Carbon-Reduction Programs in Higher Education: Demand as a Function of Program Attributes and Stakeholder Characteristics

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Abstract

Several universities have implemented, and numerous others are considering, internal carbon fees or pricing programs intended to reduce greenhouse gas emissions, finance carbon reduction programs, signal sustainability and/or prepare for future mandatory carbon reductions. To learn about preferences over potential program designs, we employ survey-based choice experiments concerning potential internal carbon-pricing programs at a flagship public university. More than 1,000 stakeholders each consider several hypothetical programs which vary in their costs, emission reductions, the initial incidence of their costs, and uses of the resulting revenue. With corrections for systematic sample selection, we estimate a random-utility model with systematic preference heterogeneity which permits us to simulate, for different constituencies, the distribution of willingness to pay for different types of programs. Median individual willlingness-to-pay estimates predict the highest cost for any given program that would be approved in a campus referendum. Mean individual willingness-to-pay amounts can be used for benefit-cost assessments.

JEL classification: Q54, Q51, Q52, D61

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1 Introduction

For the time being, 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. However, 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. CDP (2021) reports that of nearly 6,000 companies surveyed about carbon pricing in 2020, more than 2,000 disclosed that they were currently using an internal carbon price or that they planned to introduce one within the next two years.[1] Firms institute internal carbon fees or internal carbon pricing for several reasons. Some 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 fees/prices 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 non-zero carbon price, even though they might not be cost-effective today. In addition to the private sector, these strategies can also be used by academic institutions, non-profit organizations, and the public sector, as argued by Barron and Parker (2018).

Barron et al. (2020) review existing internal carbon price (ICP) tools specifically for higher education institutions, including seven universities and colleges with "broad scope" ICPs, and six

[1] For example, Microsoft, Mitsubishi, and nearly half of the 500 biggest companies, globally, factor carbon accounting into their business plans.

with air travel ICPs.[2] Studies of carbon pricing at universities also tend to treat each university as an observation, as in Lee and Lee (2021) and Lee and Lee (2022). Papers concerning an actual carbon pricing program at a single university (e.g., Gillingham et al. (2017)) tend to concentrate on how that program has been implemented and its consequences for energy savings. There has been little inquiry into internal stakeholder preferences that might help guide institutional choices across alternative potential programs that may be under consideration.

Universities are large institutions consisting of several administrative divisions and many types of stakeholders who are likely to have varying preferences concerning alternative designs of internal carbon fee or carbon pricing programs, or even whether such programs are needed at all. As Light (2020) points out, universities do not face the same types of profit, competitive, or re-election pressures that tend to limit experimentation by private firms and public regulators. But given that different groups of university stakeholders have a variety of objectives, these groups can be expected to vary in their enthusiasm about programs to reduce carbon emissions that will impose costs on individual members of the university community. Campus-wide support will depend upon the attributes of the program in question and the mix of stakeholder characteristics across the campus.

While different from the private sector, universities still have broadly similar motivations for adopting internal carbon fees/pricing programs. As do firms, they may use these programs to reduce emissions and/or raise money for future carbon-reduction projects. Analogously, universities may also see these programs as a way to develop a reputation for sustainability as a means to attract students, to advance the university's mission, or as a way to educate their students about sustainability and carbon pricing.[3]

[2]Princeton University introduced proxy prices for carbon in evaluating capital projects in about 2008, and Weber State University established a carbon fund in 2012. The earliest adoption of actual carbon charges, however, was Yale University, which pilot tested an internal carbon price in the form of a building energy fee in 2015.

[3]In the online Supplementary Materials associated with this paper, we begin with a more-detailed review of the related literature on internal carbon pricing or fees in other contexts, as well as evidence for stakeholder preferences concerning distributional consequences of programs and attitudes towards revenue recycling in particular.

For the present study, we conducted a stated-preference survey using choice experiments, in an advisory referendum format, at a large public university. This survey yielded a sample of preferences for carbon fee/pricing programs for approximately 1,000 respondents (including students, faculty, staff and other employees). In each choice scenario, respondents are asked to consider either one or two hypothetical carbon fee/pricing programs, along with a status quo alternative (where the status quo involves no such program and no out-of-pocket costs). Programs vary in the emission reductions they achieve and the likely overall 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), and the estimated parameters are used to predict individual willingness to pay (WTP) for carbon reductions as a function of program attributes and respondent characteristics.

Our specific attention to each program's distributional attributes (other than just its cost and the carbon emissions reductions it would achieve) reflects the increasing attention that has been paid to equity issues in the implementation of carbon fee/pricing programs more generally. Individuals may have different views of two programs that cost the same and deliver the same reductions in carbon emissions, yet differ in how the costs are borne across different stakeholder groups, and how the revenues produced by carbon pricing are distributed across alternative uses. In our choice scenarios, the funding for carbon emissions reduction projects can be raised, to varying extents, through (a) a simple lump-sum annual carbon fee on students, faculty and staff, (b) carbon fees on university-paid air travel, (c) charges on emissions generated through building energy use, or (d) state-government support funded by taxpayers. To varying extents, the revenue (a) can be spent for on-campus carbon reduction projects, (b) can be "recycled" back into academic programs, (c) can be spent on off-campus carbon "offsets" instead of on-campus carbon emissions reductions.[4,5]

[4]Preferences concerning international versus domestic forestry-based carbon offsets have been addressed in a choice experiment by Baranzini et al. (2018).

[5]Of course, a case with 100% of the program 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 such extreme mixes such as these among our randomized program designs.

A natural concern is that the subset of stakeholders who respond to a survey about internal carbon fee/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 assess and make adjustments for systematic sample selection.[6] Having extensive data on many characteristics of both respondents and non-respondents allows us to estimate predicted individual survey response propensities. We construct a measure of each respondent's deviation from the average response propensity among the random sample from the university population who were invited to take the survey. This de-meaned response propensity is allowed to affect the estimated marginal utility of all program attributes. 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 "benefits-function transfer" exercises. Other universities that might consider internal carbon fee/pricing programs may have systematically different stakeholders from those at the university where our study was conducted. Our estimated marginal distribution of WTP amounts depends on the distribution of incomes, political attitudes, other individual or zip-code-level demographic characteristics, and recent climate-related extreme-weather experience variables. In principle, it would be possible to simulate the demand for specific types of internal carbon fee/pricing programs within the range spanned by our randomized design, at other universities with mixes of stakeholders that differ from the mix at the university where we have fielded our survey.

[6] A protocol for identity-redaction protects campus subjects, and all data for this study have been stored on a FERPA-compliant server.

2 Survey Design and Analytical Framework

2.1 Brief Overview of Survey

Our survey was administered electronically, using the Qualtrics survey platform, in two waves—one in the late Spring of 2018 and one in the Fall of 2018. Our respondents are randomly selected from the set of all students, employees, staff and administrators affiliated with the university.[7] The survey invitation was sent to each person's email address of record with the university. The invitation states that the university is seeking input about whether, and how, to implement an internal fee for carbon emissions reductions or a 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 were offered a five-dollar incentive in the form of a digital gift certificate to the campus store.[8] On average, the survey took about twenty minutes to complete, although some respondents chose to study the optional background information in considerably more detail. In total, we collected 1,107 usable responses, representing an 8.8% response rate relative to all survey invitations. This low overall response rate makes it imperative that we assess and, if necessary, compensate for systematic selection.

A detailed description of the structure of the entire survey, and one instance of the randomized survey instrument, are provided in the online Supplementary Materials associated with this paper.[9] 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; we relegate more-detailed descriptions to the Supplementary Materials. 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

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

[8] No incentive was offered for the first 100 invitations that constituted a pre-test wave. The survey content did not change after this pre-test, so we include these invitations in our analysis.

[9] One instance of our survey is included in the Supplementary Materials, with a link to a Qualtrics demo version.

fee/pricing programs versus No Program. Each alternative is described in terms of a common set of attributes, with the No Program alternative representing the status quo. The key attributes of each internal carbon-pricing program are the percentage-point net reduction in carbon emissions that the program is projected to achieve, and the unavoidable annual cost to the respondent. But we also focus on the fact that internal carbon-pricing programs can be implemented in a wide variety of different ways. We direct our respondents' attention to the distributional consequences of the different programs, in terms of both (a) how the costs of the program would be borne, and (b) how the revenue raised by these programs might be spent.

It is technologically cost-prohibitive to meter (accurately) all carbon emissions related to a university campus, so we choose instead to focus this study on potential fees associated with two major source of emissions: air travel and building energy use. On most campuses, these tend to be some of the largest sources of carbon emissions, with building heating often being the largest.[10]

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, at the time of the survey it was not yet clear how the other details of any prospective ICP program for the university would be settled. Thus, we designed our survey to permit an assessment of how individual willingness to pay for carbon emissions reductions might vary systematically with differences in the way the costs are borne and differences in the way the revenues are used. We allow the cost of the program to be funded in four distinct ways. In addition to (a) a flat carbon fee on all students and employees, funds can be raised through (b) a fee on university-sponsored air travel, (c) a charge for the carbon emissions of campus buildings, or (d) by relying on funds raised from the state's taxpayers. Besides (a) spending the revenue raised for

[10]For the university surveyed in this study, building heat accounts for about 48 percent of total estimated carbon emissions, and university-sponsored air travel accounts for about 13 percent. Air travel and building energy use also tend to be the carbon sources for which universities have the most information about the origin and quantity of their carbon emissions.

on-campus carbon-reduction projects, (b) some of the revenue could be recycled in the form of spending on academic programs, or (c) off-campus "carbon offsets" could be purchased in lieu of on-campus carbon reductions. All choice sets offered to each respondent are randomly populated, in advance, with different mixes of program attributes, so every copy of the digital survey "instrument" is essentially unique. The only constraints are that programs offering higher carbon reductions generally cost more money, and the difference in cost between any pair of programs offered in the same choice set is constrained to be at least five dollars.[11]

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

[11] We do not employ any of the available software for efficient design of choice sets due to complexity that arises from the fact that the cost shares and revenue shares must both sum to one. Most choice set design software expects the user to specify a relatively small number of attributes, each with a relatively small number of discrete levels, and that any level of one attribute can be combined with any level of another attribute. We also wish to explore non-linearities in functional forms, so we needed enough different levels of each attribute to allow us to discriminate between different degrees of curvature. We also acknowledge 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 trade-offs. If one program in the same choice set strictly dominates another in terms of cost and effectiveness, one risks having the survey respondent wonder whether they are being tricked. Of course, sufficiently negative *distributional* consequences of a cheaper program that produces greater carbon reductions could overwhelm its cost advantage, but we will be able to infer the circumstances where this might happen from our parameter estimates.

Office of Institutional Research.[12]

2.2 Model Specification

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

The systematic component of the level of anticipated indirect utility under any given carbon reduction program is assumed to depend on the respondent's annual household income, Y^i, minus the unavoidable annual cost of the program to that person, C^i_{jt} The other key program attribute, besides 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 flat fee charged to all students and university employees, denoted as the vector $CostShare^i_{rjt}$. If all of these "other" shares are simultaneously zero, the cost of the program in question will be borne entirely as an annual flat fee charged to all students and employees.

Programs also differ in the shares of the revenue they raise that will be spent on things other

[12] The relationships between willingness to pay and subjective attitudes are very interesting, but we do not explore these correlations in the present paper because of the joint endogeneity between climate change attitudes and willingness to pay for carbon emissions reductions. We include only the relatively exogenous information about the respondent's exposure to extreme weather events over the previous 12 months.

than internal carbon-emissions reduction programs, denoted as the vector $SpendShare^i_{sjt}$. As with the cost shares, if all these other expenditure shares for a particular program are simultaneously zero, all the revenue raised by that program will be spent exclusively on internal carbon-reduction programs.

2.2.1 Homogeneous preferences

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

$$\begin{aligned}(1)\qquad U^i_{jt} &= V^i_{jt} + \eta^i_{jt} \\ &= \alpha(Y^i - C^i_{jt}) + \beta B^i_{jt} + \sum_{r=1}^{3} \gamma_r CostShare^i_{rjt} + \sum_{s=1}^{2} \delta_s SpendShare^i_{sjt} + \kappa SQ_{jt} + \eta^i_{jt}\end{aligned}$$

In logit-based binary or multiple discrete choice models suitable for analyzing people's responses to the choice questions posed in our survey, it is assumed that the *relative* anticipated indirect utility levels of the different alternatives drive the choices made by individuals. Every choice task in this study includes No Program (i.e. the status quo) as an alternative, indexed as $j = 0$, for which $SQ_{0j} = 1$. The No Program alternative involves no cost, no benefits, and thus no question about the distribution of either the costs or the revenues. Thus the utility derived from the status quo alternative is just $U^i_{0t} = \alpha(Y^i) + \kappa(1) + \eta^i_{0t}$. The difference in anticipated utility between each non-status-quo alternative j and the status quo alternative can then be written as:

$$\begin{aligned}(2)\qquad &(U^i_{jt} - U^i_{0t}) \\ &= \alpha(-C^i_{jt}) + \beta B^i_{jt} + \sum_{r=1}^{3} \gamma_r CostShare^i_{rjt} + \sum_{s=1}^{2} \delta_s SpendShare^i_{sjt} + \kappa(-1) + \varepsilon^i_{jt}\end{aligned}$$

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.[13]

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

If we were to assume that preferences are homogeneous, or that the estimated marginal utility parameters apply to a "representative consumer," it is possible to back out of the estimated preference function an expression for (a) the representative consumer's willingness to pay for a program with specified coefficients, as well as (b) this consumer's marginal willingness to pay for incremental amounts of each program attribute. Maximum annual willingness to pay for a given carbon-pricing program could be 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:

$$(3) \qquad 0 = \alpha(-C^i_{jt}) + \beta B^i_{jt} + \sum_{r=1}^{3} \gamma_r CostShare^i_{rjt} + \sum_{s=1}^{2} \delta_s SpendShare^i_{sjt} - \kappa + \varepsilon^i_{jt}$$

$$WTP^i_{jt} = C^{*i}_{jt} = (1/\alpha)\left[\beta B^i_{jt} + \sum_{r=1}^{3} \gamma_r CostShare^i_{rjt} + \sum_{s=1}^{2} \delta_s SpendShare^i_{sjt} - \kappa + \varepsilon^i_{jt}\right]$$

At the zero mean of the symmetrically distributed error term, this expression would be simple to

[13]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, most researchers find it convenient to specify anticipated indirect utility as additively separable in income, so that the level of income drops out of the model. While utility is unlikely to be linear in income overall, researchers typically rely on a locally linear approximation when annual program costs can be considered to be relatively small compared to annual income.

calculate. However, it must be remembered that the estimated maximum likelihood parameters are random variables that are asymptotically jointly normally distributed. Given that α is not constrained to be strictly positive, zero is a potential value for this parameter and the analytical expected value is therefore undefined. Many researchers, however, elect to build up a sampling distribution for the value of the implied willingness-to-pay (WTP) function. Using the approach suggested by Krinsky and Robb (1986), we make 10,000 draws from the asymptotically joint normal distribution of the maximum likelihood parameters. We combine each independent draw for a set of parameter values with the specified levels of all the attributes of a given program other than its cost—namely its percentage-point carbon reduction, B^i_{jt}, along with its non-default shares of costs, $CostShares^i_{rjt}$, $r = 1, ..., 3$, and its non-default shares of expenditures, $SpendShare^i_{sjt}$, $s = 1, 2$—to calculate one point estimate of WTP for that program. Across the 10,000 different draws from the estimated joint parameter distribution, we build up a sampling distribution for the 10,000 resulting WTP estimates, and report the mean and 5th and 95th percentiles of this distribution to convey a sense of the central tendency for total willingness to pay for such a program, as well as an approximate 90 percent confidence interval for this WTP estimate.

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

$$\frac{\partial WTP^{*i}_{jt}}{\partial B^i_{jt}} = \frac{\partial C^{*i}_{jt}}{\partial B^i_{jt}} = \frac{\beta}{\alpha} \tag{4}$$

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

$$(5)\qquad \frac{\partial WTP_{jt}^{*i}}{\partial CostShare_{rjt}^{i}} = \frac{\gamma_r}{\alpha}$$
$$\frac{\partial WTP_{jt}^{*i}}{\partial SpendShare_{sjt}^{i}} = \frac{\delta_s}{\alpha}$$

The presence of α in each denominator likewise means that a sampling distribution of estimates for each marginal WTP should likewise be built up using draws from the joint distribution of the estimated parameters, and means and 5th and 95th percentiles should be reported to convey a sense of the precision with which these WTP amounts are estimated.[14]

2.2.2 Heterogeneous preferences, distributional effects, and benefits transfer

It is a popular strategy in stated-preference research to assume that preference parameters vary randomly across respondents, and to estimate both the mean preference parameters and their standard errors (and sometimes their correlations.) This assumption dictates the use of a mixed-logit (also known as a random-parameters logit) estimator. However, we wish to do more than simply confirm that preferences are indeed heterogeneous. We wish to learn how these preferences vary *systematically* across different types of people, and we have numberous observable respondent characteristics in our data. Random-parameters mixed logit models are ideal for accommodating unobservable heterogeneity. Here, however, we wish to exploit readily observable forms of heterogeity.

Another popular approach in modeling heterogeneous preferences based on choice experiments is to allow for a small number of latent preference "classes" in the population, and to identify how

[14]We note that based on Hole (2007), there exists a user-written program in Stata to calculate, by several methods, *marginal* willingness-to-pay point estimates and standard errors associated with a conventional conditional logit specification where the index is linear in variables. However, this Stata program does not seem to be able to calculate interval estimates for total WTP for programs consisting of specified levels of the full set of attributes. Just knowing the marginal WTP estimates for each attribute and their standard errors is insufficient, because non-zero correlations among the various marginal utility parameters are ignored. Total WTP is a linear combination of correlated random parameters, so the covariances among these parameters must be taken into account in the calculations.

respondent characteristics affect the probability of that individual's membership in each of these distinct preference classes. These "finite mixture" or "latent class" models allow for heterogeneity in preferences, but do not readily permit the estimated marginal utilities derived from individual program attributes to vary in different ways with respondent characteristics. If three latent classes of preferences can be identified, for example, then there will be three distinct estimates of each marginal utility parameter that is allowed to vary across preference classes. Researchers then typically calculate the three different WTP estimates that apply for each latent preference class, and merely to discuss how different respondent characteristics influence membership in each of these three classes.

We seek a model that is more general than a latent-class specification and more suitable for being transferred to different populations with mixes of observable characteristics that differ from our estimating sample. Thus, we allow each of our eight basic preference parameters—α, β, γ_1, γ_2, γ_3, δ_1, δ_2 and κ—to vary systematically across individuals with different observable characteristics. We wish to allow our model to be useful for assessing the likely distributional consequences of any specific program, and potentially for benefit-function transfer exercises to other contexts involving similar populations with different mixes of characteristics (provided that the distribution of people's characteristics has roughly the same support). Random-parameters (mixed logit) models can confirm the presence of heterogeneity in preferences, but they are not ideal for predicting how the distributions of marginal and total WTP for specific programs would differ for populations with different observable characteristics.

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

$$\begin{aligned}(6)\qquad U^i_{jt} - U^i_{0t} &= -(\alpha' Z_i)C^i_{jt} + (\beta' Z_i)B^i_{jt} \\ &\quad + \sum_{r=1}^{3}(\gamma_r' Z_i)CostShare^i_{rjt} + \sum_{s=1}^{2}(\delta_s' Z_i)SpendShare^i_{sjt} + (\kappa' Z_i)SQ_{jt} + \varepsilon^i_{jt}\end{aligned}$$

In this more-general model, the marginal WTP for a one-percent-point reduction in carbon (and analogously for the other program attributes) would be generalized to:

$$MWTP^i_{jt} = \frac{\hat{\beta}' Z_i}{\hat{\alpha}' Z_i} \tag{7}$$

2.3 Response/Non-Response Correction

It is always a concern, with voluntary survey data, that propensity to respond to the survey may be correlated with with an invited participant's WTP, such that systematic sample selection bias may therefore distort the estimated marginal utilities and therefore the estimates of WTP. To correct at least partially for sample selection bias, we estimate an explicit model of "propensity to respond" and use the de-meaned fitted response propensities as additional individual-level characteristics in our model.[15]

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

We convert to zip-code extents a wide selection 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, converted to zip codes using HUD's cross-walk between census tracts and

[15]Rigorous Heckman-style correction models require that the error term in the selection equation and the error term in the "outcome" model be distributed joint normal. This condition is not satisfied when the outcome equation is a conditional-logit choice model for multiple alternatives.

USPS zip codes).[16] The sheer number of candidate explanatory variables means we must resort to a LASSO logit model for binary choices to select regressors for our response/nonresponse model, and we retain only those variables that minimize the out-of-sample mean-squared-error for prediction.[17]

Descriptive statistics for the LASSO-retained explanatory variables for the 12,568 people who received an invitation to participate in our survey are provided in Table S1 in the online Supplementary Material. Table S2 reports parameter estimates produced by using these LASSO-retained variables in a conventional binary logit model. We use this model to calculate a predicted response propensity (fitted logit "index") for each person in our invited group. Figure S1 among the Supplementary Materials shows the distribution of de-meaned fitted response propensities across all invited participants, along with the corresponding distribution for only those people whose responses are included in our final analysis. Across our respondent group, the mean fitted response propensity is 0.509, rather than zero. Clearly, different types of people are systematically more or less likely to respond to our survey. We need to account for the fact that our estimating sample contains people who are more likely to respond to the survey, on average, than the overall group of invitees. Response rates are generally higher for people who find the topic of the survey to be more salient (either positively or negatively). Thus it is important to correct, to the extent possible, for the over-representation in our sample of people who find the survey topic salient enough that they are motivated to complete our survey.

[16]We also assembled data from David Leip's Election Atlas for the 2016 Presidential election (originally at the county level), and (c) from the League of Conservation Voters (originally at the congressional-district level). However, it did not seem prudent, ultimately, to assign to individuals the data corresponding to such large geographic areas.

[17]We use the LASSO algorithm in the *glmnet 4.1-4* package for R (version 4.2.1), forcing into the model our indicators for the presence or absence of five different groups of ZIP code census data (very much correlated with the presence or absence of a valid U.S. zip code for each respondent), and for different categories of our administrative variables. We also employ weights to correct for our differential rates of invitations to student and employee groups in the Spring and Fall waves of our survey.

3 Results

3.1 Estimated Preference Parameters

If preferences were homogeneous, our model would have only eight parameters: the coefficient on the size of the carbon reduction, the coefficient on the cost of the program, the five coefficients capturing the distribution of costs/benefits, and a coefficient on a status-quo indicator. If people care only about the size of the reduction in carbon emissions and the cost of the program, it would not matter how the internal carbon pricing program is implemented. But it is now well-understood that people's willingness to pay for environmental goods can be influenced by their perceptions of fairness in the program. We capture the distributional features of these internal carbon pricing programs through the four different ways its costs could be borne by different groups, and three different ways in which the revenues could be used.

