest to some audiences that the climate is not actually "warming." About 61% of the sample has personally experienced at least some type of harm from extreme weather during their lifetime.[7]

[7] In other contexts, for example Cameron and Englin (1997), we have explored the propensity for respondent experience to influence both the mean and the variance in their willingness to pay for environmental public goods.

The population of interest can be coarsely categorized as either students or non-students. We include graduating seniors among the non-student population. As to our expectations for the preferences of these two broad groups, many students expect to belong to the institution for only a limited number of years and many are also still spending their parents' money. Non-students are mostly university employees, and these individuals may have an open-ended exposure to the costs involved in an internal carbon-pricing program. They are also more likely to be considering their own money, rather than someone else's.

For the university in question, the state's population is at the more-liberal end of the political spectrum. Compared to a base category of "moderate," about 67% of respondents report their ideology as somewhat liberal or very liberal. Only about 9% consider themselves to be somewhat conservative or very conservative. Controlling for these differences will be crucial in any attempt to transfer our WTP functions to any university where the campus community has different political ideologies.

Not yet included in Table 1 are the summary statistics for several characteristics of the respondent's zip code at their permanent address. It is entirely plausible that an individual's current perceptions of climate change risk have been influenced by the people to whose opinions they choose to pay attention, as demonstrated in Cameron (2005). Perceptions of climate risk strongly influence people's willingness to incur the costs of carbon emissions reductions.

4.2 Utility parameter estimates

Table 2 shows some estimates for the parameters of three models. In all cases, we control for any potential effect of deviations from mean fitted response propensity, so that the baseline parameters apply to an individual whose response propensity is the average in the invited random sample from the population. This is equivalent to simulating a zero de-meaned response propensity for everyone in the sample. Thus we treat the coefficients on these response propensity corrections as "nuisance" parameters and will not discuss them in any detail. Their presence in the model merely reduces the chance of sample selection bias in the remaining coefficients.[8]

The model in the first column in Table 2 explains choices using *only* the basic program attributes plus an indicator for the status quo alternative (as well as the incidental interactions between each attribute and the de-meaned response propensities, to counter the effects of systematic sample selection). The central program attributes are the unavoidable cost to the respondent and the percentage-point carbon reduction that the program would achieve (i.e. the program's cost and benefit attributes).

The remaining attributes outline some of the distributional consequences of each proposed program. These attributes consist of two sets of shares. The base shares in each group are omitted because each set of shares sums to one by construction. The first set of shares describes how the money to pay for the carbon reduction project would be raised. Of the four ways in which program costs could be borne, the omitted base share is via (a) a common fee on all students and employees. The alternatives consist of (b) fees on university-paid air travel, (c) building energy fees based on building use, and (d) costs borne by the state's taxpayers. The second set of shares describes how the money raised by an internal carbon price would be spent, where the omitted base share is on (a) carbon reduction projects at the university. The alternatives consist of (b) spending on academic programs, and (c) spending on carbon offsets somewhere other than at the university.

The status quo indicator allows for some systematic utility premium (or discount) to be associated with the no-program alternative that is unrelated to the cost of the program, its benefits, or its distributional consequences. This utility differential could reflect patterns of yea-saying or nay-saying, for example. It is common to include a status quo indicator to allow for anything shared by all programs, but not the no-program alternative, that is not captured by the explicit set of program attributes already discussed.

The model in the second column of Table 2 includes all of the individual statistically significant

[8]Of course, this is an ad hoc correction. It is less sophisticated than a traditional Heckman-style sample selection correction model, but no such model is yet available to make analogous corrections in conditional logit models.

heterogeneity identified in a large set of models that introduce each category of heterogeneity separately. These exploratory models are not reported in the paper. The program attributes are essentially orthogonal to each other and definitely orthogonal to respondents' characteristics, but the different types of respondent characteristics may be correlated. Thus when multiple types of heterogeneity are introduced simultaneously, some factors may be redundant. We make no pretense, at this stage, to have settled on a final specification, since we are still in the process of cleaning up additional new data about our individual respondents.[9]

The model in the third column of Table 3 shows the results from an (unapologetic, pragmatic) application of stepwise model reduction. We force all of the basic program attributes to remain in the model, but look for persistently significant dimensions of heterogeneity in the marginal utility associated with each attribute. At this stage, we are merely looking for systematic variation and exploring whether the variation that we find may be plausible. Our final specifications will employ more characteristics and pay more attention to the consequences of multicollinearity among the determinants of heterogeneity in specific marginal utility parameters.

All three specifications exhibit a strongly statistically significant decrease in utility with higher program costs, and an increase in utility with greater carbon reduction benefits. A brief outline of the model's implications includes:

- There is diminishing marginal utility from additional percentage-point reductions in carbon emissions (i.e. the quadratic term's coefficient is statistically significant);
- Several characteristics of the respondent's home zip code (permanent address for students) affect the marginal utility from greater program benefits;
- Perception of research bias and the respondent's own political ideology also affects the marginal utility from program benefits;
- The marginal utility of a percentage point reduction in carbon emissions is smaller for respondents who perceive that the research team in biased in favor of internal carbon-pricing programs;

[9] The set of available respondent characteristics variables is too vast to permit all available variables to be interacted simultaneously with all eight of the basic program attribute variables in one huge model.

- Respondents who have experienced severe winter weather over the last 12 months derive less utility from a percentage point reduction in carbon emissions;
- Compared to program that pays for 100% of the costs of carbon reductions with a flat fee on all students and employees, respondents derive more utility from a program that embodies a "polluter pays" feature to at least some extent, via costs borne as a fee on university-paid travel or building energy use fees. However this effect of air-travel fees is nonlinear, with the utility premium first rising, then declining as the share borne via air travel fees increases;
- The utility from an increase share of costs borne by the state's taxpayers varies with respondent age, first increasing and then decreasing.
- As to how the revenues collected through carbon pricing might be spent, the 61% of respondents who have ever experienced harm from climate-related extreme weather events derive positive utility from increased spending on academic programs while those who have not are unaffected by differences in this share. However, non-students derive less utility from the share spent on academic programs;
- Increased spending of program revenues on carbon offsets decreases utility, but this effect becomes less negative (and is potentially even positive) as the respondent's home community voted in larger proportions for the Democratic Party candidate in the 2016 Presidential election (and likewise becomes more negative as less of the respondent's home community voted for the Democratic Party candidate;
- The coefficient that measures the "status quo" effect in the homogeneous specification (the first column of results) suggests that, on average, there is no systematic preference for either the status quo or some type of internal carbon-pricing program. However, in the model with heterogeneous preferences, however, several factors predispose respondents to be more likely to prefer No Program (i.e. to vote against any proposed ICP program) regardless of the program's attributes:
  - A perception that the research team is biased in favor of these programs;
  - Having experienced a tornado risk in the past year (i.e. from tornado-prone areas);
  - Having experienced as least some past harm from extreme weather;
  - Being a non-student (i.e. faculty, staff, or administrator)
- Other logical factors predispose a respondent to be more likely to vote in favor of any program, regardless of its attributes:
  - Considering themselves to be either somewhat or very liberal in their political views;
  - Having experienced a heat wave over the past year.

Most of the estimated systematic differences in preferences appear to be plausible. But keep in mind that many other heterogeneous specifications remain to be explored. Fortunately, we have established that there appears to be no significant difference in preferences between the Spring and Fall waves of the survey (although preferences could have differed across these groups because of differences in the salience of climate change due to their experiences with climate-related events during the intervening summer).[10]

4.3 Implied WTP estimates for specific individual characteristics and program attributes

There is no particular point in generating the distribution of willingness-to-pay (WTP) values across the arbitrary range of essentially unique hypothetical internal carbon pricing programs described across all of the choice sets for all of the respondents to our survey. There were more than 6300 unique programs used in this study (six per respondent). This variety of programs is not drawn from any "true distribution" for which we might want to know the average WTP or the standard deviation in WTP amounts. The array of stylized programs is designed to span the relevant range of attribute mixes across any real internal carbon pricing program that could reasonably be implemented. Consequently, we elect instead to illustrate the inferences that are possible with our model by picking a selection of specific ICP programs, and calculating the willingness to pay for each program for individuals with specific sets of characteristics.

Table 3 reports patterns in the sampling distributions for our calculated WTP estimates, relative to a baseline case for each set of simulations, as we vary the identified determinants of WTP one at a time. This exercise provides some sense of the variation in WTP for an internal carbon-pricing program for a specified type of individual as the attributes of the program are changed. We will outline the results in Table 3 section by section.

[10] Some factors yet to be thoroughly explored are additional respondent characteristics. However, we plan an entirely separate analysis to be done concerning a variety of variations in the design of the choice experiments (two versus three alternatives), whether people tend to pick the larger or the smaller program when a pair of programs is offered, and systematic variation in response times, question order (burn-in versus fatigue effects), and several other design features. That inquiry will be primarily concerns with lessons for the methodology of survey design and administration.

Section 1. First, we consider the baseline case of a carbon-pricing program that involves *only* student/employee fees and spends *all* of its revenues on carbon projects. We simulate WTP for an individual with mean response propensity, mean income, mean age, a student, with moderate political views, no perception of bias on the part of the researchers, no recent experience with climate-related extreme weather events and no personal harm from extreme weather events in the past. For this type of person, this first section of the table reports both the total willingness to pay (TWTP) for the program in question, as well as the marginal willingness to pay (MWTP), across various levels of carbon reductions. The declining MWTP for this ICP is evident, being about $5 per percentage-point reduction at a 10 percentage-point reduction level, but falling to less than $2 for when the level of the reduction reaches 50 percentage points.

Suppose everybody at the university fit this description of the person described in Section 1 of Table 3. Consider the benchmark 40% carbon reduction, where the estimate of the university's current "carbon emissions related to energy use and transportation (but not counting the carbon content of other purchased production)" was described to respondents as about 61,000 metric tons. This 40% carbon reduction is approximately the amount that could be achieved if this university switched its physical plant from natural gas to green electricity. The mean willingness to pay for this type of person, $169, can be multiplied by the roughly 28,100 people at the university and divided by the 24,400 metric tons of carbon that this 40% reduction would imply, to yield an average WTP, per ton of carbon reduced, of approximately $195 per ton. Importantly, however, this type of person is NOT the mean member of the university's population of stakeholders, but merely an illustration.

An important next step in this study, of course, will be to select a specific ICP program proposal and calculate a fitted expected WTP for every person in the sample for that program. These estimates can then be summed across all of the people in the sample (with weights to correct the representativeness of the sample). If this aggregate WTP per year exceeds the actual cost of that carbon reduction program, economic theory would predict that the program in question would be overall welfare-enhancing. [11]

Section 2. This section shows how implied WTP responds to the share of program costs raised through air travel fees (with a corresponding decrease in student/employee fees, which is the baseline share). This list reveals the non-linearity of preferences (and hence WTP) in this program attribute. For people with the specified characteristics, a program with no building energy fees and no taxpayer support has maximum value if it involves about a 40% share of costs raised through air travel fees (and the remaining costs raised through student/employee fees). This maximum WTP is about $254.

Sections 3 and 4. For the other sources of revenue, considered one-at-a-time against student/employee fees, people's WTP for the program increases monotonically with the share of the costs to be borne by other people. Importantly this WTP controls for the unavoidable cost to the respondent themselves. They are individually willing to pay more if more other if other groups are also pitching in.

Sections 5 and 6. In terms of the uses of the revenue from an internal carbon-pricing program, we know from the estimates in Table 2 that our example individual (a student) is willing to pay more for a given amount of carbon reduction if more of the revenues are spent on academic programs (i.e. if more of the revenue is recycled back to them). However, they are less willing to pay for programs that spend more of their revenues on offsets. This is reasonable. While it does not matter for global carbon concentrations whether the carbon emissions are reduced at the university or somewhere else, these individuals may understand that corresponding reductions in local or regional co-pollutant emissions would not occur at the university either, which could make these types of programs less attractive. However, recall from Table 2 that if this student's permanent address was in a county with a higher-than average proportion of Democratic votes in the 2016

[11] As always, however, the distributional consequences of any such program would have to be considered. It will be important to exploit the opportunity we have to explore for empirically measurable differences in people's marginal utilities of income, since most benefit-cost analyses typically assume that this marginal utility is the same for everyone, ignore distributional effects.

Presidential election, their willingness to support programs that involve spending on offsets would be higher.

Section 7. From this Section onwards, we change the baseline program to one that has *four equal shares* in terms of the ways in which the revenue is raised and *three equal shares* in terms of the ways in which the revenues raised are spent. Section 7, as opposed to Section 1, shows that equal sharing leads to our student being willing to incur costs of about \$282 per year for an ambitious 40% carbon reduction, whereas they were willing to pay only about \$169 per year for the same-sized 40% carbon reduction when all revenues were raised through student/employee fees and all revenues were spent on carbon projects alone.