As in equation (6) and equation (7), we use interaction terms to permit the marginal utility of every feature in our offered carbon fee/pricing programs to vary systematically with respondent characteristics, and allow the LASSO algorithm to retain only those interactions that provide good out-of-sample predictive ability. Table S3 in the online Supplementary Materials displays descriptive statistics for each characteristic of the respondent (or their ZIP code) that systematically shifts at least one marginal utility in the model.[18]

Table 1 reports parameter estimates for a binary logit model using our LASSO-selected interaction terms to shift respondents' preferences among the wide range of randomly designed carbon-reduction programs proposed across the different (essentially unique) survey instruments used in our study.[19] The first thing to note for our model of program choice is that the fitted demeaned

[18]One exception, however, concerns the marginal utility of net income, given by the negative of the coefficient on the cost variable. It is common for researchers to constrain that marginal utility to be the same for all respondents, since this is an assumption implicit in benefit-cost analysis, at least as it is typically practiced in North America. We do, however, allow this marginal utility to vary systematically with our fitted response propensities, to reduce selection bias in our estimates.

[19]For our LASSO variable selection for our model of program choice in Table 1, we use the maximum value of the λ "tuning" parameter that still falls within a one-standard-error interval of the λ that minimizes the cross-validation

response propensity (from the response/non-response model in Table S2 in the online Supplementary materials) has its only discernible effect on the marginal (dis)utility of the program's cost. The higher a person's propensity to respond to our survey, the less negative is their cost coefficient (or equivalently, the smaller is their marginal utility of net income). When we simulate the implied value of the cost coefficient had everyone in the sample been only as likely to respond as the average in the population (and equally likely to respond, as would be the case for a truly random sample), we will have a larger marginal utility of income, and therefore smaller WTP estimates than an uncorrected model would produce, since the marginal utility parameter forms the denominator in our WTP formula.

The parameter estimates in Table 1, for the marginal utilities of program attributes, are the ingredients for calculating total and marginal WTP amounts for different programs and for different people. Table 1 is structured so that each of the eight basic program attributes is followed by that attribute's interactions with LASSO-selected respondent characteristics (either for their "permanent address" zip code, or individually from administrative data or some (non-attitudinal) survey responses). Any interaction term bearing a positive coefficient suggests that the marginal utility (and hence marginal WTP) for the attribute in question increases when that zip-code proportion is larger, or when the individual indicator for a characteristics is "switched on" or an individual continuous characteristic is larger.

We note here that the randomized experimental design of the different mixes of program attributes ensures that there can be no correlations between respondent's attributes and program characteristics. However, the mix of respondent characteristics across the estimating sample consists of observational data. The apparent effects of different respondent characteristics on any given marginal utility in the model can be distorted by correlations across the sample among these respondent characteristics. As in ordinary least squares models in the presence of multicollinearity,

mean-squared-error. (The MSE-minimizing λ retains about twice as many regressors.) Note that the row labels in Table 1 include unweighted sample average values for the respondent characteristics, corresponding to the descriptive statistics given in Table S3.

a model's goodness-of-fit may be very high, yet there may be statistically insignificant or counter-intuitive slope coefficients (due to omitted variables or correlations among included variables) where the algorithm cannot easily discern the ceteris paribus effects of one respondent characteristic when another is held constant. The LASSO algorithm merely seeks to maximize the predictive ability of the specification for hold-out samples from the full estimating sample.[20]

3.2 WTP for Specific Program Attributes by Representative Individuals

Of particular interest will be the overall weighted marginal distribution of the specific WTP amounts predicted for each individual in our sample. However, each person was asked about a variety of programs, so we must standardize the program in question before considering the range of fitted WTP values. Our "baseline" program will be a 40% reduction in campus carbon emissions, with all costs borne as a flat fee on all students and employees, and all revenues spent on carbon reduction programs. Thus all the terms involving the shares of costs borne in other ways or the shares of revenues spent on other things will be set to zero. WTP for the baseline program will thus be influenced only by the vectors of α, β and κ coefficients (on program costs, carbon-reduction benefits, and the status quo effect). Accordingly, types of respondent heterogeneity that affect only the γ or δ coefficients (on the non-baseline cost and spending shares) will be irrelevant for the baseline program, since all those shares are zero for the baseline program.

For any given program and any given type of individual, however, we can calculate point and interval estimates for the distribution of WTP implied by our parameter estimates by making 10,000 random draws from the joint distribution of the estimated conditional logit parameters in Table 1. For each person in our sample, we combine each parameter draw with the attributes of the

[20]We note that, across our respondents, the effects of some of the indicators for severe weather events in the last 12 months tend to be correlated with residence over the past 12 months in parts of the world that are subject to these severe weather events. To the extent that these events are more likely to occur in parts of the U.S. where people are more ideologically conservative, counter-intuitive coefficients on some of these indicators could result from omitted variables biases. We retain these interaction terms in the model because they improve the predictive ability of the specification. However, we warn against any causal interpretation of the estimated effects of these "extreme weather experience" variables.

program in question and the characteristics of the individual and calculate 10,000 point estimates of WTP, interpreting as zero any negative values that may result because there were no opportunities among our choice scenarios where respondents could choose to be paid to accept one of these programs. The could only vote against a program that would make them worse off. We then calculate the mean of this distribution, along with the 5th and 95th percentiles of the distribution and interpret these as the point and interval estimates of WTP implied by our model. We can do this for each person in our sample, and then replicate each person in proportion to the weights needed to correct for the stratification in our sampling process (Spring versus Fall survey waves, for students and employees) before calculating campus-wide median and mean WTP amounts.

For every program for which we will calculate WTP, the status-quo indicator will be set to -1 because WTP is based on utility-*differences* between each program and the status quo. The respondent characteristics that shift the status quo effect, of course, have a systematic effect on the respondent's propensity to choose the status quo, regardless of the levels of any of the attributes of the program about which they are being asked.

For our "baseline" program, Figure 1 shows the overall campus-wide marginal distribution of individual point estimates of willingness to pay. Had our model assumed that everyone had identical preferences, of course, Figure 1 would show only a single WTP amount, the same for everyone. The distribution of WTP point estimates in this figure stems entirely from the differences across the campus community in the respondent characteristics, listed in Table S3, that shift each respondent's marginal utility parameters. Based on the estimates reflected in Figure 1, the *median WTP* for the baseline program, across the entire campus population, is about \$89/year. If this program were to be put to a vote, with every member of the campus population being required to pay \$89/year, our model predicts that half of the campus population would vote for the program and half would vote against it (assuming everyone would vote). Alternatively, if a benefit-cost criterion is sought, the *mean WTP* for the baseline program is \$102/year, so that if the *total WTP* across the campus population exceeds the total campus cost of this 40% carbon emissions reduction, the program would pass a campus-level benefit-cost test.

As we consider different programs, each will have a different WTP distribution, where the different distributions in each case reflect the heterogeneous individual characteristics (and thus heterogeneous preferences) across the campus population. Table 2 will summarize our model's predicted weighted median and mean WTP amounts for different programs among specified sub-groups of the university population. Entry 1 in Table 2 is this baseline program, where the entire distribution is shown in Figure 1.[21]

3.2.1 WTP Point and Interval Estimates by Program Attributes

Before considering campus-wide distributions of WTP for non-baseline programs, we review the implications of our model concerning the dependence of WTP on the different program attributes. For this exercise, we consider in each case just one individual with specific characteristics. As individual program attributes change, one at a time, we graph the mean, as well as the 5th and 95th percentiles, of the simulated conditional distribution of WTP for that individual, based on 10,000 draws from the joint distribution of our estimated parameters. We use representative individuals for this particular exercise because campus-wide marginal distributions such as that shown in Figure 1 cannot readily show information about the *interval* estimates for each person's simulated mean WTP.

We are especially interested in the distributional consequences of these programs across three main groups in the campus community according to respondents' different roles at the university—in this case, students, faculty, and staff. We explore WTP for programs with varying levels of each program attribute, using the campus-population-weighted averages (across only people belonging to the group in question) of the full set of respondent characteristics serving as interaction variables in Table 1. For our representative student, in Figure 2, we show six profiles of simulated total WTP

[21] We include both the weighted medians and the weighted means in Table 2 because asymmetric distributions with differences between their medians and means, could lead to conflicts between a referendum voting criterion and a net benefits criterion for program choices.

point estimates and interval estimates as program attributes change. We relegate to the online Supplementary materials Figure S2 and Figure S3, the corresponding sets of six plots for faculty and staff, noting here that these WTP profiles for a person with group-average characteristics are somewhat lower for faculty, and considerably lower for staff.

For each of the graphs for students in Figure 2, the vertical dashed line benchmarks our baseline program, with a 40% carbon reduction and zero values for each of the alternative cost shares and expenditure shares. Within each of our six graphs, the heights of the curves are identical where they cross/meet this vertical dashed line. The ranges of the horizontal axes correspond to the ranges of each attribute used in our randomized designs for our choice experiments. Again, these curves are shown for an individual in the featured group *with average characteristics* (including fractional values for indicator variables). For specific real individuals, the six curves shown will be higher or lower, steeper or flatter because the marginal utility for each attribute depends on the values, for that individual, of all the interaction terms included for each program attribute in Table 1.

For a representative person with with average characteristics among the group that the university classifies as "students," graph (a) in Figure 2 shows that the simulated mean WTP for our baseline program with a 40% carbon emissions reduction is roughly \$110 with a 90% range of about \$84 to \$131. The curvature in graph (a) means that members of this group experience positive but diminishing marginal utility from reductions in carbon emissions (and thus a declining marginal WTP) for greater reductions in carbon emissions.[22]

Graphs (b), (c), and (d) Figure 2 show how WTP changes, for someone with average "student" characteristics, with increases in the share of costs borne by air travel fees, fees for building energy use, and by taxpayers. For this representative individual in the student population, there is positive but diminishing marginal WTP for the share of costs borne via air travel fees, and positive marginal WTP for the share borne as fees for building energy use. For programs that accomplish the same-

[22]The interval information, stemming from the noise in our parameter estimates, is not displayed in marginal distributions across individuals of just the simulated mean WTP amounts (as in Figure 1).

sized reduction in carbon emissions, then, graphs (b) and (c) are consistent with preferences for "user-pays" financing of carbon emissions reductions. Graph (d) suggests that students may also be more willing to pay for the same-sized emissions reduction if state taxpayers in general are also chipping in to help pay for the program (although the prediction interval in graph (d), for an individual with average student characteristics, does not appear to reject zero marginal WTP for programs with higher taxpayer shares of their cost).

Graphs (e) and (f) in Figure 2 show that for a person with average "student" characteristics, there seems to be zero marginal WTP for higher shares of the program's revenues used to fund academic programs or to pay for off-campus carbon offsets. This implies that a student *with these characteristics* is indifferent between programs that are otherwise identical but spend more or less of their revenues on academic programs. They are also indifferent between the mix of on-campus programs and carbon offsets used to achieve carbon emissions reductions. However, the signs on the coefficients for the LASSO-retained interaction terms for these two program attributes, as shown in Table 1, imply that the marginal WTP for each of these attributes *can* be either positive or negative, rather than zero, for individual students with characteristics that *differ* from the average in this group.

3.3 Campus-wide Distributions of WTP for Different Stakeholder Groups

The previous section focused on the total and marginal WTP for different configurations of program attributes for one "representative" individual: a student, for the graphs in the body of this paper. That exercise allowed us to demonstrate the precision with which our individual WTP predictions are estimated. We now return to consider campus-wide distributions of WTP for specific programs across groups of individuals in the university population. For any given program, instead of just showing the entire marginal distribution of simulated mean WTP amounts across the whole university community, as we do for our baseline program in Figure 1, we can now split our sample into specific groups of interest.

3.3.1 Distribution of WTP point estimates for baseline program, by subgroups

• ***By student/employee status***

One of our main "sample splits" of interest concerns the individual's student and/or employee status. Figure 3 splits the sample according to how each individual is classified, administratively, by the university. Any given individual may have more than one status. Rather than using a representative person with mean characteristics, we break out specific groups of people from the overall marginal distribution in Figure 1 and report separate sub-distributions of our WTP point estimates for three groups: people who are classed administratively as students, people who are classed as employees, just those employees who are not also classed as students, and just those students who are not also classed as employees. These distributions are broadly overlapping, with the range in WTP point values for each group being due to the heterogeneous characteristics within each group. The central tendency for WTP in each group is strikingly different, as summmarized in Entry 2 in Table 2. Students have a weighted median WTP point estimate of $115, for employees, the weighted median is only $79, for employees who are not also students, it is merely $38, while for students who are not also employees, it is highest, at $117. Again, we report medians in each group because this would be the cost of the baseline program that would lead half of each group to vote yes and half to vote no. The means in each group permit calculation of group-wise net benefits if group-wise program costs are also known.

• ***Other groupwise differences (summary)***

We relegate Figures containing graphs of the distributions of WTP for other interesting sample splits to the Online Supplementary Materials, where we also discuss some of the sample splits in greater detail. Here, we continue to report just the group-wise means and medians (by Entry number) in Table 2, where each entry references the relevant complete distribution(s) in the Supplementary Materials, for which Figure number have an "S" prefix.

Entry 3 in Table 2 shows that WTP estimates for the Fall wave of the survey (median WTP =$108) tend to be higher than those for earlier Spring wave (median WTP = $75), likely reflecting either people's experiences with summer heat waves and wildfires over the prior 12 months, or natural seasonal variation in the salience of climate change.

Entry 4 reports the a non-monotonic relationship between median WTP and self-reported income quintiles across the entire university population. However, this likely reflects confounding of income effects by the systematic differences by age groups shown in Entry 5. The youngest age tercile has a median WTP of $158, the middle tercile's median is $110, and the oldest age tercile (more likely to be faculty, staff, and administrators), has a median WTP of only $68.

Entry 6 suggests that citizenship also matters, although only 5.4% of the sample are non-citizens and most of these will be foreign students. U.S. citizens have a median WTP of $85, while non-citizens have a median WTP of $151. The university where we fielded our survey is recognized for its emphasis on sustainability. Foreign students, who might have applied anywhere but applied to this university, may have been signalling the relative salience of climate change programs among their interests.[23]

According to Entry 7, a person's self-identified political ideology, unsurprisingly, influences their enthusiasm about paying for programs to reduce carbon emissions. The full distributions shown in Figure S8 reveal a lot of heterogeneity within each group, but the 67.4% of the sample who consider themselves to be somewhat or very liberal has a weighted median WTP of $122 for the baseline program. Those who consider themselves to be moderate (or do not report their ideology) have a median WTP of $43, while (unsurprisingly), the mere 8.6% of the sample that identify as being somewhat or very conservative have a median WTP of only $2 per year! Nevertheless, a few individuals in this small category have much higher predicted WTP amounts, reflecting other characteristics that tend to raise their WTP.

[23]International students made up about 10% of the student population in the year of our survey (but a lower percentage of the population of both students and employees).

Given that we are considering fees, a potentially important split of the student sample concerns resident versus non-resident student status. Any fee charged to students to fund carbon-emissions reduction programs would join other fees already charged to students. Currently all charges classed as "fees" are the same for all students, but tuition rates at public universities differ substantially for resident and non-resident students. It may or may not be possible to differentiate carbon reduction program fees across these two groups, but the question could be raised. Entry 8 in Table 2 separates the student population by in-state and out-of-state "permanent residence" zip codes, as a proxy for residency status. The medians in the two groups are relatively similar—(resident median WTP = \$112; non-resident median WTP = \$129). However, the non-resident group has a distribution with a thicker upper tail.

3.3.2 Distributions of WTP point estimates for non-baseline programs

Across the entire university population, our model can simulate the distribution of WTP for a program with any specified mix of attributes spanned by our experimental design. For programs other than our baseline program, WTP can be expected to be different, and will be influenced by all of the respondent characteristics among the interaction terms affecting the marginal utilities of non-zero alternative cost or spending shares.

• Non-zero alternative cost, spending shares

To illustrate, we can compare the overall campus-wide distribution of WTP amounts for our baseline program (with a median WTP of \$89) against five specific alternative programs, each of which involves one arbitrarily selected non-zero percentage share for the different distributional dimensions of our programs. Entry 9 in Table 2 gives the means and medians for these distributions. For an otherwise baseline program, the median WTP amounts by some arbitrary specific non-zero distributional shares are as follows: (b) \$120 with 10% of the costs born as air travel fees; (c) \$142 with 50% of the costs born as building fees; (d) \$107 with 20% of the costs borne by taxpayers; (e)

$90 with 10% of the revenue spent on academic programs; and only $75 with 30% of the revenue spent on off-campus carbon offsets.

The differences in median and mean WTP described in Entry 9 highlight the risk of relying on WTP estimates calculated for "representative respondents" in any particular group (i.e., someone with group mean characteristics), such as those shown in Figure 2. For example, an individual with average student characteristics (or, similarly, for one with average faculty characteristics or average staff characteristics) exhibits no discernible relationship between individual WTP and the share of revenues spent on offsets. However, this is not true across the campus population as a whole. The 17 interaction terms for this attribute, retained by LASSO and shown in Table 1, account for the pattern of campus-wide variation that yields a lower median WTP for programs with offsets ($75 in Entry 9) than for the baseline program ($89 in Entry 1), even thought both programs achieve the same reductions in global carbon emissions. Some types of people really do prefer local carbon emissions reductions to global net reductions achieved by purchased carbon offsets. To the extent that local carbon emissions reductions are accompanied by reductions in other local co-pollutants, these preferences may be justified.

• Three "extreme" programs

A few rather-extreme programs are also worth considering. Entry 10 in Table 2 gives median and mean WTP for a first "extreme" program where the entire cost is borne in the form of building use fees. We included this program among the variety of choice sets in our experimental design. It mimics the Yale University demonstration program, and more than doubles median WTP from the $89 in Entry 1 to the $193 in Entry 10. Unfortunately, the cost of implementing a campus-wide metering system for individual buildings would be high, and its amortized costs to members of the university community would have to be factored in, along with the elasticities of energy use in the face of these charges.

For a second extreme program reported in Entry 10, all of the costs of the program would be borne by the state's taxpayers (where many members of the campus community will themselves pay state taxes). Taxpayer share of the cost of a program did not exceed 20% in our choice experiments, so this simulated WTP distribution is far from the range of programs we asked respondents to consider. Nevertheless, median WTP for such a program is also very high, at $161. Figure S11 in the Supplementary Materials, however, reveals that the predicted individual WTP amounts for this program vary remarkably widely. Many people would be very enthusiastic about such a program, but there are still many people with only modest WTP for such a program.

A third extreme program included in Entry 10 would spend all of its revenues on off-campus carbon offsets while achieving the baseline 40% reduction in (net) carbon emissions by the university. Our experimental design varied the offset spending share only up to 30%, so these estimates are markedly out-of-sample predictions. With that caveat, however, median WTP for this program is only $61, rather than the $89 in Entry 1 (for the same 40% carbon reduction). However, we note that the cost of purchasing off-campus carbon offsets amounting to 40% of the university's emissions could be substantially less than the cost of achieving those emissions via on-campus carbon projects.

Entries 11 and 12 in Table 2 separate our respondents according to their self-reported "main role" on campus. We have already explored differences in WTP for students and employees, but these sample splits permit us to see the difference between continuing students, faculty and staff. Entry 11 concerns our baseline program, where the group who consider themselves to be "staff" are revealed to have some of the lowest WTP amounts on campus. Entry 12, however, shows the substantial effect on WTP for all three groups if 10% of the costs of the program are borne as air travel fees (a "polluter-pays" scheme).

3.4 Some Near-Term Potentially Viable Programs

Our campus-wide distributions of median WTP amounts for specific programs can be interpreted as the maximum undifferentiated per-person program cost that would be approved by the campus population for the program in question.

Our choice experiment involved seven explicit attributes (and two other implied attributes in the form of the baseline shares for costs and spending). A choice experiment with seven attributes already tends to strain a respondent's cognitive capacity. Thus we elected not to proposed flat-fee programs with different levels of fees across different groups on campus. Our results reveal that non-student employees have considerably lower WTP amounts than students, which suggests that it may be controversial among the university's employees if they were to be charged the same flat fee as students (or even any fee at all).

It might thus be difficult (in practice) to charge non-student employees directly for the university's carbon-reduction program. This could be interpreted, justifiably, as a *decrease* in their monetary compensation, which could potentially cause the university to lose marginal employees. The policy could also make it difficult to recruit replacement employees with the same qualifications (unless potential new employees approve sufficiently of the university's carbon-reduction program make up for the lower monetary compensation for the job). In the online Supplementary Materials, Figure S15 reveals that people who self-identify their main role on campus as "continuing student" are willing to pay a considerably more (with a median of $131) than those whose main role is "faculty" (with a median of $74), and a lot more than those whose main role is "staff" (with a median of $25).

These big differences between students and non-student employees mean that it may be prudent to consider some form of price discrimination, where different people pay different amounts. A common across-the-board fee could still permit *net* costs to differ across groups in a form of effective price discrimination if the university nominally charges the same fee to everyone, but (perhaps temporarily) preserves non-student employee net compensation by paying that fee on behalf of non-student employees. This would involve less administrative complexity than charging each non-student employee an explicit fee and then raising compensation enough to cover the cost of the fee.[24]

Given the sensitivity of WTP to the distributional consequences of the program, it is likely that students would not be willing to pay exactly the same amounts for any given program if *only* the student population would be asked to pay the flat fee, rather than "all students and employees," as specified in our choice scenarios. Nevertheless, we can explore best-case scenarios for support for different carbon-reduction programs, as long as we keep that caveat in mind.

• ***Flat fee charged only to students***

In Table 3, we summarize some back-of-the-envelope calculations to predict likely referendum outcomes as well as benefit-cost tests at the campus level. Given that likely actual programs may price-discriminate across groups on campus when it comes to fees for any program, we have set up our voting/benefit-cost analyses in a way that permits the user to make a pairwise split of the weighted sample of respondents according to one indicator characteristic, which we call a "featured group."

Along with the program's attributes, other inputs for these simulations include the number of people in the featured group, the number in the "other" group, the approximate number of taxpayers in the state, the total cost of the program, and whether (a) just the featured group, (b) just the other group, or (c) both groups will be required to bear any flat fees, any air travel fees, any building energy fees, or taxpayer costs. This information permits us to calculate *individual-specific* program costs that we can compare to individual WTP amounts in each group, so we can predict how each (weighted) member of the different groups would vote on a referendum about the program in question. For each program, we also conduct a limited benefit-cost test for the featured group alone, for the other group alone, and across both groups, assuming that only these two groups have standing for a benefit-cost test of this scope.[25]

[24] To preserve net compensation, the subsidy would also need to be high enough to cover the marginal tax paid on this additional compensation.

[25] Of course, social net benefits will be different from these results, since carbon reductions have worldwide benefits.