Section 8. These simulations reveal the very different levels of enthusiasm for these projects by students and non-students (mostly faculty and staff). Continuing students (i.e. excluding graduating seniors in the first wave of the survey at the end of Spring quarter) are willing to pay about \$282 per year for the equal-shares benchmark program, but everyone else is willing to pay only about \$242. Non-students can expect to have to pay these costs as long as they are associated with the university, and they are "playing with their own money." This result is not surprising.

Section 9. Here, we explore how WTP for this type of program varies across the distribution of income in our sample. We use income here as a crude indicator for socioeconomic status, rather than an exact measure of disposable income. As expected, carbon emissions reductions appear to be a normal good, with WTP increasing with income levels.

Section 10. This being a university population, about 69% of the population is less than 25 years old. The statistical significance of the coefficient on the quadratic term in age means that WTP for this equal-shares benchmark program is increasing with age, but is lower for the oldest people in the sample (at age 73). Older individuals are less likely to live to see the worst consequences of continuing changes to the climate, so it is plausible that they should be willing to pay less to reduce carbon emissions.

Section 11. Our parameter estimates in Table 2 reveal that people with liberal political views are more likely to vote for some ICP rather than to prefer no program, regardless of the program's attributes. However, conditional on WTP being calculated for *some* program, WTP for any such program for liberals does not differ from that for people with either moderate or unreported political views. However, having either somewhat or very conservative views reduces a person's marginal utility from a carbon reduction, in the case of our equal-shares benchmark program, by almost half.

Section 12. Survey respondents are sometimes influenced, in their answers, by their perceptions of whether the survey instrument is biased either for or against the types of programs being entertained. Conservatives are more likely to view a neutral presentation about climate change as overstating the threat and therefore exaggerating the need for carbon pricing. Thus it is plausible that a perceived pro-ICP bias in the survey corresponds to the respondent having a lower WTP. However, about 3% of the sample perceives an anti-ICP bias in the survey. It is somewhat surprising that these thirty-or-so people are also willing to pay less (in fact much less). One possibility is that some strong environmentalists are unwilling to consider markets for pollution. Such a blanket policy rejection, however, should have shown up as a shift in the marginal utility of the status quo alternative, rather than the marginal utility of carbon reductions. This finding deserves further exploration.

Section 13. Attitudes towards the need for an internal carbon-pricing program can vary with recent exposure to potentially climate-related extreme-weather events. Our baseline is for an individual with no such recent exposure. If a respondent has experienced extremely cold weather in the last 12 months, however, WTP is about $50 lower, presumably because extremely cold weather may seem to refute that there is "global warming."

Section 14. Finally, prior harm experienced from some type of extreme weather event might increase the salience of climate-related risks. Respondents who report having experienced at least some type of harm from extreme weather are willing to pay about $60 more for our benchmark program.

Note, again, that our analysis is not yet complete. We have many additional variables yet to explore. When we have settled on a stable specification with robustly estimated utility parameters, we will employ that model to simulate sample average willingness to pay for a selection of ICPs. These calculations will permit us to estimate overall benefits to the university community from specific types of internal carbon pricing programs.

5 Conclusions and Directions for Further Research

The Oregon State government's Carbon Policy Office is currently working on proposed legislation to be introduced pre-session, in December 2018. It remains to be seen whether these proposals will have enough traction to be raised during the legislative session in 2019. It is too early to predict whether these policy proposals can be enacted by the legislature itself, or whether the question will be put to voters, as a carbon-pricing initiative has been placed before voters in Washington State in the November 2018 election. Given that our study provides some insight into the extent to which people of different descriptions are willing to bear the costs of carbon emissions reductions within one large public institution, our findings may prove relevant to the upcoming state-level debate concerning carbon pricing. Certainly, other researchers, for example Carattini et al. (2018), have begun to explore suggestions concerning the design of carbon taxes that might help to overcome public opposition to carbon pricing.

To be sufficiently informative, our survey also needed to be rather complex. Due partly to the length and complexity of the survey instrument, the completed response rate was only about 13%. Given that these low response rates were anticipated, we planned in advance to conduct a thorough and comprehensive modeling of the response/nonresponse outcome for each invited participant. For every member of the campus community who received an invitation to take the survey, we assembled administrative records from the university's Office of Institutional Research describing each individual's basic characteristics. For every zip code represented in the university population (for the "permanent addresses" of students, and current addresses for employees), we linked a host of neighborhood characteristics from the U.S. Census American Community Survey, 2016 Presidential election voting patterns, and League of Conservation Voters' ratings of Congressional representatives. Data from all four sources are used to estimate response propensities, and the estimated marginal utilities of all of the internal carbon pricing programs are allowed to vary systematically with deviations from the mean response propensity. Zeroing out this propensity is equivalent to simulating what would have been the estimated response propensities had everyone in the sample had the sample average response propensity.

We use almost 5600 choices by more than 1000 respondents to estimate preferences for ICPs. The notion of homogenous preferences is soundly rejected, and we explore a variety of dimensions of heterogeneity. Program cost and carbon-reduction benefits strongly affect preferences, as expected, but the distributional consequences of these programs are also very important to different types of people. The current draft of the paper merely scratches the surface, but illustrates that there is diminishing marginal utility of carbon reductions, and this marginal utility of carbon reductions also varies with some the individual's neighborhood characteristics (e.g. education, housing tenure, automobile access, and voting patterns) as well as with the individual's household income, perceptions of bias in the survey instrument, political ideology and recent experience with a severe winter.

Controlling for the unavoidable cost to the individual respondent and carbon-reduction benefits to be achieved, preferences for ICPs are also affected by the manner in which carbon pricing is implemented (i.e. revenue for carbon reduction projects can be raised as flat fees on all students and employees, as a "polluter-pays" type of fee on university-sponsored air travel or building energy use, and from the state's taxpayers). Preferences for programs with a higher share of overall costs borne by taxpayers are stronger for people who are more likely to respond to the survey. The effect of age is first increasing, then decreasing. Likewise, the manner of spending the revenues raised by an ICP program also influences support. Notably, non-students find less attractive those ICPs that spend a larger share of their revenues on academic programs. Programs that spent revenues on carbon offsets somewhere other than the university were less attractive, except to people from zip codes that skewed Democratic in the 2016 election.

We employ our parameter estimates to simulate a set of sampling distributions for the implied WTP for a given internal carbon-pricing program for a particular type of individual. We note here that alternative estimators, parameterized in WTP space, rather than utility space, have become increasingly common. However, some evidence suggests that models in utility space may fit better, especially when the marginal utility of net income (the negative of the coefficient on the cost attribute) is very precisely estimated. We may explore models in WTP space in subsequent revisions. While random parameters (so-called mixed logit) models are very popular, we note that they are less useful in contexts where there is a desire to shift an estimated benefits transfer function to a new context. For benefits transfer, it is preferable to have as much of the heterogeneity as possible be systematic heterogeneity, rather than purely random heterogeneity. If preferences differ with the characteristics of the university community, it is important to know *how* they differ, rather than merely that they *do* differ.

The array of potential carbon-pricing programs spanned by the design of our choice scenarios covers much of the range of programs that the university in question might consider. We believe that the fitted model will also be able to help the university understand whether their students and employees would be willing to bear the additional costs that would be implied if the university merely employed future expected carbon prices in its accounting calculations whenever it makes long-term decisions. A decision to install less carbon-intensive technology that would be warranted on a cost-minimizing basis under current conditions will mean higher costs and, one would hope, lower carbon emissions. Some variant of our ICP programs may map reasonably well to the case where an explicit social cost of carbon is factored into financial accounting procedures used to determine the university's upcoming investments in buildings and equipment.

Additional work is still to be completed, in addition to some additional exploration of newly available respondent characteristics. The key task is the final step of calculating, for any given carbon pricing program with a specified set of characteristics, a fitted WTP estimate for each person represented in the university's population, given their personal levels of all of the characteristics included in our final model. Given our aggressive efforts to correct our estimates for sample selection bias, we can be more confident that our corrected utility parameters reflect average preferences in the population, rather than reflecting disproportionately the preferences of those individuals more likely to participate in our study. Aggregating up to the implied university-wide willingness to pay for a specific carbon emissions reduction program will provide some insights about the overall welfare effects from such a program.

References

Barron, Alexander R. and Breanna J. Parker (2018), "Virtual carbon price is worth testing." *NATURE*, 553, 404.

Cai, Beilei, Trudy Ann Cameron, and Geoffrey R. Gerdes (2010), "Distributional preferences and the incidence of costs and benefits in climate change policy." *Environmental and Resource Economics*, 46, 429–458.

Cameron, TA (2005), "Updating subjective risks in the presence of conflicting information: An application to climate change." *JOURNAL OF RISK AND UNCERTAINTY*, 30, 63–97.

Cameron, TA and J Englin (1997), "Respondent experience and contingent valuation of environmental goods." *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT*, 33, 296–313.

Carattini, Stefano, Andrea Baranzini, Philippe Thalmann, Frederic Varone, and Frank Vohringer (2017), "Green Taxes in a Post-Paris World: Are Millions of Nays Inevitable?" *Environmental and Resource Economics*, 1–32.

Carattini, Stefano, Maria Carvalho, and Sam Fankhauser (2018), "Overcoming public resistance to carbon taxes." *WILEY INTERDISCIPLINARY REVIEWS-CLIMATE CHANGE*, 9.

Conte, Marc N. and Grant D. Jacobsen (2016), "Explaining Demand for Green Electricity Using Data from All U.S. Utilities." *Energy Economics*, 60, 122–130, URL `http://dx.doi.org/10.1016/j.eneco.2016.09.001`.

Gillingham, Kenneth, Stefano Carattini, and Daniel Esty (2017), "Lessons from first campus carbon-pricing scheme." *NATURE*, 551, 27–29.

Johnston, Robert J., Kevin J. Boyle, Wiktor (Vic) Adamowicz, Jeff Bennett, Roy Brouwer, Trudy Ann Cameron, W. Michael Hanemann, Nick Hanley, Mandy Ryan, Riccardo Scarpa, Roger Tourangeau, and Christian A. Vossler (2017), "Contemporary Guidance for Stated Preference Studies." *JOURNAL OF THE ASSOCIATION OF ENVIRONMENTAL AND RESOURCE ECONOMISTS*, 4, 319–405.

Lee, Jaeseung Jason and Trudy Ann Cameron (2008), "Popular support for climate change mitigation: Evidence from a general population mail survey." *ENVIRONMENTAL & RESOURCE ECONOMICS*, 41, 223–248.

Ma, Chunbo, Abbie A. Rogers, Marit E. Kragt, Fan Zhang, Maksym Polyakov, Fiona Gibson, Morteza Chalak, Ram Pandit, and Sorada Tapsuwan (2015), "Consumers' willingness to pay for renewable energy: A meta-regression analysis." *Resource and Energy Economics*, 42, 93–109, URL `http://linkinghub.elsevier.com/retrieve/pii/S0928765515000536`.

Maibach, EW, A Leiserowitz, C Roser-Renouf, Mertz CK, and K Akerlof (2011), "Global WarmingâĂŹs Six Americas screening tools: Survey instruments; instructions for coding and data treatment; and statistical program scripts." *Yale University and George Mason University. Yale Project on Climate Change Communication, New Haven, CT*.

Tables

Table 1: Descriptive statistics: For interaction terms, same order as tables; minor mismatches in means to be corrected

	mean	sd
1=fall 2018 wave (.439)	0.437	0.496
Observations	1052	

	mean	sd
1=female	0.600	0.490
1=gender not specified	0.003	0.053
Observations	1052	

	mean	sd
1=perceive pro-ICP bias (.447)	0.446	0.497
1=perceive anti-ICP bias (.029)	0.029	0.169
Observations	1052	

	mean	sd
1=somew/very liberal (.677)	0.674	0.469
1=somew/very conservative (.089)	0.090	0.287
Observations	1052	

	mean	sd
1=12 mos: coastal floods (.035)	0.035	0.184
1=12 mos: inland floods (.058)	0.058	0.234
1=12 mos: hurricane (.044)	0.044	0.205
1=12 mos: tornado (.036)	0.036	0.187
1=12 mos: sev. drought (.099)	0.097	0.296
1=12 mos: wildfire (.113)	0.113	0.317
1=12 mos: smoke (.767)	0.766	0.423
1=12 mos: severe winter (.136)	0.137	0.344
1=12 mos: heat wave (.430)	0.430	0.495
1=12 mos: other (.020)	0.021	0.143
Observations	1052	

	mean	sd
1=extr weath: any harm (.608)	0.608	0.488
Observations	1052	

	mean	sd
1=non-student (.531)	0.533	0.499
Observations	1052	

Table 2: How selected interaction terms affect utility parameter estimates (weighted, separate probit response/nonresponse model; estimates invariant to clustering at the respondent level); base case=zero value for de-meaned and nuisance interactions; persons= 1052, choices= 5594