For illustrative purposes, we consider a range of carbon-reduction programs that will all cost a total of $3 million per year to reduce emissions by 40%. Given that it is the most relevant sample split, we will treat students as the featured group, and non-students as the other group. Simulation 1 in Table 3 assesses our baseline program, where everyone pays the same flat fee, which would be $107 in this case. If this program were put to a vote, 53% of students would be in favor, but only 12% of no-students (given their respective WTP distributions). Only 46% of the campus community, overall, would approve of this program, although the campus-level net benefits would be positive, at about $1 million.

Simulation 2 concerns the same program, but bills only students the flat fee, which would now have to be $127 per student. Non-students would not be required to pay this fee. Under this configuration, only 45% of students would be in favor of the program (due to its higher cost for them), but 100% of non-students would be in favor (since they all have WTP that is greater than or equal to $0, and they would be obliged to pay $0 each). Overall, 54% of the campus community would be predicted to vote in favor of the program. Since this is the same program (except for its price discrimination, where we must assume that such price discrimination does not affect anyone's WTP), net benefits remain the same, at about $1 million.

• ***Some costs borne as air travel fees***

We know that shifting to more of a "user-pays" regime increases many people's WTP for a carbon-reduction program. Other universities, (e.g., UCLA) have experimented with air travel carbon fees. The UCLA program specified a $9 for each domestic flight, and a $25 fee for each international flight. We obtained internal data on all university-paid flight segments for the university where we fielded our survey. These data are for 2019 (the last year of data prior to the COVID-19 pandemic), and they report calculated pounds of carbon emitted on each of almost 25,000 individual

We do not estimate those extra-campus benefits in this study, although individual benefits for some people undoubtedly reflect their concerns about the welfare of the world's population in general.

flight segments. For all university-paid trip segments, we can calculate the implied social cost of carbon. For air-travel carbon emissions to be fully internalized in people's travel decisions, it would be necessary to include these costs. The average per-segment cost of carbon—across all flight segments (as opposed to complete trips) and without differentiating between domestic and international travel—was $11.06 (based on a social cost of carbon of $51/ton) or $41.19 (based on a social cost of carbon of $190 proposed recently by the U.S. EPA).

If the university's 2019 air travel was assessed air travel fees using the lower $51/ton social cost of carbon, and (crucially) if this did not discourage any travel, about $274,000 could be raised (i.e., about 9.13% of a $3 million program). If the higher proposed social cost of carbon determines the assessment, and travel patterns did not change, about $1,021,000 could be collected (or about 34% of a $3 million program). These are upper bounds, of course, because one reason for internalizing the carbon externalities is to raise the price of air travel and thus to discourage air travel. Furthermore, the air travel fees implemented by other universities, such as the UCLA plan, charge a fixed fee per trip, rather than a fee for each flight segment determined by mileage and estimated emissions/passenger/mile.

Simulation 3 in Table 3 has students paying 95% of the cost of the program as a flat fee, but everyone sharing in the 5% of the costs that are funded through air travel fees. Of course, the fee schedule for flights or flight segments required to raise this much revenue would depend on the elasticity of demand for flights paid by the university. This scheme would reduce the per-person flat fee for students to $121, but create a per-person cost of air travel fees of $5.34 for everyone on campus. But then about 52% of students would be in favor of the program, and 78% of non-students would still be willing to support it. Campus-wide net benefits would increase to almost $1.6 million.[26]

[26]We did not attempt, in our survey, to remind respondents about the likely non-zero elasticity of demand for university-paid air travel, and its implications for the effects of air travel fees. However, Baranzini and Carattini (2017) find that individuals tend to ignore the incentive effects of carbon taxation, so it is not clear what proportion of respondents would have internalized the potential follow-on effects of air travel fees in their program choices.

Simulation 4 increases the share of costs paid as air travel fees to 10%. This change increases student support for the program from 52% to 58%, and reduces non-student support by only about 1% (since per-person air travel fees are small in either case). The campus-level net benefits of the program increase to almost $2.1 million.

The last two simulations concern examples of programs with spending on offsets and taxpayer support. Suppose the same 40% net carbon emissions reduction were to be achieved entirely through offsets, and those offsets cost the same as local carbon reductions. Simulation 5 (with only students paying the flat fee) shows that achieving the same carbon reduction at the same overall cost, but through the purchase of offsets, only 44% of students would approve of the program, while 100% of non-students would again approve (since they bear none of the costs). Relative to Simulation 2, overall support would drop from 54% to 53%. However, campus-level net benefits would drop from roughly $1 million to about $587,200. The proportion of votes in favor, and the net benefits, however, could both be larger if the 40% (global net) carbon reduction could be achieved more cheaply via offset purchases. Simulation 6 returns to a program without offset purchases, but shifts 20% of the burden of the cost from the campus population to the state's taxpayers. If we assume that every member of the campus community is a taxpayer, everyone in both the student and non-student groups (and all other state taxpayers) will incur individual costs of about $0.23 per year. But the required flat fee, if charged only to students, would drop to just $102, meaning that more students would be willing to pay the total cost to them. Non-student per-person costs among the campus community would increase from $0 to just $0.23 per year, which would discourage some of their votes, but not all of them. Not surprisingly, 62% of students would vote in favor of the program, and 89% of non-students would still be in favor. Overall a campus-wide referendum would produce 66% in favor. Net benefits within the campus would be about $2,178,400. Any benefit-cost analysis at the state level, however, would need to factor in the costs to off-campus taxpayers, as well as any willingness to pay they might have for carbon reductions at their state's flagship university. We did not survey the general population of the state, so we have no data on whether this WTP may be positive for some people outside the university.[27]

3.5 Referendum Voting vs. Benefit-Cost Assessment

3.6 Average WTP per mtCO2e Reduced vs. the Social Cost of Carbon

Our survey quoted the most recent estimate of total university carbon-dioxide-equivalent emissions as about 61,000 metric tons per year. Thus a 40% reduction in these emissions would be about 24,400 mtCO2e/year. Across the campus population (quoted in our survey as 23,600 students and 4,500 faculty and staff, for a total of 28,100 people), the aggregate WTP based on a mean WTP of $102 suggests total benefits of $2,866,200 to reduce emissions by 24,400 mtCO2e, or an average of about $117 per mtCO2e. If the benefits to the university's population of removing 24,400 mtCO2e per year exceed the social costs of failing to reduce these carbon emissions, then our baseline program would seem to be warranted. Here, it makes a difference what number is assumed for the social cost of carbon (SCC). The Spring/Fall 2018 population of this university valued carbon emissions reductions at a level much higher than the current official U.S. social cost of carbon ($51), but lower than the EPA's proposed new social cost of carbon ($190). We note, however, that individual marginal WTP for carbon reductions diminishes as the size of the reduction is increased, so the across-campus average WTP per mtCO2e reduced can also be expected to decline with the size of the reduction.

3.7 Potential Changes Since the Year of the Survey

Some caution is necessary in extrapolating preference parameters estimated from a 2018 survey to the current year. There appears to be at least seasonal variation in willingness to pay for carbon reductions, as evidenced by the shift in the distribution of WTP amounts between the Spring 2018

[27]It is possible to simulate likely voting results and campus-level benefit-cost tests for a wide variety of different programs besides those discussed in this section. In the online Supplementary Materials, Table S4 provides similar calculations for a set of six additional arbitrary programs.

and Fall 2018 survey waves. Given that many people seem to confuse weather with climate, however, it is unsurprising that the salience of climate change might be greater in the fall, after the heat of summer, than it is in the spring. Given that our survey did not include further waves in different time periods, we cannot technically reject a steady upward trend in WTP for carbon reductions, but we sought to reduce the effects of seasonality on our overall estimates by sampling in at least these two different periods.

How might preferences for carbon reduction programs have changed since 2018? The region where this university is located suffered from severe wildfires in 2020, and a long-term drought in the broader region has continued. The issue of climate change may have become more salient for members of this university community. But the COVID-19 epidemic may also have distracted people's attention from climate change problems. If the overall shift in concern about climate change dominates in the longer term, however, it is likely that median WTP for a 40% emissions reduction (or for any other size of emissions reduction) is larger now than it was during the Spring and Fall of 2018. It is at least fortunate that our survey was in the field entirely prior to the pandemic.

Medium-run individual preferences for carbon emissions reductions may have remained essentially the same. However, changes across the university community in the mix of characteristics that determine individual preferences across different program (i.e. all the variables listed in Table S3 that appear among the interaction terms in our model) can change the campus-wide distribution of WTP amounts. If the preference *function* has remained relatively stable, our fitted model could be applied to the university's current population—with its somewhat different mix of the various respondent characteristics used in our models. Point estimates of WTP for any given carbon-reduction program could be simulated afresh for each of the *current* members of the campus community to see whether systematic shifts in the characteristics of the campus population may have had a discernible effect on overall median WTP or on median WTP within any particular group.[28]

4 Conclusions and Directions for Further Research

We have described the findings from a stated-preference choice experiment designed to explore preferences for alternative internal carbon pricing programs in a university context. Our model can estimate the entire WTP distribution across the campus community, for arbitrary proportional carbon reductions within the domain of such programs offered in our choice experiments. Only some of the possible combinations of program features and stakeholder groups have been discussed specifically in this paper. Our approach nevertheless allows us to assess the amount and distribution of stakeholder support for any of a wide variety of carbon-reduction programs.

Our estimates suggest that there exists substantial support in a university environment for local climate action in the form of internal carbon pricing programs. Median predicted individual WTP amounts for several segments of the university population exceed currently prevailing estimates of the social cost of carbon.

We find substantial evidence that the *design* of the program influences demand for internal carbon pricing. Respondents have preferences over the initial incidence of the program's costs. They prefer programs where costs are linked to emissions. Even for programs with the same cost to the individual, we find that support is higher when costs depart from being simply across-the-board flat fees and involve some "user-pays" components. Additionally we find that some methods of revenue recycling may actually decrease support for these programs among some constituencies. The share of the carbon reduction achieved through the purchase of offsets, however, seems to have a negative overall effect on people's willingness-to-pay for carbon reductions. Someone with the average characteristics across students, faculty, or staff would appear to be relatively indifferent

[28] Such calculations, however, would require a slight modification to our model specification, to exclude any variables other than program preferences that were collected by our survey, as we would not have any such survey responses for a new set of stakeholders.

whether carbon reduction projects are local, or are achieved through offsets. However, the mix of characteristics across the university population reveals that median enthusiasm for programs that reduce emissions through offsets is less than for programs that reduce emissions on campus.

Only about 45% of students on this campus would vote in favor of a $3 million/year program to reduce carbon emissions by 40% if students alone were each asked to pay a sufficient flat fee. But this assumes that student WTP is not adversely affected by the knowledge that non-student employees will not be charged the same flat fee. However, 100% of non-students are willing to pay at least $0 and would likely vote in favor of such a program, making overall campus support about 54%. If the program is funded 5% by air travel fees that ultimately are born equally by everyone on campus, 52% of students would approve of the program, even though only 78% of non-students would then vote in favor, for overall support of 56%.

Our survey and choice model were designed to facilitate benefit transfer exercises across universities. This paper uses the same survey data employed in Walch (2019). The final chapter of that dissertation estimates a model based on only the census ZIP code data in our original sample, and then transfers that model to construct WTP estimates for another (stylized) university based on publicly available data for that university. However, the original mid-sized public university where our survey was conducted does not have a medical school or an engineering school, and neither is it a Land Grant institution, so our estimated models based on its original survey data may not be well-suited to predict systematic differences in preferences for carbon programs among students, faculty or staff in those different academic environments.

Nevertheless, our survey instrument itself has been designed using a template that could be adapted quickly to substitute current background data for other colleges and universities. Thus an analog to our survey could readily be implemented for any other campus. The analysis phase, however, requires access to at least the available institutional data on characteristics for every invited survey participant (where the available data may be different for different institutions), and it would be necessary to download and assemble any ZIP-code-level census data, or geo-coded data from other sources, that the researcher wishes to use to capture neighborhood-level effects on people's preferences.

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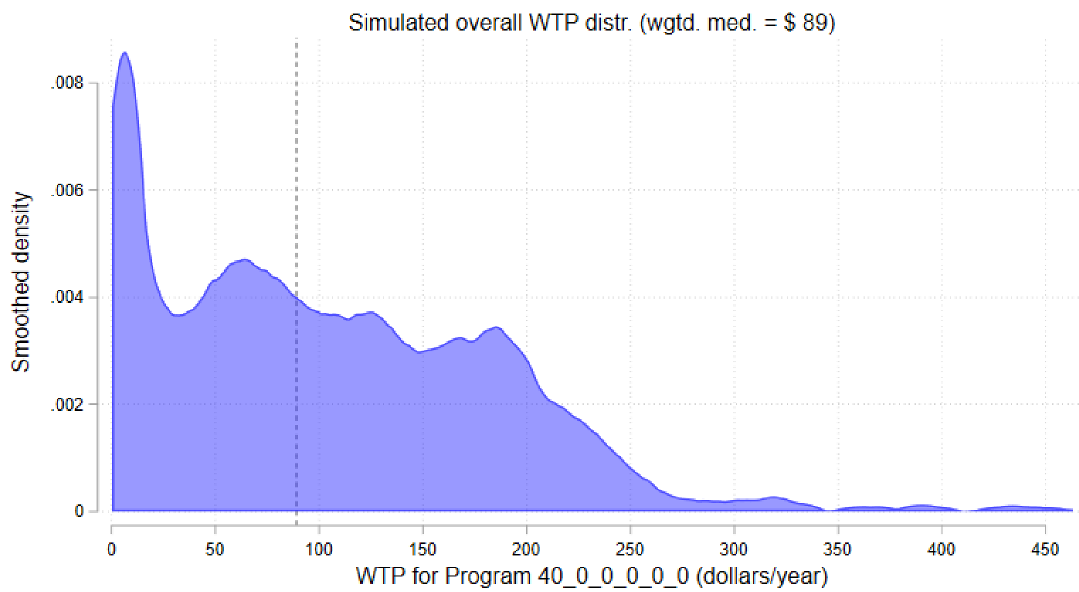
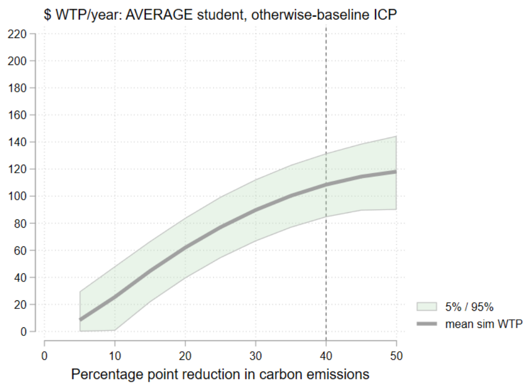
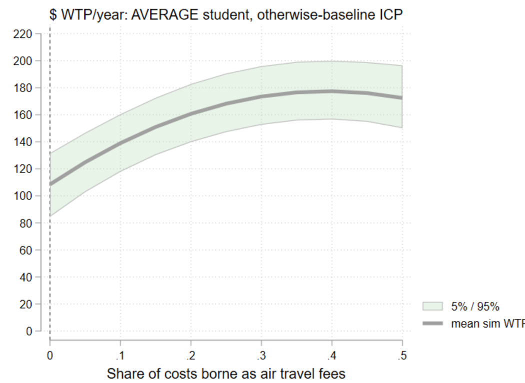


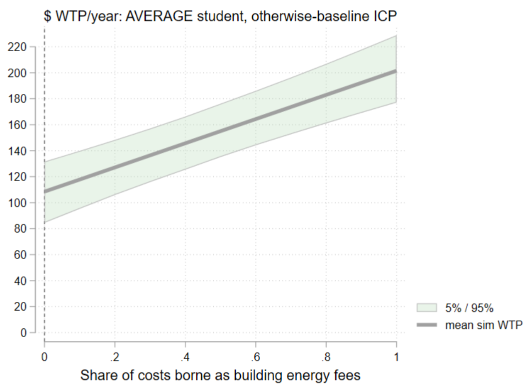
Figure 1: Distribution of predicted individual expected values of WTP for a 40% carbon emissions reduction, where all costs are borne as a flat fee on all students and employees, and all revenues are spent on carbon-reduction programs (campus-population-weighted distributions); individual point estimates of expected WTP are based on 10,000 random draws from the joint distribution of estimated parameters. Heterogeneity stems from differences in respondent characteristics and thus in their preferences for this program. NOTE: Here, and in the figures to follow, Program "a_b_c_d_e_f" has an "a"% carbon reduction, with "b"% of costs born as air travel fees, "c"% of costs born as building fees, and "d"% borne by taxpayers (where the baseline program has 100% of costs born as a flat fee on all students and employees), and spends "e"% of revenue on academic programs and "f"% on offsets (where the baseline program spends 100% of revenues on carbon-reduction projects).



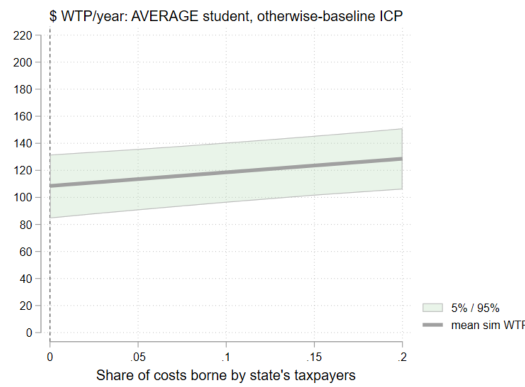
(a) % Carbon reduction



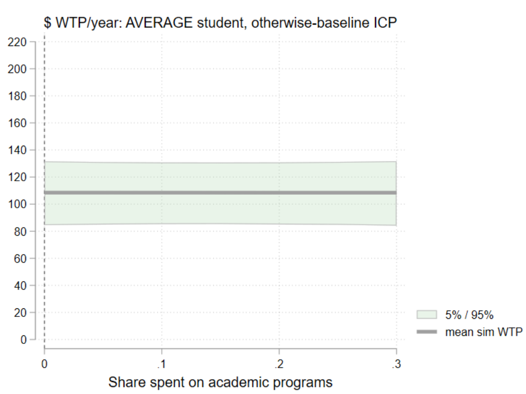
(b) Costs borne by: Air travel fees



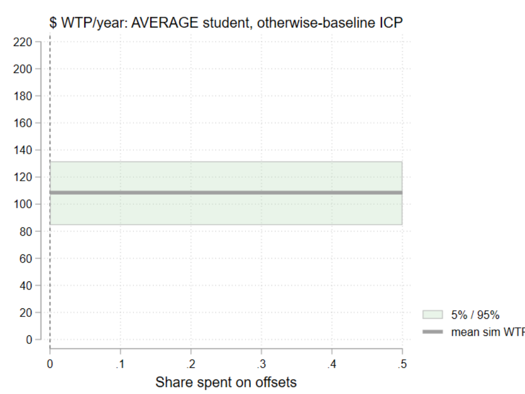
(c) Costs borne by: Building fees



(d) Costs borne by: Taxpayers



(e) Revenue spent on: Academic programs



(f) Revenue spent on: Offsets

Figure 2: **For a student with sample average student characteristics**: Point and interval estimates of WTP (each based on 10,000 draws from the joint distribution of the estimated model parameters) as a function of program attributes: (a) Annual WTP for carbon reduction programs of different sizes when all costs are borne via a flat fee on all students and employees; (b)-(d) Annual WTP for a 40% carbon reduction as cost shares borne in other ways are individually increased from zero; (e)-(f) Annual WTP for a 40% carbon reduction as expenditure on things other than carbon programs increases from zero

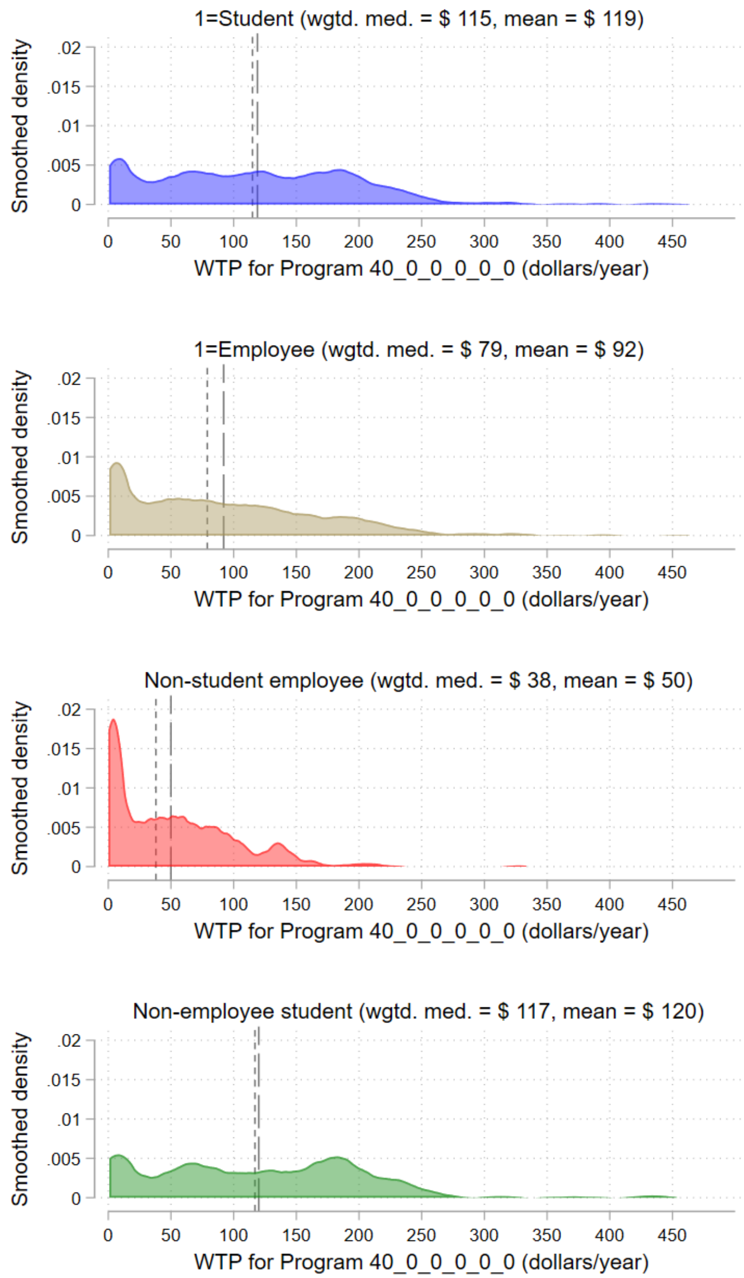


Figure 3: Distributions of predicted individual point estimates of WTP (campus-population-weighted) by administrative designation as "student" and as "employee," Given that the presence of student employees means that these first two groups are not mutually exclusive, we also include the distribution for employees who are not also students. These distributions are for a 40% carbon emissions reduction where all costs are borne as a flat fee on all students and employees, and all revenues are spent on carbon-reduction programs.