	Base vars (homogeneous)	plus Base vars × selected	plus Base vars × selected (Minimal)
1=chosen alt			
unavoid cost to resp.	-0.00632***	-0.00755***	-0.00747***
	(0.00106)	(0.00107)	(0.00104)
× demeaned resp propensity	-0.000238	-0.000496	
	(0.00297)	(0.00305)	
pct-point carbon reduction	0.0132***	0.0413***	0.0429***
	(0.00364)	(0.0107)	(0.0106)
× pct-point carbon reduction		-0.000264	-0.000288*
		(0.000166)	(0.000165)
× demean zip pr 25 yrs+, grad, prof degr		-0.135***	-0.139***
		(0.0522)	(0.0521)
× demean zip pr Renter occupied		-0.0508***	-0.0458**
		(0.0189)	(0.0189)
× demean zip pr No vehicles available		-0.209***	-0.212***
		(0.0738)	(0.0738)
× demean zip pr Dem Pres. votes 2016		0.0788**	0.0770**
		(0.0354)	(0.0353)
× 1=gender not specified		-0.131***	-0.130***
		(0.0468)	(0.0476)
× demeaned hhld inc ('000)		0.0000831***	0.0000842***
		(0.0000322)	(0.0000321)
× 1=perceive pro-ICP bias (.447)		-0.00808**	-0.00796*
		(0.00412)	(0.00410)
× 1=perceive anti-ICP bias (.029)		-0.0210*	-0.0209*
		(0.0113)	(0.0112)
× 1=somew/very conservative (.089)		-0.0249***	-0.0249***
		(0.00745)	(0.00746)
× 1=12 mos: severe winter (.136)		-0.00932*	-0.00923*
		(0.00542)	(0.00541)
× demeaned resp propensity	0.0108	0.00676	

Continued on next page

Table 2 – continued from previous page

	(0.0102)	(0.0107)	
cost share air travel fees	1.212***	3.198***	3.207***
	(0.157)	(0.477)	(0.476)
× cost share air travel fees		-4.045***	-4.107***
		(0.946)	(0.943)
× demean zip pr Renter occupied		1.713	
		(1.044)	
× demeaned resp propensity	-0.215	-0.226	
	(0.478)	(0.495)	
cost share bldg energy fees	0.913***	0.950***	0.932***
	(0.107)	(0.111)	(0.110)
× demeaned resp propensity	-0.108	-0.178	
	(0.305)	(0.318)	
cost share taxpayers	0.674**	1.074***	1.215***
	(0.313)	(0.383)	(0.392)
× demean Avg 2017 LCV zip (pop wgtd)		-0.0217	
		(0.0137)	
× individual's age, if known		0.0553**	0.0569**
		(0.0235)	(0.0234)
× individual's age squared, if known		-0.00218**	-0.00283**
		(0.00110)	(0.00123)
× demeaned resp propensity	0.896	2.429**	2.588**
	(0.850)	(1.023)	(1.047)
spend share acad. prog	0.0865	-0.298	-0.341
	(0.228)	(0.385)	(0.387)
× 1=extr weath: any harm (.608)		1.289***	1.308***
		(0.446)	(0.446)
× 1=non-student (.531)		-1.009**	-0.887**
		(0.512)	(0.440)
× demeaned resp propensity	-0.425	0.366	
	(0.625)	(0.749)	
spend share offsets	-0.325*	-0.282	-0.432**
	(0.171)	(0.209)	(0.169)
× demean zip pr Dem Pres. votes 2016		5.284**	4.817*

Continued on next page

Table 2 – continued from previous page

		(2.587)	(2.662)
× individual's age squared, if known		-0.000861	
		(0.000678)	
× demeaned resp propensity	-0.000584	0.599	
	(0.627)	(0.695)	
status quo w/ no prog	0.0433	0.573**	0.566**
	(0.124)	(0.250)	(0.247)
× 1=gender not specified		-4.911***	-4.880***
		(1.385)	(1.402)
× 1=perceive pro-ICP bias (.447)		0.500***	0.508***
		(0.167)	(0.166)
× 1=somew/very liberal (.677)		-0.880***	-0.877***
		(0.161)	(0.161)
× 1=12 mos: tornado (.036)		0.630*	0.602*
		(0.325)	(0.324)
× 1=12 mos: heat wave (.430)		-0.430***	-0.427***
		(0.138)	(0.138)
× 1=extr weath: any harm (.608)		0.251*	0.261*
		(0.149)	(0.149)
× 1=non-student (.531)		0.300	0.359**
		(0.187)	(0.180)
× demeaned resp propensity	1.190***	1.072***	0.927***
	(0.337)	(0.374)	(0.258)
No. alternatives	13310	13310	13310
Max. log-likelihood	-7335.37	-7005.03	-7010.39
Clustering	caseid	caseid	none
Base case WTP (40% C red)	83.43		
Implied lower CI	56.36		
Implied upper CI	110.50		

t standard errors in parentheses; preliminary estimates pending additional sociodemographic data
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: 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, mean income, mean age, student, moderate, no perceived bias, no recent extreme weather, no harm from extreme weather		
10	54.04***	5.01***
	(34.01, 75.76)	(3.37, 6.81)
15	78.11***	4.62***
	(50.74, 107.85)	(3.31, 6.04)
25	120.36***	3.83***
	(83.53, 160.59)	(3.09, 4.62)
35	154.76***	3.05***
	(114.66, 198.56)	(2.29, 3.81)
40 (initial benchmark case)	169.01***	2.65***
	(129.49, 212.20)	(1.62, 3.66)
45	181.30***	2.26**
	(142.92, 222.99)	(0.9, 3.58)
50	191.62***	1.87*
	(154.33, 231.04)	(0.13, 3.54)
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, mean income, mean age, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
0 share	169.01***	2.65***
	(129.49, 212.20)	(1.62, 3.66)
0.20 share	234.04***	"
	(187.29, 287.24)	
0.25 share (second benchmark)	243.30***	"
	(195.48, 298.82)	
0.40 share	254.31***	"
	(205.52, 311.16)	
0.60 share	229.84***	"
	(180.08, 286.70)	
0.80 share	160.60***	"
	(88.19, 234.88)	
1.00 share	46.62	"
	(-80.05, 169.27)	
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, mean income, mean age, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		

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0 share	169.01***	2.65***
	(129.49, 212.20)	(1.62, 3.66)
0.20 share	194.42***	"
	(153.31, 240.65)	
0.25 share (second benchmark)	200.78***	"
	(159.18, 248.03)	
0.40 share	219.84***	"
	(176.02, 270.70)	
0.60 share	245.25***	"
	(198.05, 300.77)	
0.80 share	270.67***	"
	(219.16, 332.13)	
1.00 share	296.08***	"
	(239.89, 363.54)	
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, mean income, mean age, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
0 share	169.01***	2.65***
	(129.49, 212.20)	(1.62, 3.66)
0.20 share	202.26***	"
	(157.49, 252.29)	
0.25 share (second benchmark)	210.57***	"
	(163.90, 262.88)	
0.40 share	235.50***	"
	(179.70, 298.03)	
0.60 share	268.75***	"
	(199.10, 347.31)	
0.80 share	302.00***	"
	(216.89, 399.19)	
1.00 share	335.24***	"
	(232.75, 450.55)	
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, mean income, mean age, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
0 share	169.01***	2.65***
	(129.49, 212.20)	(1.62, 3.66)
0.20 share	159.76***	"
	(117.07, 205.55)	
0.33 share (second benchmark)	153.74***	"
	(105.29, 204.84)	

Continued on next page

Table 3 – continued from previous page

0.40 share	150.51***	"
	(98.74, 205.10)	
0.60 share	141.25***	"
	(77.10, 209.30)	
0.80 share	132.00***	"
	(52.84, 213.91)	
1.00 share	122.75**	"
	(27.97, 220.22)	
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, mean income, mean age, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
0 share	169.01***	2.65***
	(129.49, 212.20)	(1.62, 3.66)
0.20 share	157.20***	"
	(117.80, 199.17)	
0.33 share (second benchmark)	149.52***	"
	(109.39, 192.12)	
0.40 share	145.38***	"
	(104.58, 188.51)	
0.60 share	133.57***	"
	(89.40, 179.34)	
0.80 share	121.75***	"
	(73.64, 171.00)	
1.00 share	109.94***	"
	(56.79, 163.68)	
7. By carbon reduction, but with EQUAL shares for costs and spending		
(40% carbon reduction, student/employee fees only, spend revenues on carbon projects only)		
Characteristics: mean response propensity, mean income, mean age, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
10	166.89***	5.01***
	(112.61, 229.15)	(3.37, 6.81)
15	190.97***	4.62***
	(133.20, 257.90)	(3.31, 6.04)
25	233.22***	3.83***
	(169.77, 306.76)	(3.09, 4.62)
35	267.62***	3.05***
	(201.93, 344.30)	(2.29, 3.81)
40 (initial benchmark case)	281.87***	2.65***
	(216.32, 357.76)	(1.62, 3.66)
45	294.16***	2.26**
	(229.52, 368.83)	(0.9, 3.58)

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50	304.48***	1.87*
	(240.89, 377.57)	(0.13, 3.54)
8. By continuing student or not		
(40% carbon reduction, equal cost shares (.25), equal spending shares (.33))		
Characteristics: mean response propensity, mean income, mean age, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
Continuing student	281.87***	2.65***
	(216.32, 357.76)	(1.62, 3.66)
Not continuing student	242.30***	"
	(180.04, 312.95)	
9. By deviations from sample mean household income		
(40% carbon reduction, equal cost shares (.25), equal spending shares (.33))		
Characteristics: mean response propensity, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
-64.818 (min = 15)	252.07***	1.91**
	(186.17, 326.37)	(0.74, 3.02)
-57.318 (20th %ile = 22.5)	255.51***	2.00***
	(190.04, 329.86)	(0.85, 3.08)
-17.31 (40th %ile = 62.5)	273.91***	2.46***
	(208.55, 349.36)	(1.41, 3.47)
0 (at mean = 79.82)	281.87***	2.65***
	(216.32, 357.76)	(1.62, 3.66)
7.68 (60th %ile = 87.5)	285.40***	2.74***
	(219.71, 361.90)	(1.71, 3.75)
32.68 (80th %ile = 112.5)	296.90***	3.03***
	(229.78, 375.94)	(1.97, 4.06)
145.18 (max = 225)	348.62***	4.32***
	(265.39, 445.81)	(2.84, 5.85)
10. By deviations from sample mean age		
(40% carbon reduction, equal cost shares (.25), equal spending shares (.33))		
Characteristics: mean response propensity, continuing student, moderate ideology, no perceived bias, no recent extreme weather, no harm from extreme weather		
-3.33 (min = 18)	274.31***	2.65***
	(209.72, 349.40)	(1.62, 3.66)
-1.33 (20th %ile = 20)	279.11***	"
	(213.97, 354.57)	
-.331 (40th %ile = 21)	281.21***	"
	(215.86, 356.99)	
0 (mean = 21.33)	281.87***	"
	(216.32, 357.76)	
3.668 (60th %ile = 25)	287.70***	"
	(221.77, 364.31)	
15.6685 (80th %ile = 37)	288.57***	"
	(222.34, 365.85)	

Continued on next page

Table 3 – continued from previous page

51.6685 (max = 73)	123.65	"
	(-45.28, 297.71)	
11. By liberal, conservative ideology		
(40% carbon reduction, equal cost shares (.25), equal spending shares (.33))		
Characteristics: mean response propensity, mean income, mean age, continuing student, no perceived bias, no recent extreme weather, no harm from extreme weather		
Moderate or unknown political ideology	281.87***	2.65***
	(216.32, 357.76)	(1.62, 3.66)
Conservative political ideology	145.47***	-0.76
	(62.47, 231.05)	(-3.00, 1.21)
12. By perceived bias of researchers		
(40% carbon reduction, equal cost shares (.25), equal spending shares (.33))		
Characteristics: mean response propensity, mean income, mean age, continuing student, moderate ideology, no recent extreme weather, no harm from extreme weather		
No perceived bias	281.87***	2.65***
	(216.32, 357.76)	(1.62, 3.66)
Perceived pro-ICP bias	238.43***	1.57**
	(176.43, 307.81)	(0.39, 2.64)
Perceived anti-ICP bias	166.95**	-0.22
	(55.27, 281.71)	(-3.08, 2.42)
13. By respondent's experience with extreme weather in last 12 months		
(40% carbon reduction, equal cost shares (.25), equal spending shares (.33))		
Characteristics: mean response propensity, mean income, mean age, continuing student, moderate ideology, no perceived bias, no harm from extreme weather		
No extreme weather events	281.87***	2.65***
	(216.32, 357.76)	(1.62, 3.66)
Extreme cold	231.58***	1.40
	(157.54, 314.55)	(-0.16, 2.87)
14. Any prior experience with extreme-weather harm?		
(40% carbon reduction, equal cost shares (.25), equal spending shares (.33))		
Characteristics: mean response propensity, mean income, mean age, continuing student, moderate ideology, no perceived bias, no recent extreme weather		
No prior harm	281.87***	2.65***
	(216.32, 357.76)	(1.62, 3.66)
Some prior harm	340.51***	"
	(270.04, 423.50)	

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

A Appendix: 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.[12] 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.