Table 1: Conditional logit parameter estimates using campus-population-weighted sample. Variables selected by LASSO methods applied to the set of implied all-pairwise choices, using the maximum value of λ within one standard error of the λ that minimizes the cross-validation MSE. (The MSE-minimizing λ retains about twice as many regressors.) Row labels include unweighted sample average values for variables.

	Estimate	Std.Err.
(α) Program's cost to household (range: 22 to 232)	-0.00946***	(0.00110)
$\times$ Demeaned response propensity (.509)	0.00122	(0.000829)
(β) Percentage-point C reduction (range: 10 to 50)	0.0415***	(0.0145)
$\times$ Percentage-point C reduction (range: 10 to 50)	-0.000422**	(0.000167)
$\times$ 1=have relevant ZIP data for set 1	-0.00981	(0.00892)
$\times$ zip pr: Race: Asian alone (.025)	0.00809	(0.0944)
$\times$ zip pr: U.S. citizen, naturalized (.021)	0.388***	(0.142)
$\times$ zip pr: Housing: Incompl. kitchen (.005)	-0.212	(0.286)
$\times$ zip pr: Housing: Incompl. plumbing (.002)	-0.702	(0.656)
$\times$ zip pr: House values: 50K-100K (.035)	-0.0250	(0.0871)
$\times$ zip pr: Rental rates: Less than 500 (.036)	0.0280	(0.0616)
$\times$ zip pr: Rental rates: 2.5K-3K (.002)	-0.357	(0.383)
$\times$ 1=Individual's age known (.759)	0.00435	(0.00890)
$\times$ Demeaned indiv. age, squared	0.00000593	(0.00000669)
$\times$ 1=not U.S. citizen (.054)	0.0121	(0.00745)
$\times$ 1=Employee (.695)	0.00274	(0.00548)
$\times$ 1=empl.group: Classified staff (.134)	-0.00625	(0.00718)
$\times$ 1=empl.org: Design (.032)	0.00781	(0.0106)
$\times$ 1=empl.org: Library (.026)	-0.0259*	(0.0137)
$\times$ 1=Student (.706)	-0.00307	(0.00813)
$\times$ 1=stu.school: Law (.022)	-0.00590	(0.0117)
$\times$ 1=stu.dept: Biology (.033)	0.00110	(0.00881)
$\times$ 1=stu.dept: Chemistry (.022)	-0.0169*	(0.00932)
$\times$ 1=Fall 2018 survey wave (.419)	0.00360	(0.00451)
$\times$ 1=last 12 mos: Sev. drought (.097)	-0.0118*	(0.00668)
$\times$ 1=last 12 mos: Wildfire (.111)	-0.00554	(0.00578)
$\times$ 1=last 12 mos: Severe winter (.138)	-0.0128**	(0.00521)
$\times$ 1=Somewhat or very conserv (.086)	-0.0159	(0.00972)
$\times$ 1=Hhld income reported (.867)	0.0115**	(0.00517)
$\times$ Demeaned hhld inc in '000s if known (0)	0.0000827**	(0.0000331)
(γ_1) Cost share: Air-travel fees (range: 0 to .5)	0.0388***	(0.00832)
$\times$ Cost share: Air-travel fees (range: 0 to .5)	-0.000415***	(0.0000955)
$\times$ 1=have relevant ZIP data for set 3	0.00543	(0.00546)
$\times$ zip pr: Housing: Multi-unit (.096)	-0.0256*	(0.0155)
$\times$ zip pr: Rental rates: 3K up (.003)	-0.433	(0.267)
$\times$ zip pr: Rural (.064)	-0.00579	(0.0115)
$\times$ 1=Non-white (.379)	-0.00541*	(0.00298)
$\times$ 1=Employee (.695)	-0.00130	(0.00377)
$\times$ 1=empl.org: Design (.032)	0.0136*	(0.00746)
$\times$ 1=empl.org: Other (.143)	-0.00460	(0.00467)
$\times$ 1=Student (.706)	-0.00564	(0.00415)
$\times$ 1=stu.dept: Biology (.033)	0.00707	(0.00702)
$\times$ 1=last 12 mos: Heat wave (.423)	0.00281	(0.00295)
$\times$ 1=main role: Admin (.046)	-0.00753	(0.00728)
(γ_2) Cost share: Building energy fees (range: 0 to 1)	0.00854*	(0.00510)
$\times$ 1=have relevant ZIP data for set 1	-0.000918	(0.00391)
$\times$ zip pr: Moved: From abroad (.003)	0.278	(0.292)
$\times$ zip pr: Rental rates: 2.5K-3K (.002)	-0.226	(0.170)
$\times$ 1=Employee (.695)	0.000112	(0.00281)
$\times$ 1=empl.group: Classified staff (.134)	-0.00267	(0.00350)
$\times$ 1=empl.group: Graduate employee (.087)	0.00470	(0.00414)
$\times$ 1=empl.org: Education (.024)	-0.00660	(0.00770)
$\times$ 1=Student (.706)	-0.00278	(0.00297)

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× 1=stu.dept: Chemistry (.022)	-0.00695	(0.00570)
× 1=Fall 2018 survey wave (.419)	0.000743	(0.00208)
× 1=Somewhat or very liberal (.674)	0.00432**	(0.00217)
(γ_3) Cost share: Taxpayers (range: 0 to .2)	0.0141	(0.0126)
× 1=have relevant ZIP data for set 3	-0.0111	(0.0101)
× zip pr: Ltd English, spk Spanish (.005)	0.786**	(0.331)
× zip pr: Rental rates: 2.5K-3K (.002)	-0.540	(0.599)
× zip pr: Rural (.064)	-0.0180	(0.0278)
× 1=Employee (.695)	-0.00245	(0.00762)
× 1=empl.org: Education (.024)	-0.0314	(0.0204)
× 1=empl.org: Library (.026)	-0.0283	(0.0214)
× 1=Student (.706)	-0.00384	(0.00814)
× 1=stu.school: Design (.067)	0.0178	(0.0137)
× 1=stu.school: Educ. (.04)	0.0368**	(0.0163)
× 1=stu.school: Business (.068)	-0.0230*	(0.0128)
× 1=stu.school: Other (.082)	0.0280**	(0.0122)
× 1=stu.dept: Biology (.033)	0.0190	(0.0162)
× 1=stu.dept: Envir. Studies (.024)	0.0286*	(0.0166)
× 1=last 12 mos: Heat wave (.423)	0.00811	(0.00605)
(δ_1) Spending share: Academic programs (range: 0 to .3)	0.00439	(0.0115)
× 1=have relevant ZIP data for set 3	-0.000432	(0.00840)
× zip pr: Race: Black alone (.009)	0.375**	(0.147)
× zip pr: Rental rates: 2.5K-3K (.002)	-0.883*	(0.483)
× zip pr: Rental rates: 3K up (.003)	-0.524	(0.485)
× zip pr: Heating: Bottled gas (.008)	0.141	(0.222)
× zip pr: Heating: Solar (.0003)	-2.784**	(1.238)
× 1=from Asia (.002)	-0.151***	(0.0535)
× 1=Non-white (.379)	-0.0144***	(0.00476)
× 1=Individual's age known (.759)	-0.0164	(0.0108)
× Demeaned indiv. age, if known (0)	-0.000208	(0.000264)
× 1=Employee (.695)	0.000671	(0.00709)
× 1=empl.group: Classified staff (.134)	-0.00542	(0.00768)
× 1=empl.group: Student employee (.18)	0.00479	(0.00800)
× 1=Student (.706)	0.0151	(0.00961)
× 1=stu.dept: Psychology (.031)	-0.0166	(0.0109)
× 1=last 12 mos: Heat wave (.423)	0.00332	(0.00443)
× 1=main role: Admin (.046)	-0.00820	(0.0106)
(δ_2) Spending share: Carbon offsets (range: 0 to .5)	-0.00430	(0.00754)
× 1=have relevant ZIP data for set 1	0.00794	(0.00611)
× zip pr: Moved: From abroad (.003)	1.372**	(0.616)
× zip pr: Housing: Multi-unit (.096)	-0.0799**	(0.0315)
× zip pr: Housing: Incompl. kitchen (.005)	0.0232	(0.350)
× zip pr: Rental rates: 3K up (.003)	-0.0162	(0.275)
× 1=not U.S. citizen (.054)	0.00812	(0.00787)
× 1=Employee (.695)	-0.00828*	(0.00484)
× 1=empl.group: Career non-tenure (.054)	-0.0162	(0.00990)
× 1=empl.group: Student employee (.18)	0.0111**	(0.00560)
× 1=empl.org: Business (.021)	0.0283	(0.0179)
× 1=Student (.706)	-0.00183	(0.00537)
× 1=stu.school: Other (.082)	0.0168**	(0.00771)
× 1=stu.dept: Chemistry (.022)	-0.00862	(0.0106)
× 1=stu.dept: Human Physiology (.024)	-0.0255**	(0.0106)
× 1=last 12 mos: Inland floods (.059)	0.0123	(0.00789)
× 1=last 12 mos: Hurricane (.043)	0.00611	(0.00814)
× 1=main role: Admin (.046)	-0.0166	(0.0113)
(κ) Status quo, no program	1.827***	(0.572)
× 1=have relevant ZIP data for set 3	0.0280	(0.641)
× zip pr: Moved: Diff. cnty, same st (.037)	12.18**	(5.250)
× zip pr: Moved: From abroad (.003)	-22.54	(23.00)
× zip pr: House values: 50K-100K (.035)	2.069	(3.180)
× zip pr: Rental rates: Less than 500 (.036)	1.133	(2.316)

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Table 1 – continued from previous page

× zip pr: Heating: Bottled gas (.008)	-14.40*	(8.133)
× zip pr: Industry: Information (.018)	-22.18	(17.32)
× 1=Individual's age known (.759)	-0.227	(0.488)
× Demeaned indiv. age, if known (0)	0.0597***	(0.0166)
× Demeaned indiv. age, squared	-0.00174***	(0.000616)
× 1=Employee (.695)	-0.389	(0.349)
× 1=empl.group: Classified staff (.134)	0.237	(0.387)
× 1=empl.group: Student employee (.18)	0.0687	(0.303)
× 1=empl.org: Education (.024)	0.219	(0.509)
× 1=Student (.706)	-0.405	(0.494)
× 1=stu.school: Undeclared (.041)	-0.172	(0.313)
× 1=Fall 2018 survey wave (.419)	0.0386	(0.188)
× 1=last 12 mos: Tornado (.034)	0.792**	(0.338)
× 1=last 12 mos: Heat wave (.423)	-0.265	(0.173)
× 1=main role: Staff (.208)	0.227	(0.282)
× 1=main role: Admin (.046)	0.230	(0.383)
× 1=Somewhat or very liberal (.674)	-0.732***	(0.181)
× 1=Somewhat or very conserv (.086)	0.458	(0.384)
Max. log-likelihood	-6792.11	
No. respondents	1,107	
No. choices	5,834	
No. alternatives	13,848	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Only one of the indicators for Census zip-code data for variable set 1 and set 3 can be successfully included among the shifters for any of the main attributes, so we use whichever one is not dropped by the estimation algorithm.

Table 2: Summary statistics for fitted marginal and conditional distributions for WTP, by program, noting the corresponding figures containing graphs of the complete density functions (included either in the body of the paper or among the online Supplementary Materials). Program key: a_b_c_d_e_f, where a = % carbon reduction, b = % of cost as air travel fees, c = % of cost as building energy fees, d = % of cost borne by state taxpayers, e = % of revenue spent on academic programs, f = % of revenue spent on off-campus offsets. Percent of cost borne as flat fees is 100-b-c-d; percent of spending for on-campus carbon reduction programs is 100-e-f.

Description	Program key	Population	Group	Med. WTP/yr	Mean WTP/yr
1. Campus-wide WTP distribution (see Figure 1)					
Baseline program	40_0_0_0_0_0	Campus	Everyone	89	102
2. Differences in WTP by student/employee status (see Figure 3)					
Baseline program	40_0_0_0_0_0	Campus	Students	115	119
"	"	"	Employees	79	92
"	"	"	Non-student empl.	38	50
"	"	"	Non-empl. students	117	120
3. Differences in WTP by survey wave (see Figure S4)					
Baseline program	40_0_0_0_0_0	Campus	Spring wave	75	94
"	"	"	Fall wave	108	111
4. Differences in WTP by income quintile (see Figure S5)					
Baseline program	40_0_0_0_0_0	Campus	1^{st} quartile	103	108
"	"	"	2^{nd} quartile	84	90
"	"	"	3^{rd} quartile	79	97
"	"	"	4^{th} quartile	103	120
5. Differences in WTP by age tercile (see Figure S6)					
Baseline program	40_0_0_0_0_0	Campus	Youngest tercile	158	146
"	"	"	Middle tercile	110	118
"	"	"	Older tercile	68	75
6. Differences in WTP by citizenship status (see Figure S7)					
Baseline program	40_0_0_0_0_0	Campus	U.S. citizens	85	99
"	"	"	Non-citizens	151	144
7. Differences in WTP by political ideologies (see Figure S8)					
Baseline program	40_0_0_0_0_0	Campus	Liberal	122	128
"	"	"	Moderate	43	60
"	"	"	Conservative	2	18
8. Differences in student WTP by residency (see Figure S9)					
Baseline program	40_0_0_0_0_0	Students	Residents	112	113
"	"	"	Non-resid.	129	149
9. Selected non-baseline programs (see Figure S10)					
10% air travel	40_10_0_0_0_0	Campus	Everyone	120	126
50% bldg fees	40_0_50_0_0_0	"	"	142	143
20% taxpayers	40_0_0_20_0_0	"	"	107	118
10% acad. progr.	40_0_0_0_10_0	"	"	90	101

Continued on next page

Table 2 – continued from previous page

Description	Program key	Population	Group	Med. WTP/yr	Mean WTP/yr
30% offsets	40_0_0_0_0_30	"	"	75	95
10. Selected extreme programs (see Figure S11)					
100% bldg fees	40_0_100_0_0_0	Campus	Everyone	193	188
100% taxpayers	40_0_0_100_0_0	"	"	161	203
100% offsets	40_0_0_0_0_100	"	"	61	99
11. Baseline program, by self-reported main role on campus (see Figure S15)					
Baseline program	40_0_0_0_0_0	Campus	Cont. Students	131	133
"	"	"	Faculty	74	77
"	"	"	Staff	25	42
12. With 10% of cost borne as air travel fees, by reported main role on campus (see Figure S16)					
10% air travel	40_10_0_0_0_0	Campus	Cont. Students	161	159
"	"	"	Faculty	105	107
"	"	"	Staff	46	60

Table 3: Examples of predicted referendum voting percentages and overall campus-level net benefits, by featured subgroup in the campus population versus all others, and overall (based on individual WTP amounts for simulations of different carbon-reduction programs using our estimated utility-function parameters. Assumes individuals will vote for a program if their individual WTP exceeds their individual cost. Benefits are based on average WTP within a group times the number of people in that group.)

Simulation:	(1)	(2)	(3)	(4)	(5)	(6)
Featured group	Students	Students	Students	Students	Students	Students
No. People in featured group	23,600	23,600	23,600	23,600	23,600	23,600
Other group	Non-students	Non-students	Non-students	Non-students	Non-students	Non-students
No. People in other group	4,500	4,500	4,500	4,500	4,500	4,500
No. Taxpayers in state	2,600,000	2,600,000	2,600,000	2,600,000	2,600,000	2,600,000
Main program attributes - emissions reduction and overall cost:						
% Carbon emissions reduction	40	40	40	40	40	40
Total cost/year of program	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 3,000,000
How costs will be borne:						
% Cost in flat fees	100	100	95	90	100	80
Who pays flat fees?	Everyone	Students	Students	Students	Students	Students
% Cost as air travel fees	0	0	5	10	0	0
Who pays air travel fees?			Everyone	Everyone		
% Cost as building energy fees	0	0	0	0	0	0
Who pays building energy fees?						
% Cost paid by taxpayers	0	0	0	0	0	20
Who pays taxpayer costs?						Everyone
How revenues will be spent:						
% Spent on C programs	100	100	100	100	0	100
% Spent on acad. programs	0	0	0	0	0	0
% Spent on offsets	0	0	0	0	100	0
By group: Types of per-person costs with this program						
Featured group:						
Per-person flat fees per year	$ 107	$ 127	$ 121	$ 114	$ 127	$ 102
Per-person air travel fees per year	$ 0	$ 0	$ 5.34	$ 11	$ 0	$ 0
Per-person building energy fees per year	$ 0	$ 0	$ 0	$ 0	$ 0	$ 0
Per-person tax increase per year	$ 0	$ 0	$ 0	$ 0	$ 0	$ .23
Other group:						
Per-person flat fees per year	$ 107	$ 0	$ 0	$ 0	$ 0	$ 0
Per-person air travel fees per year	$ 0	$ 0	$ 5.34	$ 11	$ 0	$ 0
Per-person building energy fees per year	$ 0	$ 0	$ 0	$ 0	$ 0	$ 0

Continued on next page

Table 3 – continued from previous page

Simulation:	(1)	(2)	(3)	(4)	(5)	(6)
Per-person tax increase per year	$ 0	$ 0	$ 0	$ 0	$ 0	$ .23
Overall per-person costs by group, with this program						
Overall per-person cost, featured group per year	$ 107	$ 127	$ 126	$ 125	$ 127	$ 102
Overall per-person cost, other group per year	$ 107	$ 0	$ 5.34	$ 11	$ 0	$ .23
Costs to state taxpayers						
Total cost to off-campus state taxpayers per year	$ 0	$ 0	$ 0	$ 0	$ 0	$ 593,537
Per-taxpayer cost, state taxpayers, per year	$ 0	$ 0	$ 0	$ 0	$ 0	$ .23
Referendum on program, by group						
Referendum vote share yes for featured group	53 %	45 %	52 %	58 %	44 %	62 %
Referendum vote share yes for other group	12 %	100 %	78 %	77 %	100 %	89 %
Referendum on program, overall						
Campus-wide referendum vote share yes	46 %	54 %	56 %	61 %	53 %	66 %
Benefit-cost assessment, for campus						
Campus-wide benefits per year	$ 3,988,400	$ 3,988,400	$ 4,578,400	$ 5,097,600	$ 3,587,200	$ 4,578,400
Campus-wide cost per year	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 2,400,000
Campus-wide net benefits per year	$ 988,400	$ 988,400	$ 1,578,400	$ 2,097,600	$ 587,200	$ 2,178,400

A APPENDIX: Online Supplementary Materials

These materials accompany the paper entitled "Carbon-Reduction Programs in Higher Education: Demand as a Function of Program Attributes and Stakeholder Characteristics" by Trudy Ann Cameron (cameron@uoregon.edu) and Ryan Walch (ryanswalch@gmail.com).

A.1 Our work in relation to the broader literature

Authors such as Bento and Gianfrate (2020), Bento et al. (2021), and Riedel et al. (2021) have explored the determinants of different firms' decisions to adopt internal carbon pricing, with observations across firms. However, the extent to which individual stakeholders within a given institution are willing to bear the costs of these programs, or how stakeholder preferences vary with program design, is relatively unknown. A better understanding of individual preferences for internal carbon-pricing programs with different features would increase our sense of when and where institutional carbon emissions reduction programs may be acceptable to an institution's stakeholders. In addition, understanding preferences over the design of private carbon-pricing programs may also clarify some aspects of how the population in general might react to alternative designs for eventual governmental carbon-pricing programs (at either the state or the national level).

For a discussion of ICP programs in the private sector, see Ahluwalia (2017) and Camuzeaux and Medford (2016). The most simple ICP program involves a carbon levy on individual divisions, which is then used to fund carbon reduction programs. ICPs can also be used to meet emission reduction goals for the institution or merely as a trial run for an anticipated future mandatory government carbon pricing program. Institutions may also consider adding accounting charges based on the anticipated lifetime emissions of new (or replacement) buildings, equipment or technologies that the institution is considering whether to acquire.

A variety of alternative carbon fee/pricing programs could be implemented, and a given program's attributes can be expected to influence stakeholder support. In this study we differentiate potential programs according to some of their distributional consequences and how the revenue they raise is recycled within the institution. There is evidence in other contexts that people do care about the distributional consequences of climate-related programs. For national-level climate policies, Lee and Cameron (2008), and Cai et al. (2010) explore preferences concerning (i) the distribution of costs of climate-change mitigation programs across groups, and (i) the distribution across country groups of the benefits of these programs (i.e. the avoided damages). Groh and Ziegler (2018) find that individuals prefer a "polluter-pays approach," followed by an "ability to pay" approach, which in turn is preferred to a program that distributes costs equally across households. Brannlund and Persson (2012) find evidence for distributional preferences within a developing country. The literature thus strongly suggests that distributional consequences can have a strong influence on people's willingness to bear the costs of climate change mitigation programs more broadly.

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

A.2 Some important features of our survey implementation

A demo version of our survey can be viewed at the following link:

https://oregon.qualtrics.com/jfe/form/SV_5jcbuGPc1ArgFdX

The design for our choice experiments (i.e., the attribute levels and mixes for the different alternatives presented to respondents) was created off-line and linked to the Qualtrics survey. The fields for the experimental design, as well as identifiers for campus-specific facts, are contained in a separate .csv file, uploaded to the survey as "embedded data." This structure was designed to make adaptation of our survey to other campuses as simple as possible. For example, one page in the tutorial section in the survey is coded within Qualtrics as follows, where the "${e://Field/...}" information is retrieved from the associated .csv file:

> Some facts about ${e://Field/school}'s carbon footprint: Counting both part-time and full-time categories, the university currently has about ${e://Field/nstudents} students, and about ${e://Field/nstaff} faculty and staff.
>
> The most recent estimate of the university's carbon emissions related to energy use and transportation (but NOT counting the carbon content of other purchased products) is about ${e://Field/totalco} metric tons of carbon dioxide equivalent emissions.
>
> This survey will focus on the two most significant sources of carbon emissions that would be the easiest for a university to cover with an internal carbon pricing program:
>
> 1. Building energy use, fuelled by ${e://Field/heatfuel}, produces the equivalent of about
>
> • ${e://Field/heatco} metric tons of carbon dioxide each year
>
> • ${e://Field/heatpct}% of total university-related carbon emissions
>
> 2. Air travel produces the equivalent of about
>
> • ${e://Field/airco} metric tons of carbon dioxide each year
>
> • ${e://Field/airpct}% of total university-related carbon emissions

Thus, our survey can be tailored to apply to a different university or college by swapping the original .csv file for one with a different university name and all of the other data unique to each university or college which might conduct the same type of survey.

The email addresses to which each survey invitation was distributed were obtained in cooperation with the university's Office of Instructional Research (OIR). Randomly generated respondent identifiers were generated. The OIR received the identifiers and linked each invited respondent's identifier to their institutional data, including the current zip code of non-student employees and the zip code of each student's high school, as a proxy for the zip code of their "permanent address." Email information was then stripped from the resulting data and the OIR "profile" data were merged with the data on each response/non-response outcome and the choice-experiment preferences across carbon-emissions-reduction programs among invitees who chose to complete the survey.