[12]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 research 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 for the Spring 2018 sample used the following design:

- 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.[13]

[13]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 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

The full specification, as well as a more-parsimonious model that retains only those variables or indicators with persistently statistically significant coefficients, are shown in Table XX.

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 overfiting 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 then simpler methods of mode selection.

For the response non-response model we use a form of regularization known as Lasso[14]. 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

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

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

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.[15]. 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[16] 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.

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

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

Table 4: Response/nonresponse model, fitted using probit (includes sampling weights for Spring wave)

	Full model	Parsimonious
complete_toincome		
zipcode prop. Black or African American alone	-0.879	
	(1.284)	
zipcode prop. American Indian, Alaska Native alone	-0.168	
	(2.324)	
zipcode prop. Asian alone	-0.370	
	(1.030)	
zipcode prop. Native Hawaiian, Other Pac. Islander alone	4.708	
	(4.445)	
zipcode prop. Some other race alone	-0.176	
	(0.902)	
zipcode prop. U.S. citizen, born in PR or U.S. Island Areas	0.0741	
	(9.958)	
zipcode prop. U.S. citizen, born abroad, American parent(s)	-3.835	
	(8.225)	
zipcode prop. U.S. citizen by naturalization	1.649	
	(1.979)	
zipcode prop. Not a U.S. citizen	1.612	1.706^{*}
	(1.471)	(0.936)
zipcode prop. Renter occupied	0.766^{*}	0.524^{*}
	(0.417)	(0.305)
zipcode prop. AGE - Under 5 years	-0.725	
	(7.460)	
zipcode prop. AGE - 5 to 9 years	-0.801	
	(5.586)	
zipcode prop. AGE - 10 to 14 years	0.559	
	(7.433)	
zipcode prop. AGE - 15 to 19 years	-1.337	
	(3.148)	
zipcode prop. AGE - 20 to 24 years	2.425	
	(2.373)	
zipcode prop. AGE - 25 to 29 years	-9.315^{*}	-6.669^{**}
	(5.176)	(2.710)

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zipcode prop. AGE - 30 to 34 years	-0.914 (6.911)	
zipcode prop. AGE - 35 to 39 years	2.113 (6.836)	
zipcode prop. AGE - 45 to 49 years	-4.041 (6.498)	-6.573* (3.512)
zipcode prop. AGE - 50 to 54 years	-3.504 (6.604)	
zipcode prop. AGE - 55 to 59 years	11.92** (6.042)	10.87*** (4.089)
zipcode prop. AGE - 60 to 64 years	4.650 (6.540)	
zipcode prop. AGE - 65 to 69 years	-1.547 (7.723)	
zipcode prop. AGE - 70 to 74 years	-2.392 (9.715)	
zipcode prop. AGE - 75 to 79 years	-25.48** (12.81)	-19.00** (8.321)
zipcode prop. AGE - 80 to 84 years	20.99 (14.51)	27.21*** (9.181)
zipcode prop. AGE - 85 years and over	10.43 (9.096)	
zipcode prop. Moved; from different county, same state	2.052 (1.920)	
zipcode prop. Moved; from different state	6.175** (2.817)	4.493** (1.829)
zipcode prop. Moved; from abroad	-4.268 (7.182)	
zipcode prop. Male householder, no spouse, family hhld	3.203 (3.156)	4.619** (2.292)
zipcode prop. Female householder, no spouse, family hhld	0.329 (1.516)	
zipcode prop. Nonfamily household	0.558 (0.637)	0.669 (0.433)
zipcode prop. 25 yrs+, Less than 9th grade	-0.168	

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	(2.639)	
zipcode prop. 25 yrs+, 9th to 12th grade, no diploma	3.753	
	(3.193)	
zipcode prop. 25 yrs+, High school grad. (incl. equiv.)	-0.291	
	(2.111)	
zipcode prop. 25 yrs+, Associate's degree	0.617	
	(3.506)	
zipcode prop. 25 yrs+, Bachelor's degree	2.347	1.499**
	(1.801)	(0.746)
zipcode prop. 25 yrs+, Graduate or professional degree	-1.087	-1.247
	(1.564)	(0.799)
zipcode prop. Limited English, Spanish	0.475	
	(2.124)	
zipcode prop. Limited English, Other Indo-European lang.	-4.099	
	(4.220)	
zipcode prop. Limited English, Asian and Pacific Island lang.	-1.540	
	(4.229)	
zipcode prop. Limited English, Other languages	8.344	
	(15.26)	
zipcode prop. Income less than $10,000	0.486	
	(2.599)	
zipcode prop. Income $10,000 to $14,999	0.354	
	(3.329)	
zipcode prop. Income $15,000 to $24,999	-1.704	
	(2.589)	
zipcode prop. Income $25,000 to $34,999	2.764	3.694**
	(2.898)	(1.487)
zipcode prop. Income $35,000 to $49,999	1.081	
	(3.068)	
zipcode prop. Income $75,000 to $99,999	0.379	
	(3.258)	
zipcode prop. Income $100,000 to $149,999	-0.901	
	(2.548)	
zipcode prop. Income $150,000 to $199,999	0.0502	

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	(3.078)	
zipcode prop. Income \$200,000 or more	3.470	2.418**
	(2.115)	(1.002)
zipcode prop. Housing units - 1-unit, attached	2.190**	1.322*
	(0.985)	(0.723)
zipcode prop. Housing units - 2 units	-0.482	
	(2.192)	
zipcode prop. Housing units - 3 or 4 units	2.427	
	(1.860)	
zipcode prop. Housing units - 5 to 9 units	-1.130	
	(1.994)	
zipcode prop. Housing units - 10 to 19 units	5.053***	3.411**
	(1.927)	(1.397)
zipcode prop. Housing units - 20 or more units	1.054	
	(1.018)	
zipcode prop. Housing units - Mobile home	0.566	
	(1.471)	
zipcode prop. Housing units - Boat, RV, van, etc.	-6.350	
	(12.55)	
zipcode prop. Housing built 2010 to 2013	0.0163	
	(9.346)	
zipcode prop. Housing built 2000 to 2009	1.423	
	(7.872)	
zipcode prop. Housing built 1990 to 1999	-0.243	
	(7.711)	
zipcode prop. Housing built 1980 to 1989	0.196	
	(7.793)	
zipcode prop. Housing built 1970 to 1979	1.988	0.858*
	(7.796)	(0.503)
zipcode prop. Housing built 1960 to 1969	0.389	
	(7.771)	
zipcode prop. Housing built 1950 to 1959	1.545	1.484**
	(7.851)	(0.707)
zipcode prop. Housing built 1940 to 1949	2.414	