The zip code information permits us to match all invitees to census data for the zip codes associated with their record. Thus we are able to exploit individual-level institutional data and census zip-code-level about all invitees to explain the response/nonresponse decisions of all invitees. The individual-level institutional data can also be exploited as a source of heterogeneity in preferences. In many survey contexts, researchers will have considerably less information about every invitee, but among campus populations, most universities and colleges will maintain similar institutional databases. Surveys that use consumer panels, however, should acquire all panelist "profile" information that the company can make available, and be certain to negotiate to receive this information for everyone who is invited to take the survey, not just people who provide a complete response.

Our survey was designed specifically to be taken on mobile devices, given that substantial numbers of students would be invited to participate. It was deemed imperative for every choice set to be fully visible on a single smart-phone screen, so that the levels of all attributes could be viewed easily, without scrolling. This formatting consideration made it imperative for us to provide a means of instant access, from each choice task summary, to information about how respondents are to interpret each attribute. We accomplish this using javascript code, which can be embedded in any page of a Qualtrics survey. In the training module, we explain how any text in blue font leads to a "pop-up" modal that lets them review information about that word or phrase. Pop-ups are preferable to ordinary links to external web pages because the respondent stays on the same page of the survey. Compared to Qualtrics' native pop-up implementation, our javascript method is also more flexible. For example, it permits campus-specific embedded data to be displayed inside the pop-up, and also accommodates pop-ups within pop-ups.[29]

A.3 Survey components

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, and 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 public discussions, in the Western U.S. states of 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

[29] We are grateful to Casey Williams for building the prototype for this code, which we have used in this survey and several others.

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. As noted above, optional 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.[30]

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.[31]

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

[30]Our survey was optimized for the screens of smartphones, but displays equally well on larger tablets or on desktop or laptop monitors. Qualtrics makes it possible to design alternative versions of a survey, with the version to be displayed determined by the platform's recognition of the hardware being used. Given the extensive use–and complexity–of the pop-up modals in our survey, however, we were reluctant at the time to risk making inconsistent edits in two or more different versions of the survey.

[31]Our survey was conducted prior to the COVID-19 pandemic and the resulting introduction of extensive remote learning opportunities, many of which have continued until the present. If it is to be used again, our survey would need to be adapted to reflect this new reality.

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 them if these costs 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.

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 fundamentally anti-carbon-pricing respondents prior to the end of the survey.

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

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

Perceived researcher bias. Respondents were asked “Overall, the wording of this survey made it seem that the researchers conducting this study really wanted me to choose..." The options included “some carbon-pricing program, rather than No Program,” “No Program, rather than some carbon-pricing program,” “The best alternative for me, personally, based on all of the features of the programs,” and “Not sure/couldn’t tell.” The goal in survey design is to have the majority of people choose one of the last two options. However, perceptions such as these can be jointly endogenous with the respondent’s own attitudes toward climate change, so we do not seek to simulate what would have been people’s WTP amounts if everyone chose “the best alternative for me....”

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. Questions such as these are useful for assessing construct validity, but climate change attitudes are jointly endogenous with WTP, so we do not employ indicator variables for these responses as regressors in our main model.

Sociodemographics. The survey directly 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.4 Choice set design

As mentioned above, 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 generic 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 an "efficient" design for the mix of attributes among the choice sets. We elected instead to randomize the portfolio of admissible combinations of shares for each potential carbon-pricing program. We then pair 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 these basic benefits and costs. It is possible that one program might dominate the other on these two dimensions, yet be less preferred solely because of its distributional consequences, we did not wish to risk proposing too many of these types of choices. Any future use of this survey might include such combinations, however, to examine how people behave when confronted with what might seem like "no-brainer" choices in terms of the benefit and cost attributes.

The levels for each program attribute were drawn at random from the following sets of values:

- 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 (where repetitions in these lists increase the odds that a given value will be

used)

  - 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 (i.e., the percentage-point carbon reduction), one value is drawn randomly from the list. For the shares of program costs, and also for the uses of program revenues, 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.[32]

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

[32]In the Spring 2018 design, we specifically limited the possible shares to that range of values more likely to be relevant in any prospective real program for the university in question. In the Fall 2018 design, we extended the range 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, on average, to expenditure on carbon offsets, and only students appeared to respond systematically to expenditure on academic programs.

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 avoid implausible precision.)

A.5 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 target 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 fee/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 the Spring and Fall waves, for which we employ corrective sampling weights). 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, about representativeness of the respondent sample.

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 (where zip codes are 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-emissions-reduction programs. 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).[33]

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 a logit model, with the binary outcome defined as 1 = completed survey and 0 = nonresponse or incomplete survey. In the presence of a large number of potential explanatory variables, there is a danger of finding statistical relationships between variables that exist merely due to chance and do not reflect the actual data generating process. One approach to limit over-fitting is to use regularization, a technique where a penalty is assigned to the inclusion of variables. This

[33]We also connect each zip code to election results at the county level for every county in the U.S., for the 2012 and 2016 Presidential elections, given that the 2020 election had not yet taken place when the survey was fielded. 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. However, these variables are at such a coarse spatial scale relative to people's zip codes that we do not employ them in our main model.

penalty decreases the model variance due to variable selection and thus will produce lower levels of prediction error than simpler methods of model selection.

For the response/non-response model we use a form of regularization known as LASSO.[34] The probability of response is modeled by estimating a binary logit model with a penalty term in the likelihood function equal to the sum of the absolute value of each coefficient. We therefore want to find a vector of β's that maximize the following log-likelihood function

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

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, in practice, that 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.[35]. 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 is then computed using each holdout sample.[36] The value of λ we use for the response/nonresponse model estimates for this paper is the one that minimizes the mean-squared prediction error across the various holdout samples. Our goal is to calculate an individual-specific "propensity to respond" variable that reflects observable characteristics of people invited to participate in our survey.

[34]LASSO (now often written simply as "lasso") is an abbreviation for Least Absolute Shrinkage and Selection Operator.

[35]We estimate our lasso models using the glmnet 4.1-4 package in R version 4.2.1.

[36]In this case, the measure of model fit is the deviance, equal to two times the negative of the log-likelihood function, associated with the Deviance Information Criterion, a generalization of the Akaike Information Criterion

A.6 Additional WTP profiles and distributions

A.6.1 For "average" faculty and "average" staff: WTP by program attribute

Figures S2 and S3 shows a set of graphs for faculty and staff, respectively, analogous to those for students in Figure 2 in the body of the paper. The graphs in Figure S2 are constructed for a person with average characteristics among people who consider their main role at the university to be "faculty" or who the university classifies as "non-tenure-track faculty (NTTFs)." Similarly, Figure S3 employs the average characteristics of people who consider their main role at the university to be "staff" or who the university designates as "classified staff." We continue to use the same vertical scale for all six graphs in each of these figures, and it is easy to see that main-role-faculty/NTTF, and especially main-role-staff/classified-staff, are willing to pay less for carbon emissions reductions than are students. For a person with average main-role-faculty/NTTF characteristics, the interval estimate rejects zero WTP for our baseline program, but does not reject zero WTP for programs with less than about a 35% carbon reduction. Graph (e) in Figure S2 shows that there is a discernibly negative *marginal* WTP by main-role-faculty/NTTF for greater shares of revenue being spent on academic programs.

For a person with average main-role-staff/classified-staff characteristics, it appears from Figure S3 that it is not to be possible to reject a zero WTP for a baseline program that produces even a 50% reduction in carbon emissions. For programs with non-baseline shares of costs and uses of revenue, however, there appear to be some types of programs for which a person with average main-role-staff/classified-staff characteristics would have an interval estimate of WTP that does not include zero: (i) if the share of costs borne as air travel fees is greater than about %15, or (ii) if the share of costs borne as fees for building energy use is greater than about 50%. This representative main-role-staff/classified-staff individual does not want any of the costs of a carbon emissions reduction program to be borne by taxpayers or any revenue from the program to be spent on academic programs or offsets.

A.6.2 WTP for baseline program: by Fall/Spring survey waves (seasonality)

Figure S4 stacks the marginal distributions of simulated mean WTP for the two waves of our survey. Median WTP for Spring respondents was only \$75, but after the heat of the summer and early fall, the median for Fall respondents was \$108. Given that the distribution of characteristics among these two groups is little different, the Spring/Fall distinction will capture any differences in the indicators summarizing each respondent's personal experience over the last 12 months with inland floods, hurricanes, tornados, severe drought, wildfire, severe winter or heat waves, where Table 1 in the body of the paper shows that indicators for all of these extreme events are retained by LASSO as shifters of the marginal utility of at least one program attribute.

A.6.3 WTP for baseline program: by self-reported household income quartile

We asked each respondent "What is the total annual income of the HOUSEHOLD in which you live?" and offered intervals from "less than \$20,000" through "\$200,000 or more." In retrospect, we probably should have pressed students to distinguish between their parental family's income and the income of the household where they live as a student. Figure S5 shows that simulated WTP amounts vary widely within each income quartile, and the medians of each distribution are not monotonic across quartiles.

A.6.4 WTP for baseline program: by terciles of the age distribution (independent of role)

Figure S6 shows the distribution of simulated mean WTP for the baseline program for three age terciles. The youngest tercile has a median simulated WTP of \$158, the middle tercile has a median of \$110, while the oldest tercile has a median WTP of only \$68.

A.6.5 WTP for baseline program: by citizenship

About 5.4% of the campus population are not U.S. citizens. Figure S7 reveals that the median WTP for U.S. citizens on campus is \$85, but for the non-citizen group it is strikingly larger, at \$151. Among students, at least, non-citizens have come to the U.S. from another country to study, and they could have applied to many universities. The university in this survey has a reputation for sustainability, and may have attracted foreign students (and perhaps faculty) with a particular interest in sustainability. Alternatively, members of the global community who are not U.S. citizens may feel a greater urgency than the average U.S. citizen to reduce carbon emissions. This implies that non-citizen members of the campus community are willing to pay more for programs to reduce the university's carbon emissions.

A.6.6 WTP for baseline program: by self-reported political ideology

As at many universities, the campus population is relatively liberal. As is the case nationally in the U.S. we can expect that members of the campus community who identify as "somewhat or very liberal" are more willing to bear the costs of carbon emissions reductions than those who are more conservative. Figure S8 shows marked differences across these groups. Those who identify as liberal have a median simulated WTP of \$122, moderates and those who choose not to report their ideology have median WTP of only \$43, while the 8.6% of the campus population that report being "somewhat or very conservative" have a median WTP of only \$2! Nevertheless, there are individuals within the "liberal" group who are willing to pay very little and others who are willing to pay a lot. Note that in Figure S8, we use different scales on the vertical axis of each distribution, since the height of the density for the conservative group would flatten the other two densities so far as to obscure their shapes if they were displayed on the same vertical scale.

A.6.7 WTP for baseline program: by resident versus non-resident student status

If the ZIP code of a student's previous educational institution is in the same state as the university we have surveyed, that student is deemed a "resident" student. Otherwise, they are deemed to be a "non-resident" student. Given that this university is a public university, tuition for non-resident undergraduate students is roughly three times as high as undergraduate student tuition for residents; graduate tuition is about twice as high for non-resident students. Mandatory fees, however, are the same for both groups of undergraduates and both groups of graduate students. Presumably, any flat fee for all students and employees would fall into the mandatory fee category. However, it is reasonable to ask whether the implied distributions of individual WTP for carbon reductions differ across resident and non-resident students. Note that we do not specifically allow the marginal utilities for our program attributes to vary systematically with resident/non-resident status, so the differences in WTP between these two groups stem from differences in all the other characteristics between these two groups, which are included through all the interactions between program attributes and respondent characteristics in the model in Table 1.

Figure S9 shows that non-resident students, given that they have already revealed that they are willing to pay more in tuition, are also willing to pay somewhat more every year for a baseline program that reduces carbon emissions by 40%.[37]

A.6.8 WTP: by share of costs borne as air travel fees

A non-zero fee applied to university-paid air travel is the most-likely near-term user-pays component of any carbon-emissions reduction program at the university where our choice experiments were conducted. Our model suggests that people are more willing to pay the costs of a carbon emissions program if more of the cost is borne as air-travel fees. To illustrate, consider what happens to the distribution of WTP amounts for programs as the share of the cost borne as air travel fees increases from 1% to 5% to 10% to 15%. We break out these effects for three groups: people who

[37] The university in question had about 48% nonresident students in the year of our survey.

report their main role on campus as "continuing students," "faculty," and "staff." See Figures S12, S13 and S14.

To permit across-group comparisons of programs with different percentages of the cost borne as air travel fees, we also combine the three groups in Figure S15 for a program with 0% of its cost borne as air travel fees, and in Figure S16 for aprogram with 10% of the cost as air travel fees.

These distributions, however, do not reflect the main constraints on raising money for the program via air travel fees. We are not able to factor in any consideration of the price elasticity of demand for university-paid air travel. Excessive air travel fees might also drive travelers to somehow purchase their tickets off the university's books, reducing the amount of revenue achievable through this channel.

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A.7 Additional Figures

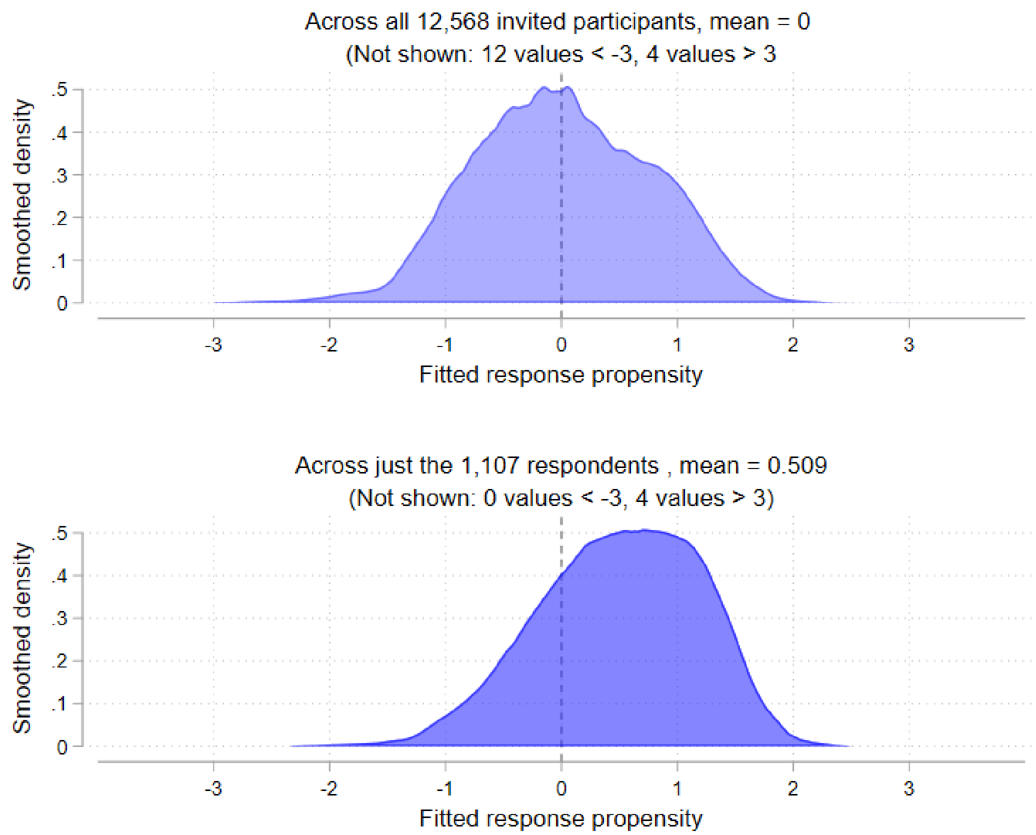
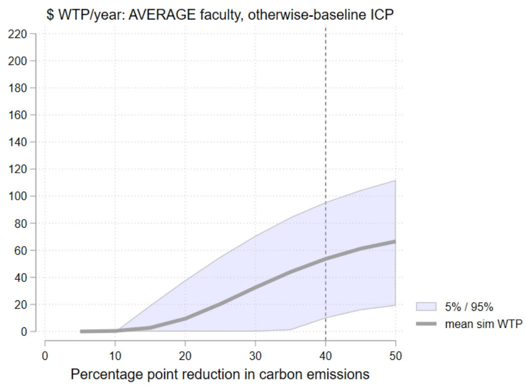
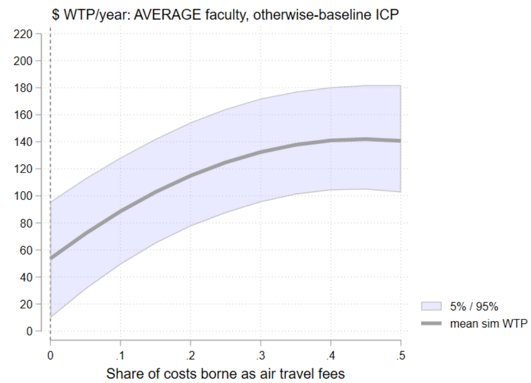


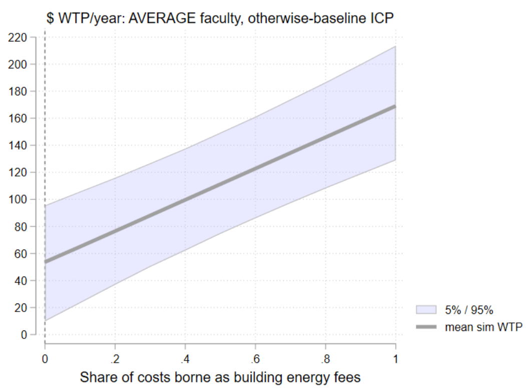
Figure S1: Fitted response propensities based on the model in Table S2, de-meaned relative to the average response propensity across all invited participants. Top density: for the universe of invited survey participants (a stratified random sample from the campus population). Bottom density: for the 1,107 respondents whose choices are used in the analysis. People in our sample were systematically more likely to complete the survey, on average, than the average person invited. We control for de-meaned response propensities during estimation, and then simulate everyone having the same response propensity as the average among all invited participants.



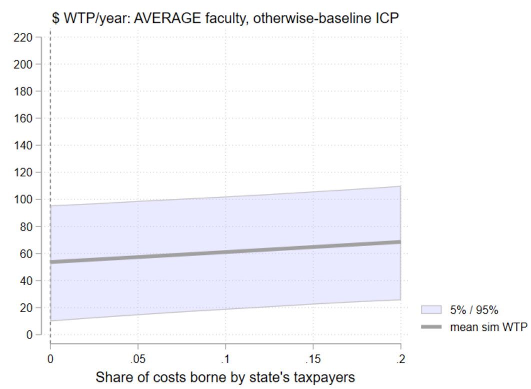
(a) % Carbon reduction



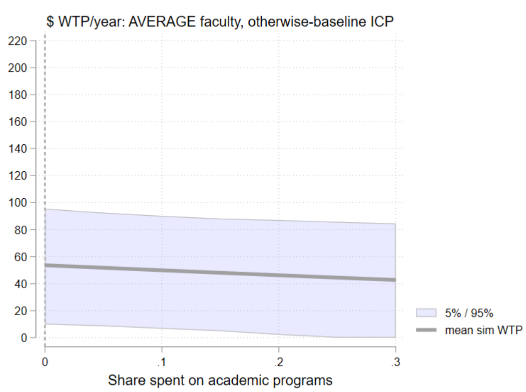
(b) Costs borne by: Air travel fees



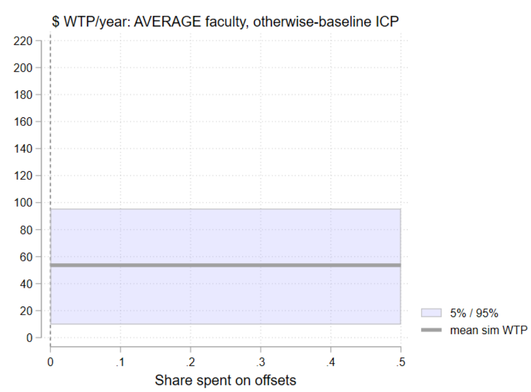
(c) Costs borne by: Building fees



(d) Costs borne by: Taxpayers

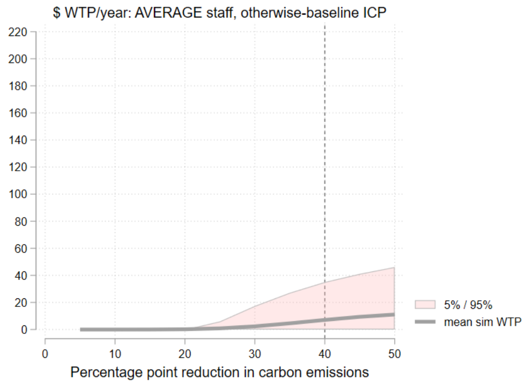


(e) Revenue spent on: Academic programs

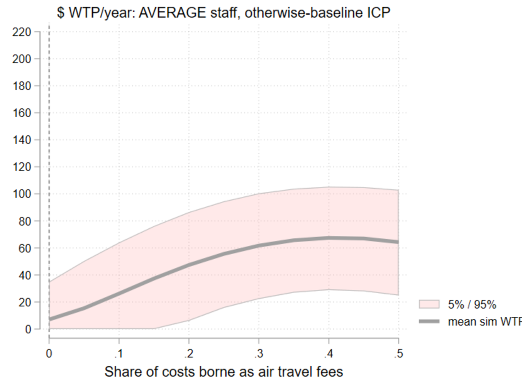


(f) Revenue spent on: Offsets

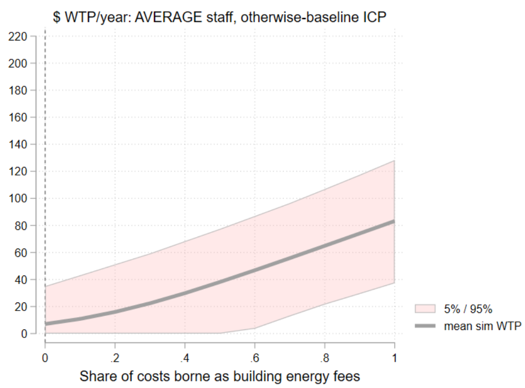
Figure S2: **For a faculty member with sample average faculty characteristics**: Point and interval estimates of WTP (each based on 10,000 draws from the joint distribution of the estimated model parameters) as a function of program attributes. See description for Figure **??**. Note: any negative values predicted for WTP are interpreted as zero, since respondents were not offered payment to accept these programs.



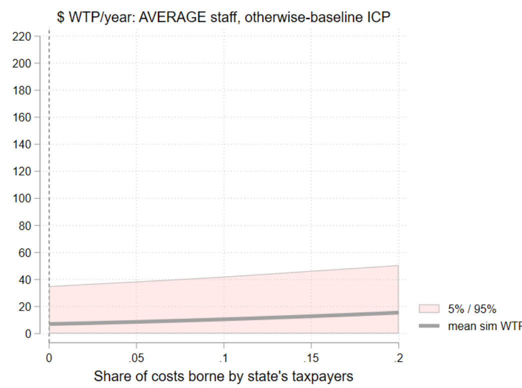
(a) % Carbon reduction



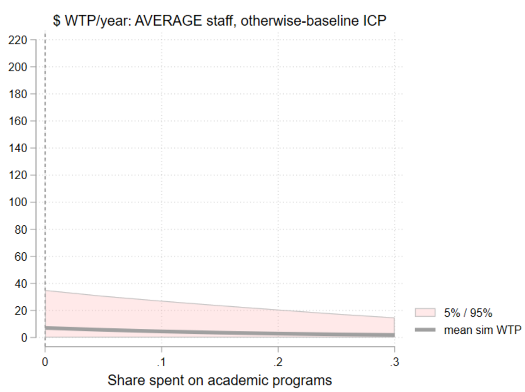
(b) Costs borne by: Air travel fees



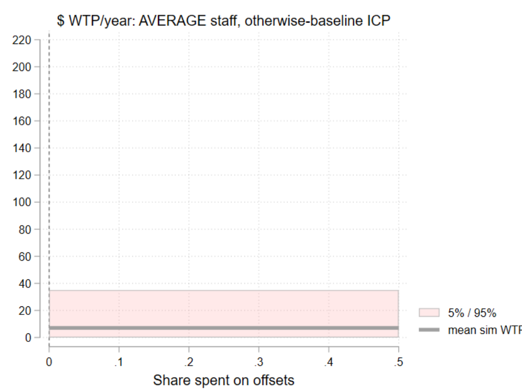
(c) Costs borne by: Building fees



(d) Cost borne by: Taxpayers



(e) Revenue spent on: Academic programs



(f) Revenue spent on: Offsets

Figure S3: **For a staff member with sample average staff characteristics**: Point and interval estimates of WTP (each based on 10,000 draws from the joint distribution of the estimated model parameters) as a function of program attributes. See description for Figure **??**. Note: any negative values predicted for WTP are interpreted as zero, since respondents were not offered payment to accept these programs.

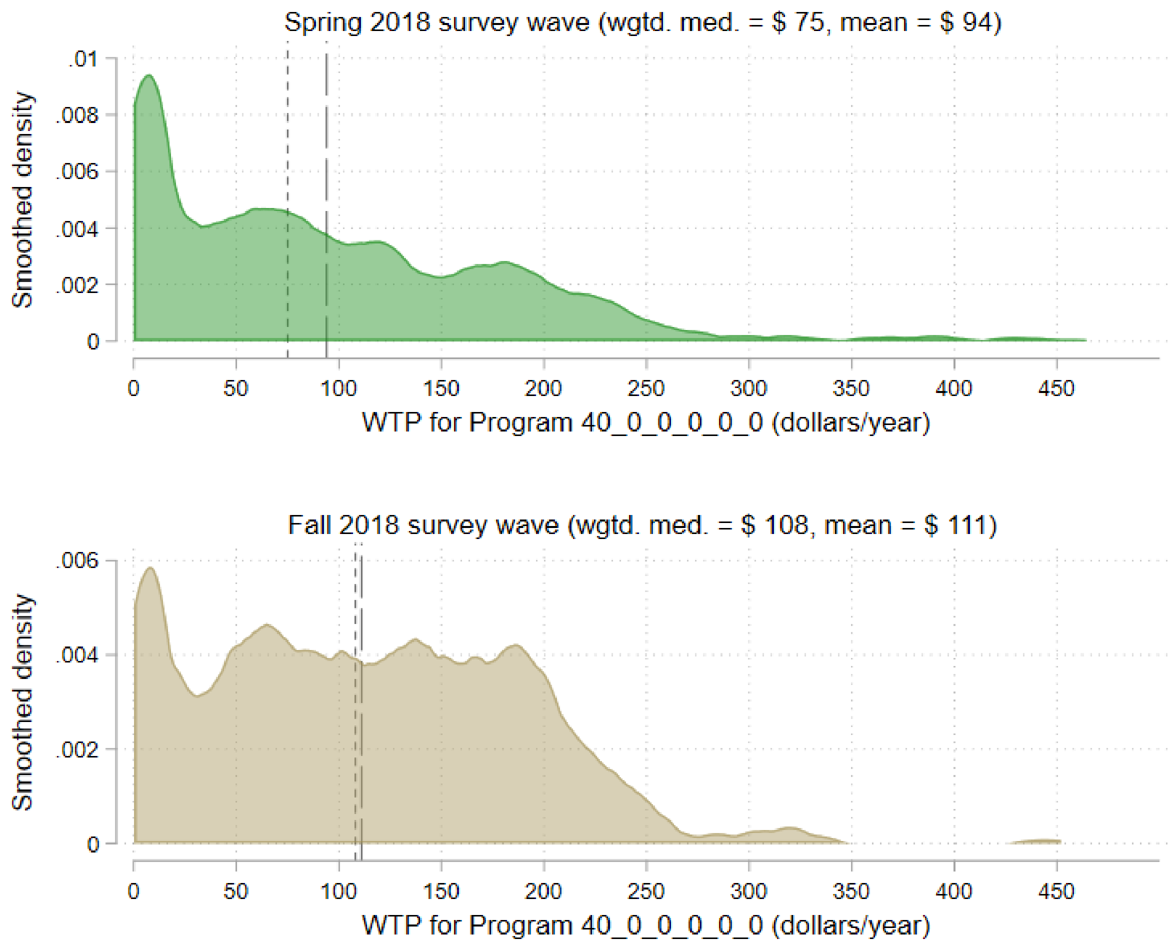


Figure S4: By Spring and Fall survey waves: WTP for a 40% carbon emissions reduction, flat fee on all students and employees, spending on carbon reduction programs only; population-weighted distributions. Differences in WTP may be seasonal, in response to recent weather conditions.

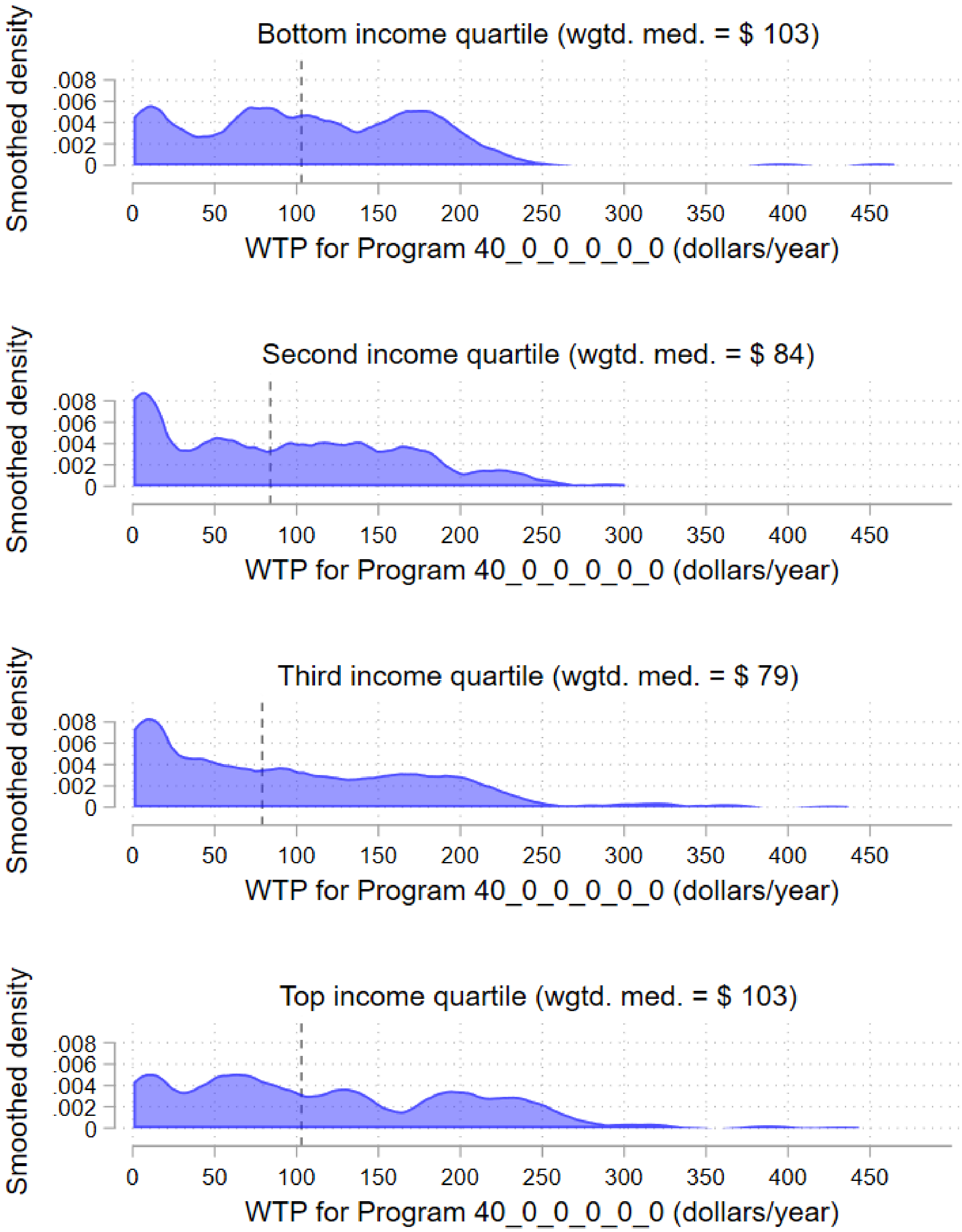


Figure S5: Differences in WTP for a 40% carbon emissions reduction, by reported household income quartile; full sample, population-weighted distributions. Note that median WTP by quartile is not monotonic in income. Students may report household income for their parental family or for their own household. Heterogeneity within each income group is explained by other respondent characteristics.

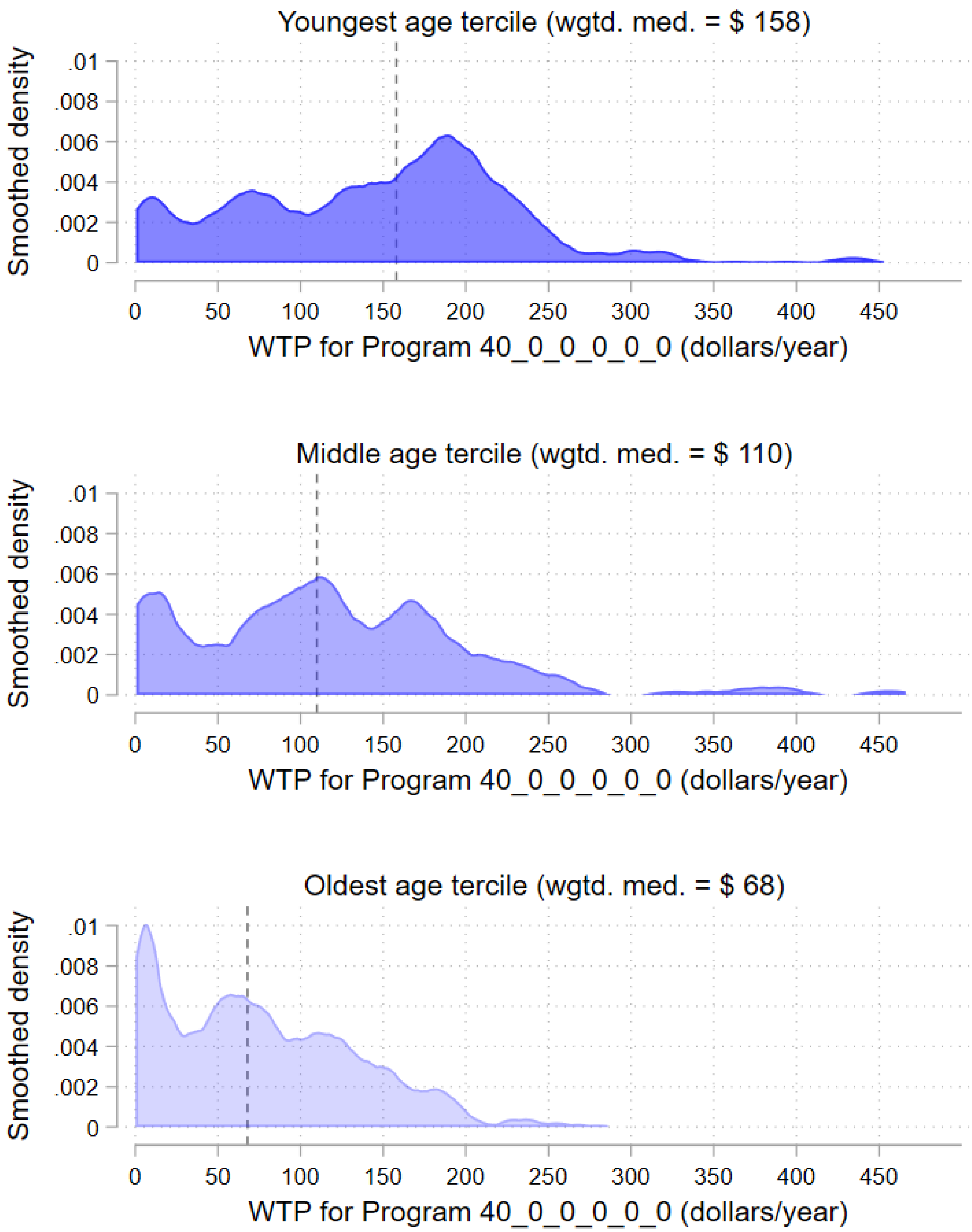


Figure S6: Differences in WTP for a 40% carbon emissions reduction, by age terciles in the full sample, population-weighted distributions

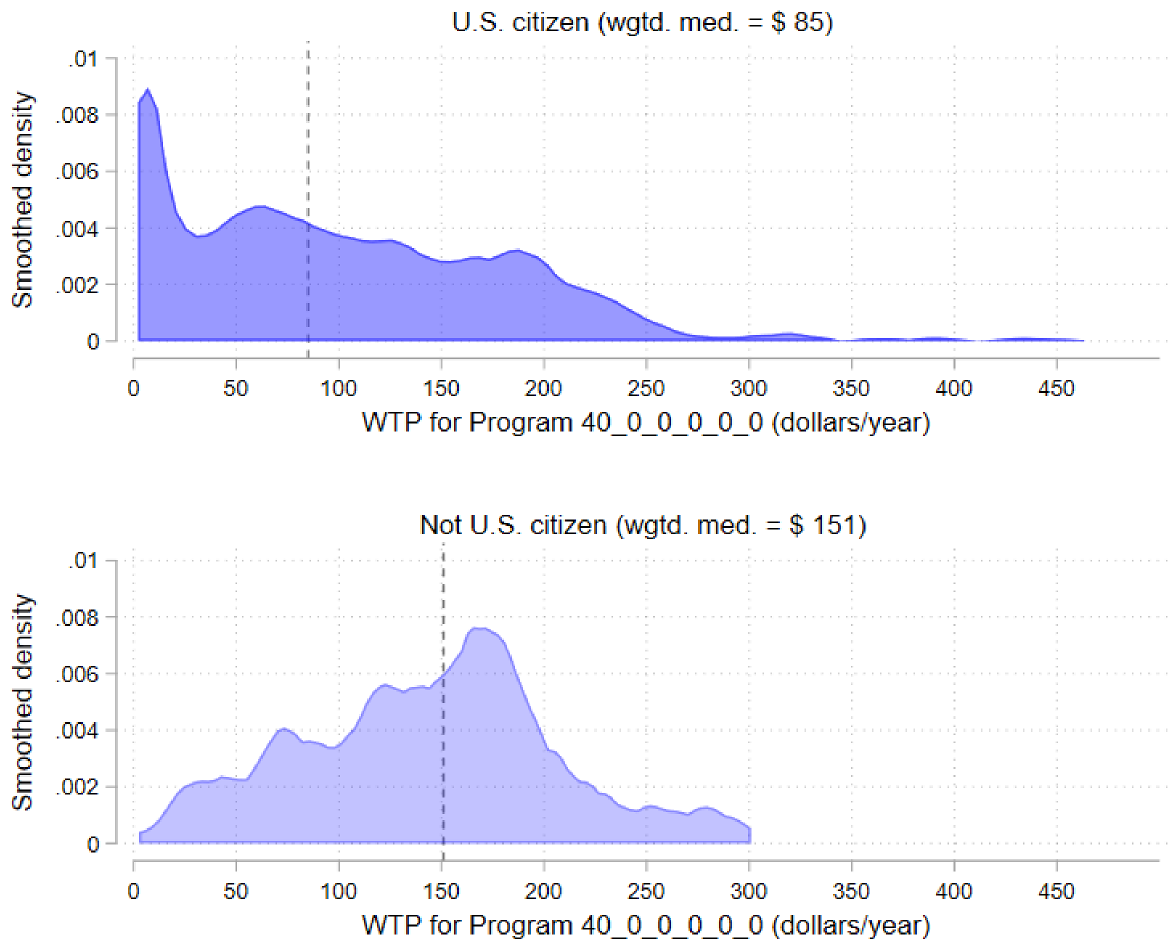


Figure S7: Differences in WTP for a 40% carbon emissions reduction, by citizenship status; full sample, population-weighted distributions. Only 5.4% of the sample are non-citizens.

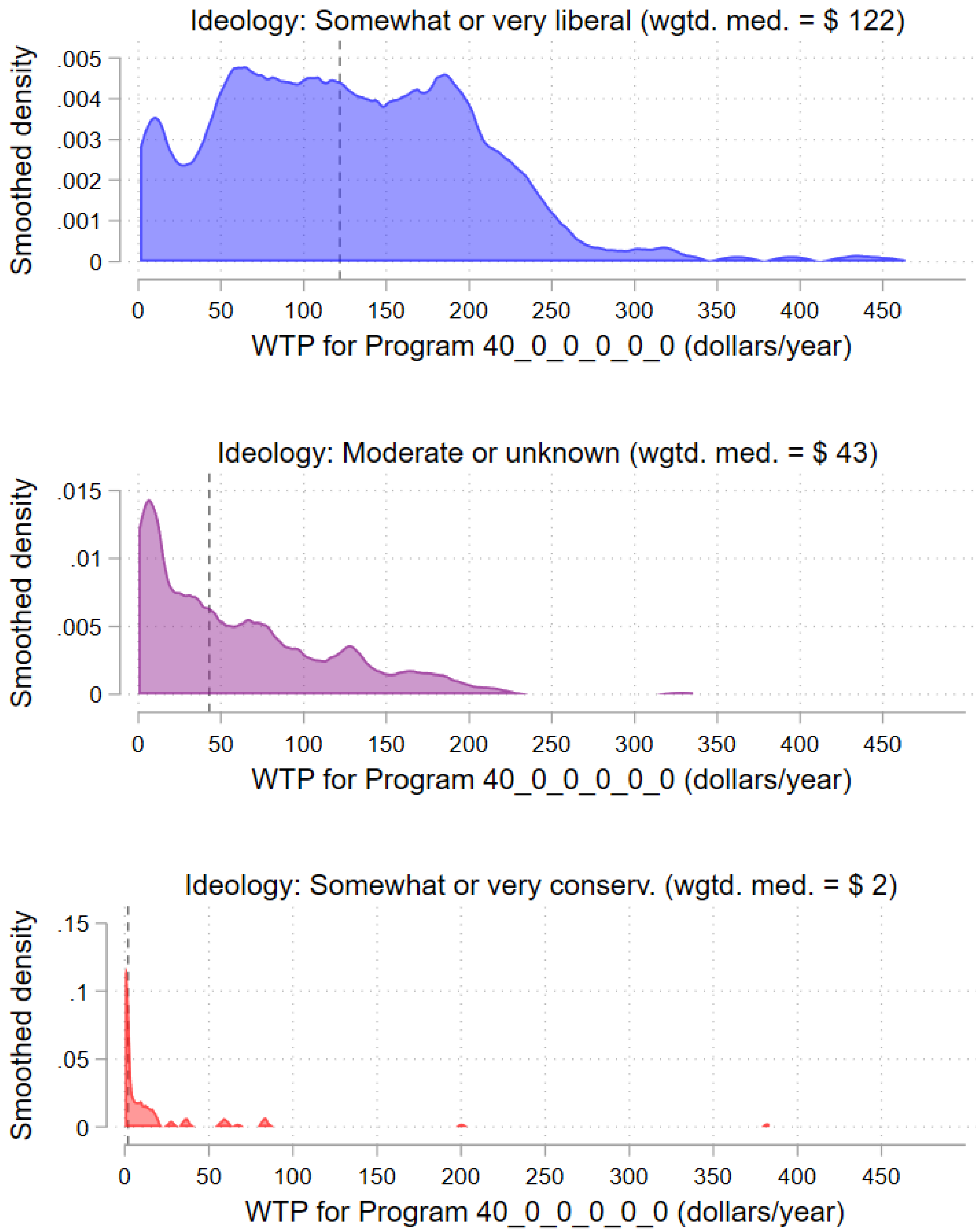


Figure S8: By self-reported political ideology: Differences in WTP for a 40% carbon emissions reduction, baseline program; population-weighted distributions (figures kept separate because they have very different vertical scales). 67.4% of the sample report being "Somewhat or very liberal," but only 8.6% report being "Somewhat or very conservative."