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	(7.819)	
zipcode prop. Housing built 1939 or earlier	1.950	0.949*
	(7.846)	(0.497)
zipcode prop. Housing with 1 room	5.165	6.271***
	(3.567)	(2.279)
zipcode prop. Housing with 2 room	-8.538***	-7.102***
	(3.194)	(2.240)
zipcode prop. Housing with 3 rooms	-0.856	
	(2.267)	
zipcode prop. Housing with 4 rooms	-3.295	-3.115***
	(2.196)	(1.008)
zipcode prop. Housing with 6 rooms	-1.968	-2.136*
	(2.488)	(1.129)
zipcode prop. Housing with 7 rooms	0.589	
	(2.336)	
zipcode prop. Housing with 8 rooms	-1.308	
	(2.598)	
zipcode prop. Housing with 9 rooms or more	0.122	
	(1.576)	
zipcode prop. Moved-in 2010 to 2014	5.100	6.403***
	(3.672)	(2.164)
zipcode prop. Moved-in 2000 to 2009	3.615	5.068***
	(3.297)	(1.855)
zipcode prop. Moved-in 1990 to 1999	7.417**	6.240***
	(3.558)	(2.283)
zipcode prop. Moved-in 1980 to 1989	-2.162	
	(4.015)	
zipcode prop. Moved-in 1979 and earlier	3.964	5.227*
	(3.929)	(2.778)
zipcode prop. No vehicles available	-4.838**	-3.586**
	(2.089)	(1.505)
zipcode prop. Housing lacking complete plumbing	-0.256	
	(10.48)	
zipcode prop. Housing lacking complete kitchen	4.052	

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	(4.803)	
zipcode prop. No telephone service available	-0.437	
	(4.021)	
zipcode prop. House value less than \$50,000	0.188	
	(1.864)	
zipcode prop. House value \$50,000 to \$99,999	0.114	
	(1.321)	
zipcode prop. House value \$100,000 to \$149,999	-0.0871	
	(1.734)	
zipcode prop. House value \$200,000 to \$299,999	-0.652	
	(1.254)	
zipcode prop. House value \$300,000 to \$499,999	0.353	
	(0.913)	
zipcode prop. House value \$500,000 to \$999,999	-0.958	
	(1.052)	
zipcode prop. House value \$1,000,000 or more	-1.820	-1.208***
	(1.127)	(0.432)
zipcode prop. Rent Less than \$500	0.901	
	(0.922)	
zipcode prop. Rent \$500 to \$999	-0.371	
	(0.559)	
zipcode prop. Rent \$1,500 to \$1,999	0.695	
	(0.835)	
zipcode prop. Rent \$2,000 to \$2,499	-0.418	
	(1.201)	
zipcode prop. Rent \$2,500 to \$2,999	0.132	
	(1.506)	
zipcode prop. Rent \$3,000 or more	0.208	
	(1.059)	
zipcode prop. Democratic votes 2016 Pres elect.	-0.852	-0.490
	(0.631)	(0.314)
zipcode prop. Libertarian votes 2016 Pres elect.	-0.330	
	(11.50)	
zipcode prop. Green Party votes 2016 Pres elect.	12.48	

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	(17.11)	
zipcode prop. Other votes 2016 Pres elect.	5.242	5.785***
	(7.531)	(1.778)
Avg 2017 LCV score across people in zip	-0.00412	
	(0.0135)	
Avg lifetime LCV score across people in zip	-0.00179	
	(0.0144)	
Proportion of zip with Dem representative	0.417	
	(0.567)	
American Indian or Alaska Native	-0.291	
	(0.235)	
Asian	0.186**	0.207***
	(0.0825)	(0.0801)
Black or African American	-0.425**	-0.423**
	(0.175)	(0.175)
Hispanic or Latino	-0.178**	-0.155**
	(0.0723)	(0.0717)
Native Hawaiian	-0.700	-0.693
	(0.453)	(0.453)
Nonresident alien	-0.165	
	(0.157)	
Race and ethnicity unknown	0.165**	0.172**
	(0.0712)	(0.0700)
Two or more races	-0.178**	-0.162*
	(0.0889)	(0.0882)
=1 if individual's age known	0.452	0.270**
	(0.300)	(0.135)
Individual's age, if known	-0.00456	
	(0.0123)	
Individual's age squared, if known	0.0000530	
	(0.000150)	
U.S. citizen	0.308**	0.416***
	(0.133)	(0.0740)
=1 if employee, =0 otherwise	0.150***	0.138***

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	(0.0501)	(0.0463)
Individual is non-tenure-track faculty	-0.118	
	(0.0964)	
Individual is staff	-0.0182	
	(0.0796)	
Individual has courtesy appointment	-0.422**	-0.396**
	(0.167)	(0.158)
Individual is short-term faculty	-0.122	
	(0.128)	
Individual is an administrator	-0.00203	
	(0.0789)	
=1 if student, =0 otherwise	-0.548***	-0.552***
	(0.115)	(0.109)
Student: business admin	-0.117	-0.105
	(0.0757)	(0.0717)
Student: community education	-0.240***	-0.240***
	(0.0732)	(0.0680)
Student: journalism and communications	-0.279***	-0.259***
	(0.0823)	(0.0797)
Student: psychology	-0.0598	
	(0.105)	
Student: undeclared	0.100	
	(0.104)	
Student: economics	-0.0885	
	(0.132)	
Student: biology	0.227**	0.234**
	(0.112)	(0.110)
Student: general social science	-0.330**	-0.304**
	(0.140)	(0.140)
Student: human physiology	-0.108	
	(0.117)	
Student: political science	-0.0878	
	(0.140)	
Constant	-7.426	-7.597***
	(8.488)	(1.816)

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Observations	7659	7659

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

Figure 1: Distribution of fitted propensity to take and finish survey
(six negative outliers omitted)