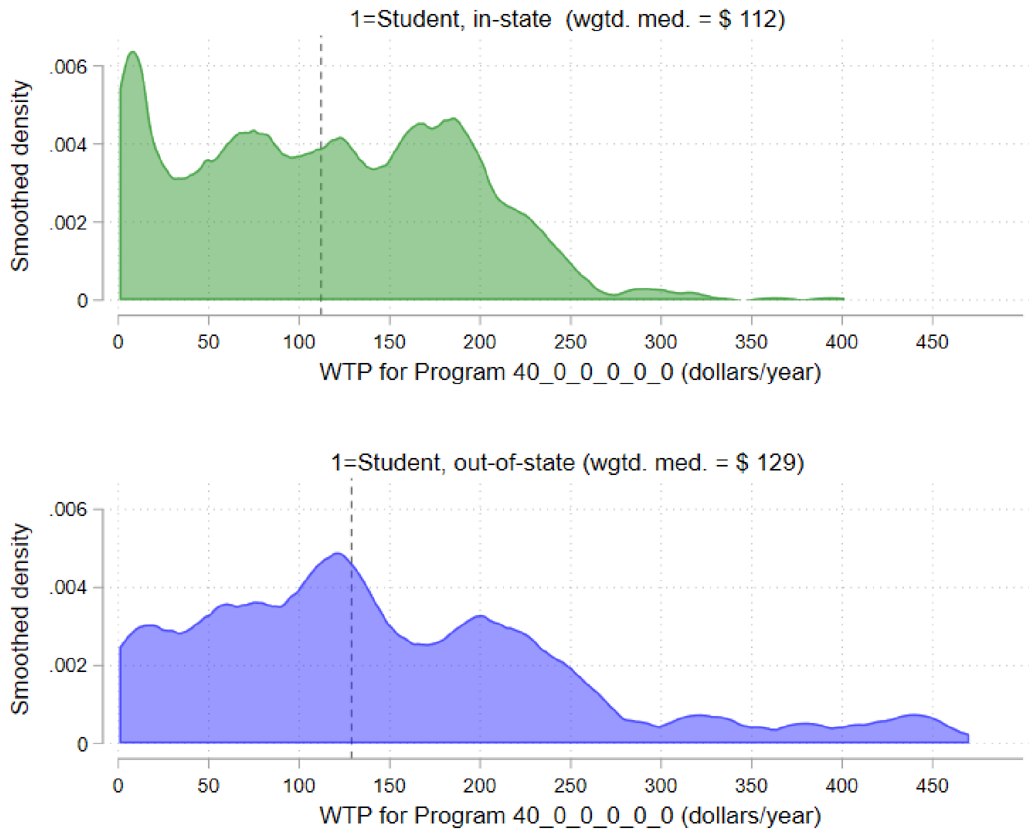
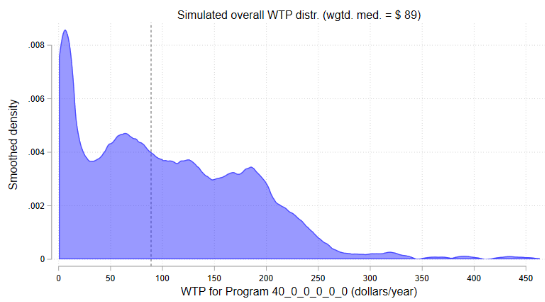
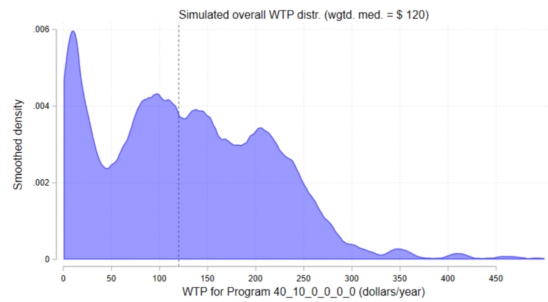


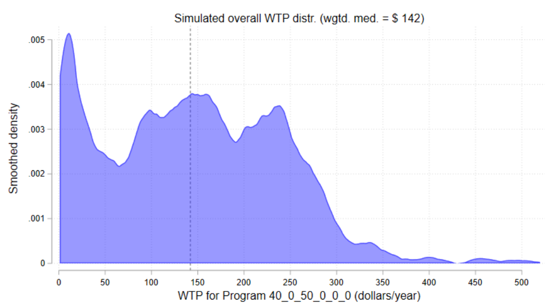
Figure S9: Distributions of predicted individual point estimates of WTP (campus-population-weighted) by administrative designation as "student," separated into in-state (i.e., "resident") and out-of-state (i.e., "non-resident") students based on the zip code of their last school. We cannot, however, distinguish between undergraduate and graduate students. These distributions are for a 40% carbon emissions reduction where all costs are borne as a flat fee on all students and employees, and all revenues are spent on carbon-reduction programs.



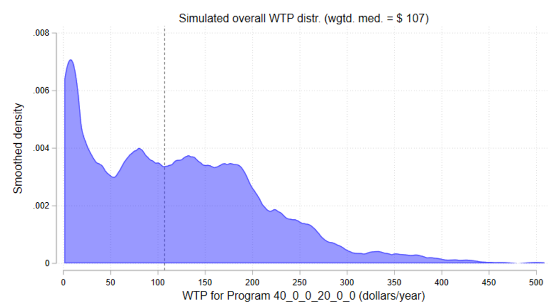
(a) Reference: Baseline program



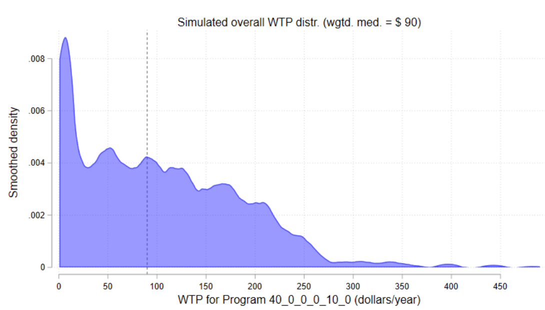
(b) 10% Costs borne by air travel fees



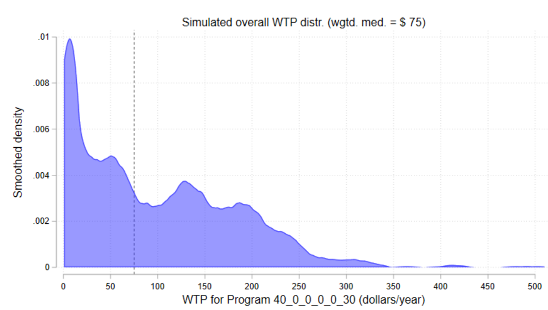
(c) 50% Costs borne by building fees



(d) 20% Costs borne by taxpayers



(e) 10% Revenue spent on academic programs



(f) 30% Revenue spent on offsets

Figure S10: Campus-wide distributions of WTP for programs as the model's six non-baseline shares are individually changed from zero to arbitrary other levels. Any other arbitrary level within the range of the choice-experiment design could also be simulated.

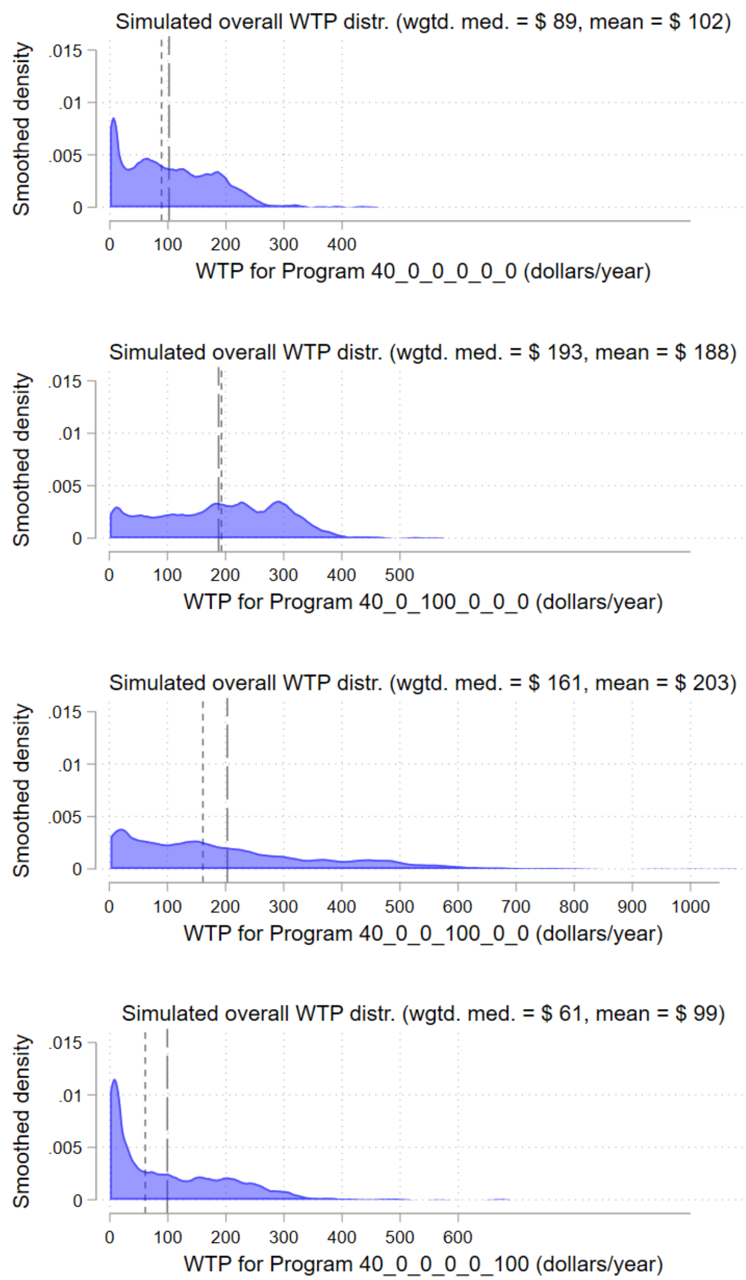


Figure S11: Selected "extreme" programs. Distributions of predicted individual point estimates of WTP (campus-population-weighted) for our baseline program (top), compared to programs where costs are borne 100% as building fees (second, like a campus-wide version of the Yale demonstration program, which is within the domain of our randomized choice sets), a program funded entirely by taxpayers (third), and one that achieves these carbon emissions reductions entirely through off-campus offset purchases (bottom). The design of our choice sets included a maximum cost share for taxpayers of only 20%, and maximum spending on offsets of only 50%. The final two distributions thus project WTP beyond the range of the attributes described to any respondent in the estimating sample.

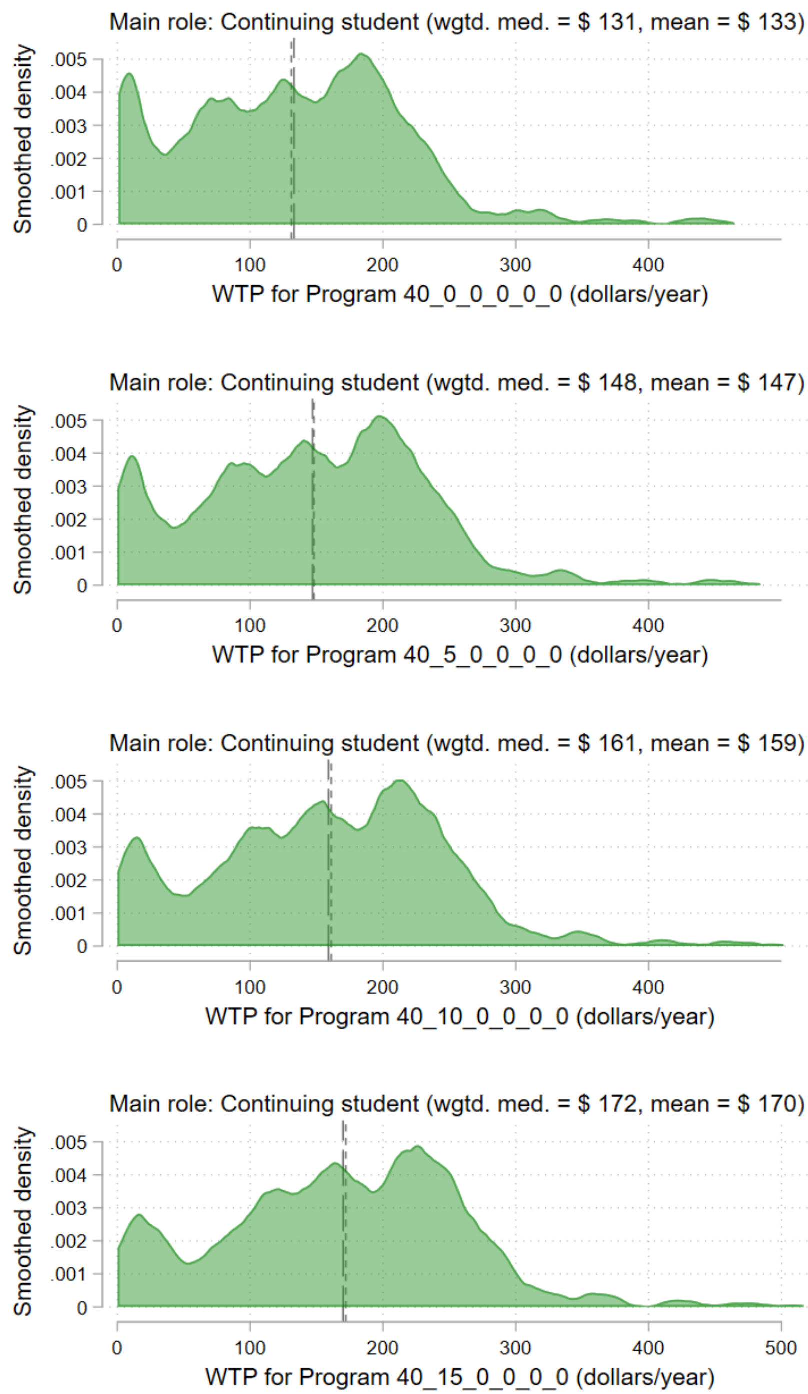


Figure S12: Effects of program designs including different levels of air travel fees. For respondents who report their main role on campus as "continuing student": population-weighted distributions of WTP for a 40% carbon emissions reduction as the share of costs borne via air travel fees (rather than just as a flat fee on all students and employees) increases from 0% to 5% to 10% to 15%.

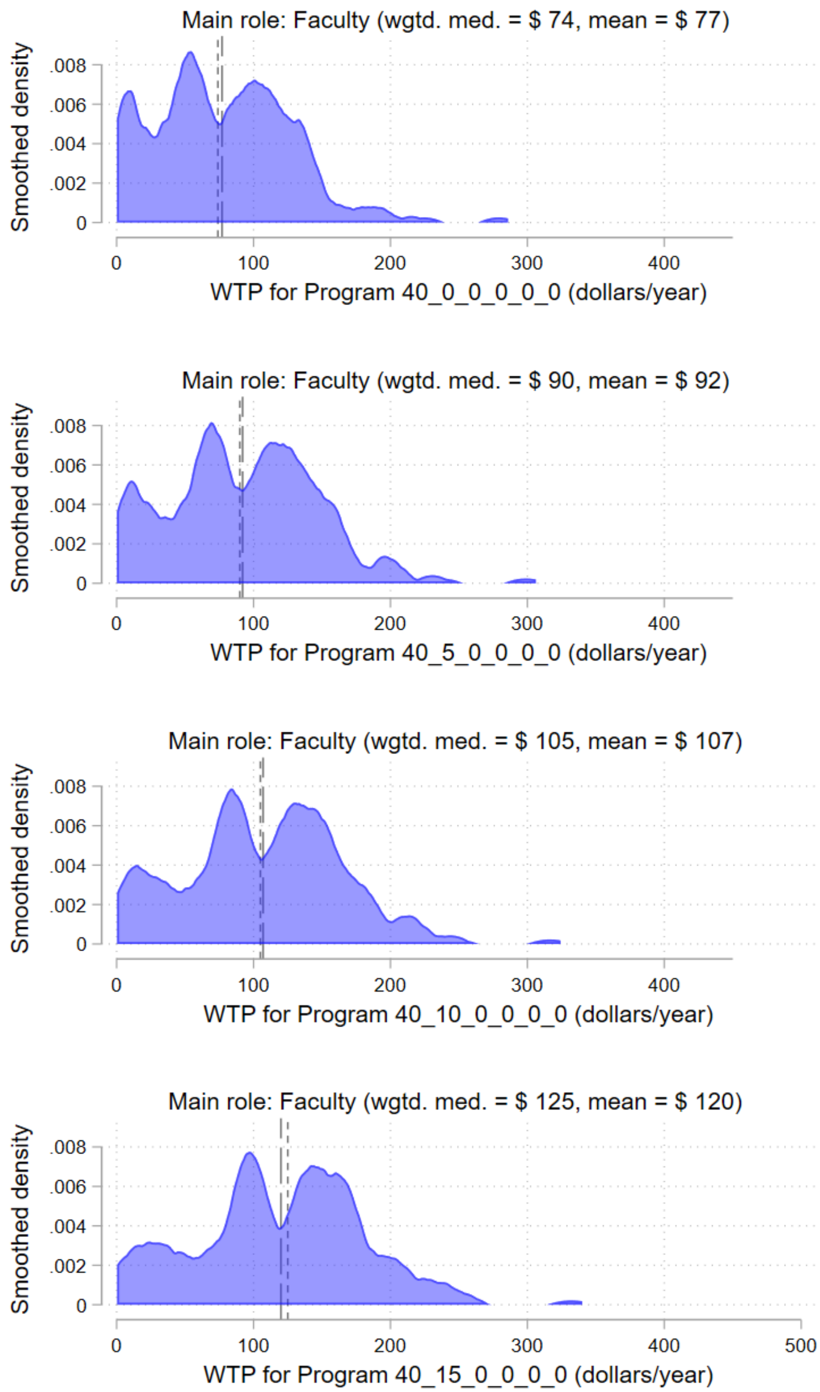


Figure S13: Effects of program designs including different levels of air travel fees. For respondents who report their main role on campus as "faculty": population-weighted distributions of WTP for a 40% carbon emissions reduction as the share of costs borne via air travel fees (rather than just as a flat fee on all students and employees) increases from 0% to 5% to 10% to 15%.

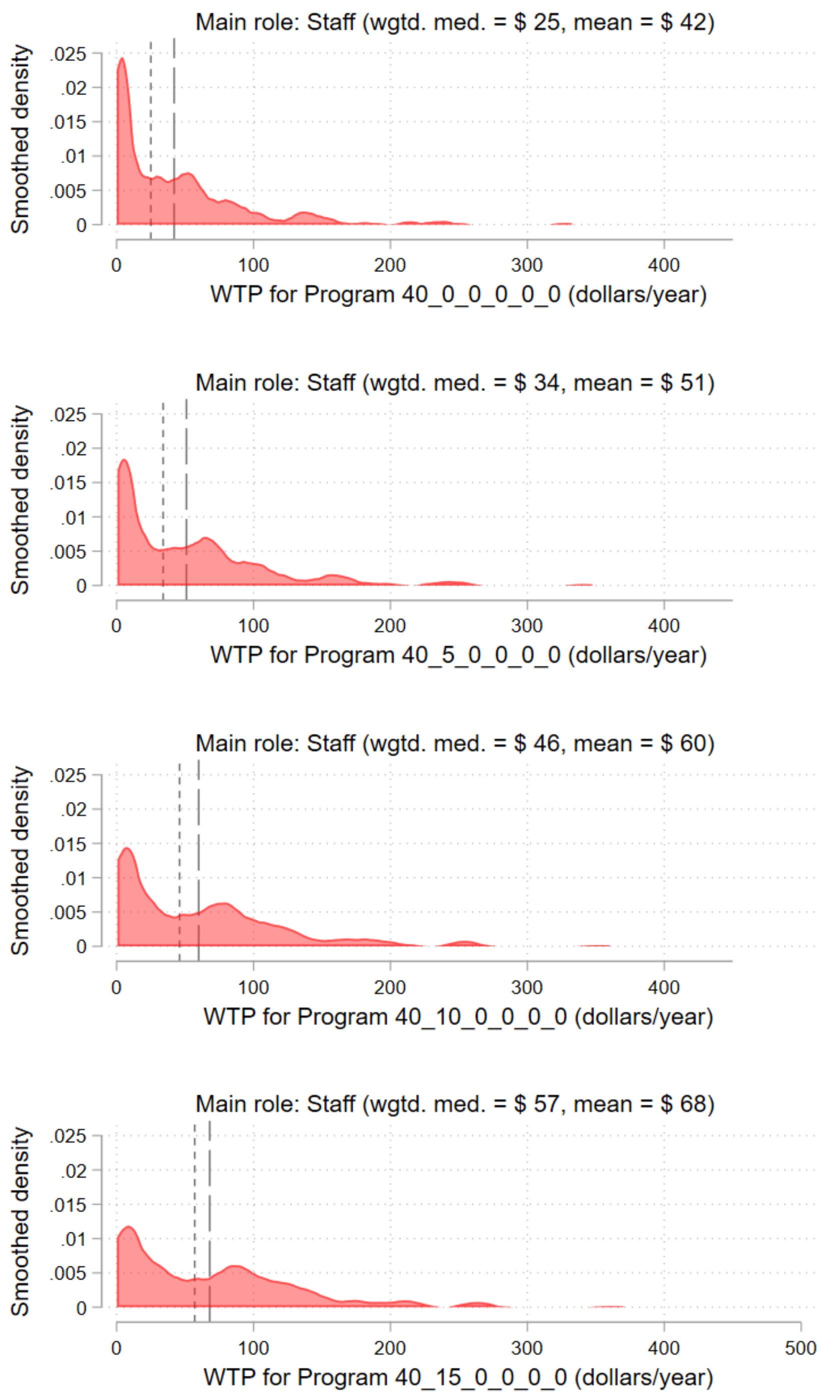


Figure S14: Effects of program designs including different levels of air travel fees. For respondents who report their main role on campus as “staff”: population-weighted distributions of WTP for a 40% carbon emissions reduction as the share of costs borne via air travel fees (rather than just as a flat fee on all students and employees) increases from 0% to 5% to 10% to 15%.

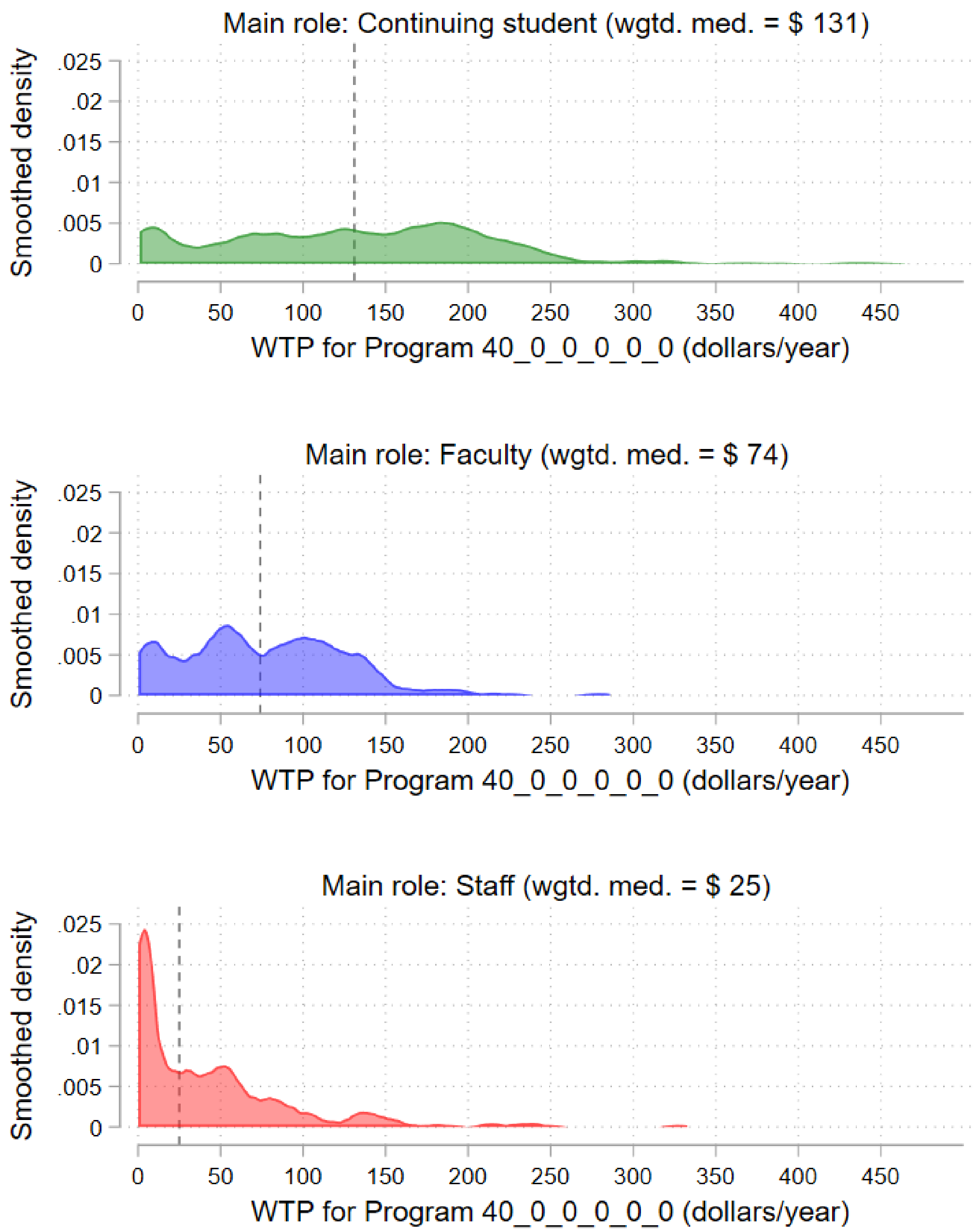


Figure S15: Distributions of predicted individual point estimates of WTP (campus-population-weighted) for three different self-reported "main roles" at the institution: for a 40% carbon emissions reduction where all costs are borne as a flat fee on all students and employees, and all revenues are spent on carbon-reduction programs. Distributions broken out by respondents' self-described "main role" on campus.

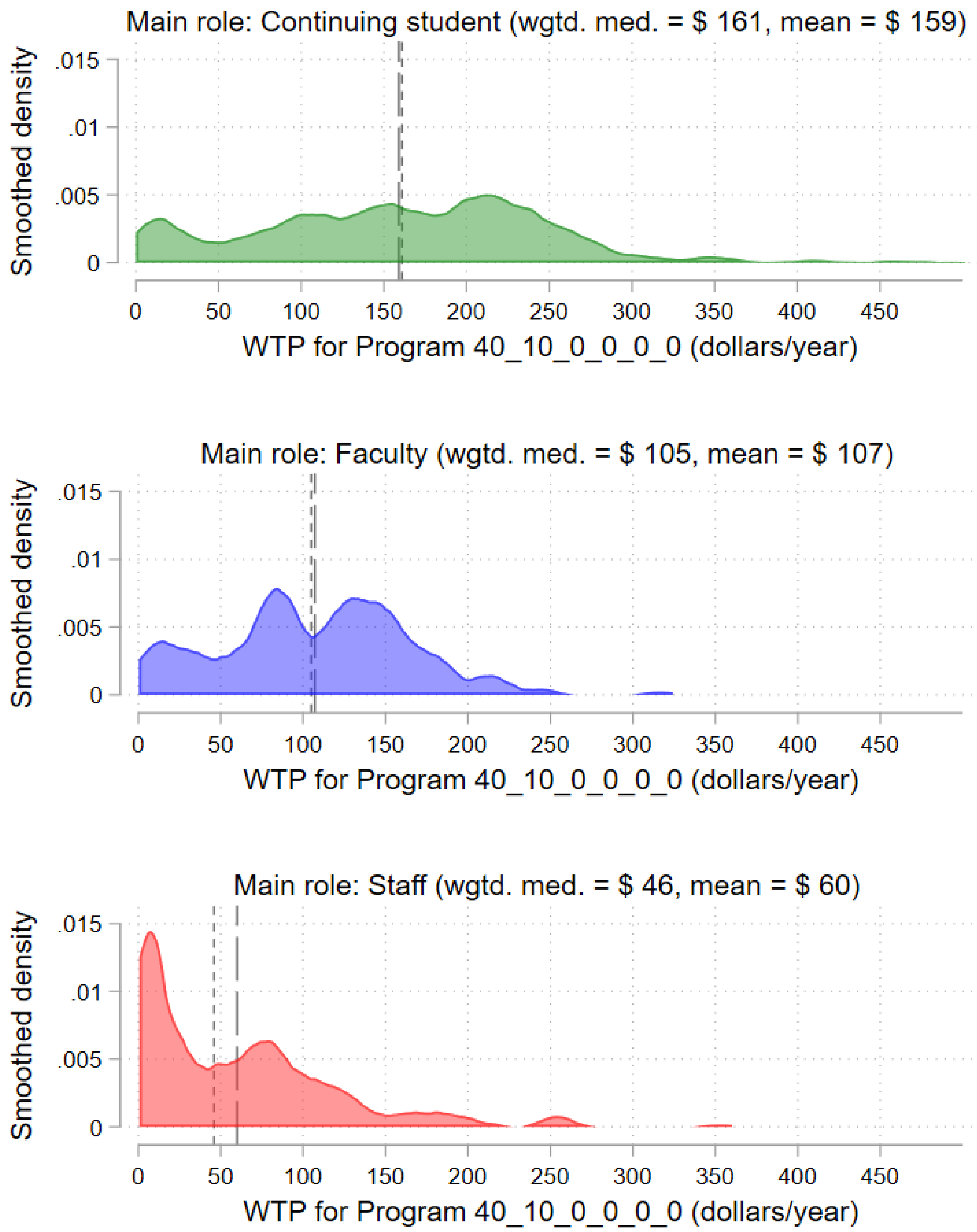


Figure S16: Distributions of predicted individual point estimates of WTP (campus-population-weighted) for three different self-reported "main roles" at the institution: for a 40% carbon emissions reduction where 95% of the costs are borne as a flat fee on all students and employees, 5% of the costs are raised from air travel fees, and all revenues are spent on carbon-reduction programs. Distributions broken out by respondents' self-described "main role" on campus.

A.8 Additional Tables

Table S1: Descriptive statistics: Response-nonresponse model. Response rate of 8.8% is relative to ALL survey invitations, rather than being simply a completion rate among people who started the survey. These explanatory variables represent the subset from a larger universe of available variables, selected by LASSO estimation of a binary logit selection model (where we use the lambda value that minimizes the cross-validation mean-squared-error).

	mean	sd
1=respondent; 0=nonrespondent	0.088	
Permanent-address zip code proportions:		
1=have zip prop. by race	0.837	0.369
1=have zip code average LCV variables	0.950	0.219
zip pr: Black or African American alone	0.010	0.031
zip pr: Aged 80 to 84 years	0.010	0.006
zip pr: Moved; from abroad	0.003	0.004
zip pr: Male householder, no spouse, family hhld	0.024	0.016
zip pr: Housing units - 5 to 9 units	0.021	0.027
zip pr: Housing units - mobile	0.056	0.044
zip pr: Housing with 2 room	0.016	0.019
zip pr: Housing with 3 rooms	0.054	0.038
zip pr: Housing with 8 rooms	0.055	0.034
zip pr: Housing lacking complete kitchen	0.005	0.008
zip pr: House value less than 50,000	0.076	0.046
zip pr: House value 50,000 to 99,999	0.033	0.035
zip pr: House value 1,000,000 or more	0.005	0.017
zip pr: Commute by walking	0.024	0.027
zip pr: Commute 45 to 59 min	0.032	0.036
zip pr: Commute 60 to 89 min	0.034	0.020
zip pr: Heat with solar	0.001	0.003
zip pr: Heat with other fuel	0.005	0.005
zip pr: Industry agric/for/fish/hunt/mine	0.016	0.022
zip pr: Industry wholesale trade	0.018	0.014
zip pr: Industry arts/enter/recr/accom/food	0.084	0.043
zip pr: Industry public admin	0.035	0.021

Continued on next page

Table S1 – continued from previous page

Administrative data–individual characteristics		
1=have individual's gender	0.997	
1=female	0.532	
1=Amer. Indian, Alaska Native	0.008	
1=Asian	0.053	
1=Black or African American	0.019	
1=Hispanic or Latino	0.093	
1=Native Hawaiian	0.003	
1=Nonresident alien	0.089	
1=Race and ethnicity unknown	0.098	
1=Two or more races	0.055	
1=individual's age is known	0.852	
Individual's age squared, if known	627.871	737.862
1=have individual's citizenship status	0.841	
1=not U.S. citizen	0.105	
1=empl.group: career non-tenure-track	0.041	
1=empl.group: courtesy appointment	0.016	
1=empl.group: graduate employee	0.052	
1=empl.group: officer of administration	0.075	
1=empl.group: student employee	0.184	
1=empl.group: other employee	0.024	
1=have employee home organization	0.502	
1=empl.org: Athletics	0.026	
1=empl.org: Arch and Allied Arts	0.005	
1=empl.org: Business	0.018	
1=empl.org: Facilities	0.014	
1=empl.org: Education	0.028	
1=empl.org: Journalism	0.011	
1=empl.org: Law	0.008	
1=empl.org: PhysEd and Rec	0.015	
1=empl.org: Research	0.028	
1=empl.org: Music and Dance	0.010	
1=empl.org: UGS	0.013	
1=empl.org: Housing	0.069	
1=empl.org: Univ. Adv.	0.006	
1=empl.org: Univ. Comm.	0.003	
1=stu.school: Design	0.058	

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Table S1 – continued from previous page

1=stu.school: Journalism	0.081
1=stu.school: Other	0.077
1=stu.dept: Biology	0.030
1=stu.dept: Chemistry	0.014
1=stu.dept: Counseling Psych	0.014
1=stu.dept: Environmental Studies	0.016
1=stu.dept: General Social Science	0.025
1=stu.dept: Law	0.014
1=stu.dept: Music	0.015
1=stu.dept: Psychology	0.045
1=initial 100, no gift card	0.000
1=Spring sample, student	0.398
1=Fall sample, employee	0.057
No. emailed survey invitations	12,568

Table S2: Response-nonreponse model estimates. Explanatory variables selected using campus-population-weighted LASSO binary logit estimation after rendering all three-way choices in the sample into the two corresponding implied pairwise choices. The estimates shown in this table are from a follow-up conditional logit model with both two-way and three-way choices, estimated using conventional methods.

Explanatory variables	Estimate	Std. Err.
Permanent-address zip code proportions:		
1=have zip prop. by race	1.076**	(0.475)
1=have zip code average LCV variables	-0.284	(0.211)
zip pr: Black or African American alone	-3.150	(2.228)
zip pr: Aged 80 to 84 years	7.674	(11.65)
zip pr: Moved; from abroad	-10.66	(13.05)
zip pr: Male householder, no spouse, family hhld	5.853	(4.544)
zip pr: Housing units - 5 to 9 units	-2.816	(3.189)
zip pr: Housing with 2 room	-4.476	(4.210)
zip pr: Housing with 3 rooms	1.281	(2.873)
zip pr: Housing with 8 rooms	4.169*	(2.271)
zip pr: Housing lacking complete kitchen	4.924	(6.349)
zip pr: House value less than 50,000	-2.127	(1.935)
zip pr: House value 50,000 to 99,999	-1.730	(1.677)
zip pr: House value 1,000,000 or more	-5.268	(5.100)
zip pr: Housing units - mobile	-1.148	(1.676)
zip pr: Commute by walking	2.101	(1.512)
zip pr: Commute 45 to 59 min	-4.376	(2.757)
zip pr: Commute 60 to 89 min	-2.443	(3.960)
zip pr: Heat with solar	-25.16	(26.74)
zip pr: Heat with other fuel	-18.27	(11.19)
zip pr: Industry agric/for/fish/hunt/mine	0.550	(1.836)
zip pr: Industry wholesale trade	3.422	(5.471)
zip pr: Industry arts/enter/recr/accom/food	-2.471	(2.263)
zip pr: Industry public admin	-3.539	(3.339)
Administrative data–individual characteristics		
1=have individual's gender	-0.506	(0.545)
1=female	0.283***	(0.0672)
1=Amer. Indian, Alaska Native	-0.669	(0.429)

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Table S2 – continued from previous page

1=Asian	0.218	(0.141)
1=Black or African American	-0.922**	(0.366)
1=Hispanic or Latino	-0.278**	(0.131)
1=Native Hawaiian	-1.131	(1.025)
1=Nonresident alien	-0.430	(0.321)
1=Race and ethnicity unknown	0.169	(0.119)
1=Two or more races	-0.231	(0.166)
1=individual's age is known	-0.920	(0.591)
Individual's age squared, if known	0.0000312	(0.0000602)
1=have individual's citizenship status	0.902	(0.566)
1=not U.S. citizen	-0.298	(0.276)
1=empl.group: career non-tenure-track	-0.366**	(0.169)
1=empl.group: courtesy appointment	-1.049***	(0.289)
1=empl.group: graduate employee	0.240	(0.184)
1=empl.group: officer of administration	-0.0228	(0.122)
1=empl.group: student employee	-0.145	(0.172)
1=empl.group: other employee	-0.399**	(0.203)
1=have employee home organization	0.827***	(0.163)
1=empl.org: Athletics	-0.873***	(0.243)
1=empl.org: Arch and Allied Arts	-1.358**	(0.598)
1=empl.org: Business	-0.288	(0.230)
1=empl.org: Facilities	-0.333	(0.242)
1=empl.org: Education	-0.705***	(0.217)
1=empl.org: Journalism	-0.403	(0.302)
1=empl.org: Law	0.0434	(0.306)
1=empl.org: PhysEd and Rec	-0.687**	(0.323)
1=empl.org: Research	0.172	(0.165)
1=empl.org: Music and Dance	-0.743**	(0.341)
1=empl.org: UGS	-0.250	(0.276)
1=empl.org: Housing	-0.530***	(0.145)
1=empl.org: Univ. Adv.	-0.414	(0.350)
1=empl.org: Univ. Comm.	0.292	(0.387)
1=stu.school: Design	0.285**	(0.137)
1=stu.school: Journalism	-0.245	(0.161)
1=stu.school: Other	-0.115	(0.138)
1=stu.dept: Biology	0.260	(0.188)
1=stu.dept: Chemistry	0.466**	(0.235)

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Table S2 – continued from previous page

1=stu.dept: Counseling Psych	-0.439	(0.336)
1=stu.dept: Environmental Studies	0.758***	(0.218)
1=stu.dept: General Social Science	-0.128	(0.275)
1=stu.dept: Law	0.532**	(0.256)
1=stu.dept: Music	0.588**	(0.265)
1=stu.dept: Psychology	-0.219	(0.189)
Survey wave information		
1=Fall sample, employee	0.370***	(0.118)
1=Spring sample, student	-0.265***	(0.0847)
1=initial 100 invitations, no gift card	4.109***	(1.173)
Constant	-2.399***	(0.548)
No. of emailed survey Invitations	12,568	

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

Table S3: Descriptive statistics: Sources of heterogeneity in preferences, identified by LASSO variable selection in choice model

	mean	sd
Permanent-address zip code proportions:		
1=have relevant ZIP data for variable set 1	0.902	0.298
1=have relevant ZIP data for variable set 3	0.901	0.299
zip pr: Race: Black alone	0.009	0.015
zip pr: Race: Asian alone	0.025	0.031
zip pr: U.S. citizen, naturalized	0.021	0.017
zip pr: Moved: Diff. cnty, same st	0.037	0.019
zip pr: Moved: From abroad	0.003	0.004
zip pr: Ltd English, spk Spanish	0.005	0.009
zip pr: Housing: Multi-unit	0.096	0.099
zip pr: Housing: Incompl. plumbing	0.002	0.003
zip pr: Housing: Incompl. kitchen	0.005	0.008
zip pr: House values: 50K-100K	0.035	0.024
zip pr: Rental rates: Less than 500	0.036	0.041
zip pr: Rental rates: 2.5K-3K	0.002	0.010
zip pr: Rental rates: 3K up	0.003	0.007
zip pr: Heating: Bottled gas	0.008	0.013
zip pr: Heating: Solar	0.000	0.002
zip pr: Industry: Information	0.018	0.008
zip pr: Rural	0.064	0.140
Administrative data–individual characteristics		
1=from Asia	0.002	0.042
1=Non-white	0.379	0.485
1=Individual's age known	0.759	0.428
De-meaned indiv. age, if known	0.000	10.201
1=Not U.S. citizen	0.054	0.227
1=Employee	0.695	0.461
1=empl.group: Career non-tenure	0.054	0.227
1=empl.group: Classified staff	0.134	0.340
1=empl.group: Graduate employee	0.087	0.282
1=empl.group: Student employee	0.180	0.384
1=empl.org: Business	0.021	0.143

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Table S3 – continued from previous page

1=empl.org: Design	0.032	0.175
1=empl.org: Education	0.024	0.154
1=empl.org: Library	0.026	0.160
1=empl.org: Other	0.143	0.350
1=Student	0.706	0.456
1=stu.school: Design	0.067	0.250
1=stu.school: Educ.	0.040	0.195
1=stu.school: Business	0.068	0.251
1=stu.school: Law	0.022	0.146
1=stu.school: Other	0.082	0.275
1=stu.school: Undeclared	0.041	0.198
1=stu.dept: Biology	0.033	0.180
1=stu.dept: Chemistry	0.022	0.146
1=stu.dept: Envir. Studies	0.024	0.154
1=stu.dept: Human Physiology	0.024	0.154
1=stu.dept: Psychology	0.031	0.173
Survey Data - Reported individual characteristics		
1=Somewhat or very liberal	0.674	0.469
1=Somewhat or very conserv	0.086	0.280
1=Fall 2018 survey wave	0.419	0.494
1=last 12 mos: Inland floods	0.059	0.235
1=last 12 mos: Hurricane	0.043	0.204
1=last 12 mos: Tornado	0.034	0.182
1=last 12 mos: Sev. drought	0.097	0.296
1=last 12 mos: Wildfire	0.111	0.314
1=last 12 mos: Severe winter	0.138	0.345
1=last 12 mos: Heat wave	0.423	0.494
1=main role: Staff	0.208	0.406
1=main role: Admin	0.046	0.210
1=Hhld income reported	0.867	0.340
De-meaned hhld inc in ’000s if known	-0.000	55.433
Based on response propensity model		
De-meaned response propensity	0.509	0.728
Observations	1,107	

Note to Table S3: One person in the sample is missing Census zip-code data for variable set 3 (travel modes, commuting time, heating fuel, industry, and urban/rural). The correlation between the indicators for set 1 and set 3 is 0.9972, so the clogit algorithm is able to retain only one or the other of these indicators. In the estimating sample, the indicator for set 1 is perfectly correlated with that for sets 2, 4, and 5.

Table S4: More examples of predicted referendum voting percentages and overall campus-level net benefits, by featured subgroup in the campus population versus all others, and overall (based on individual WTP amounts for simulations of different carbon-reduction programs using our estimated utility-function parameters. Assumes individuals will vote for a program if their individual WTP exceeds their individual cost. Benefits are based on average WTP within a group times the number of people in that group.)

Simulation:	(1)	(2)	(3)	(4)	(5)	(6)
Featured group	Students	Students	Students	Students	Students	Students
No. People in featured group	23,600	23,600	23,600	23,600	23,600	23,600
Other group	Non-students	Non-students	Non-students	Non-students	Non-students	Non-students
No. People in other group	4,500	4,500	4,500	4,500	4,500	4,500
No. Taxpayers in state	2,600,000	2,600,000	2,600,000	2,600,000	2,600,000	2,600,000
Main program attributes - emissions reduction and overall cost:						
% Carbon emissions reduction	40	20	35	30	40	40
Total cost/year of program	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 3,000,000	$ 2,500,000
How costs will be borne:						
% Cost in flat fees	65	65	100	65	65	65
Who pays flat fees?	Students	Everyone	Students	Students	Students	Students
% Cost as air travel fees	5	5	0	5	5	5
Who pays air travel fees?	Everyone	Everyone		Everyone	Everyone	Everyone
% Cost as building energy fees	20	20	0	20	20	20
Who pays building energy fees?	Everyone	Everyone		Everyone	Everyone	Everyone
% Cost paid by taxpayers	10	10	0	10	10	10
Who pays taxpayer costs?	Everyone	Everyone		Everyone	Everyone	Everyone
How revenues will be spent:						
% Spent on C programs	90	90	70	90	90	90
% Spent on acad. programs	0	0	10	0	0	0
% Spent on offsets	10	10	20	10	10	10
By group: Types of per-person costs with this program						
Featured group:						
Per-person flat fees per year	$ 83	$ 69	$ 127	$ 83	$ 83	$ 69
Per-person air travel fees per year	$ 5.34	$ 5.34	$ 0	$ 5.34	$ 5.34	$ 4.45
Per-person building energy fees per year	$ 21	$ 21	$ 0	$ 21	$ 21	$ 18
Per-person tax increase per year	$ .12	$ .12	$ 0	$ .12	$ .12	$ .10
Other group:						
Per-person flat fees per year	$ 0	$ 69	$ 0	$ 0	$ 0	$ 0
Per-person air travel fees per year	$ 5.34	$ 5.34	$ 0	$ 5.34	$ 5.34	$ 4.45
Per-person building energy fees per year	$ 21	$ 21	$ 0	$ 21	$ 21	$ 18

Continued on next page

Table S4 – continued from previous page

Simulation:	(1)	(2)	(3)	(4)	(5)	(6)
Per-person tax increase per year	$ .12	$ .12	$ 0	$ .12	$ .12	$ .10
Overall per-person costs by group, with this program						
Overall per-person cost, featured group per year	$ 109	$ 95	$ 127	$ 109	$ 109	$ 92
Overall per-person cost, other group per year	$ 26	$ 95	$ 0	$ 26	$ 26	$ 23
Costs to state taxpayers						
Total cost to off-campus state taxpayers per year	$ 296,628	$ 296,628	$ 0	$ 296,628	$ 296,628	$ 247,190
Per-taxpayer cost, state taxpayers, per year	$ .12	$ .12	$ 0	$ .12	$ .12	$ .10
Referendum on program, by group						
Referendum vote share yes for featured group	67 %	57 %	40 %	61 %	67 %	71 %
Referendum vote share yes for other group	66 %	9 %	100 %	58 %	66 %	67 %
Referendum on program, overall						
Campus-wide referendum vote share yes	67 %	49 %	50 %	61 %	67 %	70 %
Benefit-cost assessment, for campus						
Campus-wide benefits per year	$ 5,451,600	$ 3,516,400	$ 3,256,800	$ 4,578,400	$ 5,451,600	$ 5,451,600
Campus-wide cost per year	$ 2,700,000	$ 2,700,000	$ 3,000,000	$ 2,700,000	$ 2,700,000	$ 2,250,000
Campus-wide net benefits per year	$ 2,751,600	$ 816,400	$ 256,800	$ 1,878,400	$ 2,751,600	$ 3,201,600